The economics of targeting systemic drivers of mental health using dynamic simulation modelling

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Statement of originality

This is to certify that the content of this thesis is my own work. This thesis has not been submitted for any other degree or purpose.

I certify that the intellectual content of this thesis is the product of my own work, and that all assistance received in preparing this thesis and all sources have been acknowledged.

[redacted]

Paul Crosland

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Author contribution statement

For all chapters of this thesis I conceived of the research topic, conducted the analysis and research of literature, had primary responsibility for writing, and primary responsibility for the submission and review process with journals. I am first author and corresponding author for all four peer-reviewed journal articles.

The research was conducted for the Right Care, First Time, Where you Live project. Ian B. Hickie, Jo-An Occhipinti and Yun Ju Christine Song obtained funding from the BHP Foundation and managed the program.

Further detail is provided below on author contribution per chapter following the Contributer Role Taxonomy (CRediT). There is no author contribution table for Chapter 5 because I had sole responsibility for writing this section, with feedback provided from the three PhD supervisors only.

[redacted]

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As supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statements above and below are correct.

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Chapter 1: Literature review

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Chapter 2: Modelling Study 1 – cost-utility analysis

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Catherine Vacher		✓				✓			✓					✓
Adam Skinner		✓				✓			✓					✓
Andrea N Natsky		✓				✓			✓					✓
Sebastian Rosenberg														✓
Raphael Hasudungan		✓												✓
Sam Huntley							✓							✓
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Kristen Tran		✓												✓
Seyed Hossein Hosseini		✓				✓			✓					✓
Catherine Vacher		✓				✓			✓					✓
Adam Skinner		✓				✓			✓					✓
Jordan van Rosmalen													✓	✓
Sebastian Rosenberg														✓
Frank Iorfino														✓
Victoria Loblay														✓
Olivia Iannelli		✓					✓							✓
Sarah Piper		✓					✓							✓
Yun Ju Christine Song				✓			✓	✓						✓
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Chapter 4: Modelling Study 3 – optimisation analysis

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Kim-Huong Nguyen		✓				✓			✓		✓			✓
Kristen Tran		✓												✓
Catherine Vacher		✓				✓			✓					✓
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Artificial Intelligence

No content produced by generative AI tools has been used in the preparation of this thesis.

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I am an employee of the Brain and Mind Centre, University of Sydney.

I have no conflicts of interest to declare.

Publications constituting this thesis

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Only first author articles constituting this thesis are listed here. My University of Sydney profile contains a full list of research publications.

Presentations related to this thesis

Oral presentation: ‘Cost effectiveness of eight system-level strategies for enhancing youth mental health’. Australian Health Economics Society, Adelaide, September 2023.

Invited oral presentation: ‘Combining system dynamics and local knowledge to generate economic evidence for mental health’. Oxford Mental Health Economics and Policy, online, April 2024.

Oral presentation: ‘Combining system dynamics and local knowledge to generate economic evidence for mental health in ACT’. Right Care, First Time, Where You Live Symposium, Sydney, November 2024.

Invited oral presentation: ‘Combining system dynamics and local knowledge to generate economic evidence for mental health’. Centre for Disability Research and Policy, University of Sydney and research collaborators seminar, online, February 2025.

Oral presentation: ‘The economic value of improving the social determinants of mental health’. Sydney Health Economists Discussion group, online, May 2025.

Invited oral presentation: ‘The economic value of improving the social determinants of mental health’. Queensland Brain Injury Collaborative, University of Queensland, online, August 2025.

Oral presentation: ‘Exploring the optimal mix of interventions and mental health services capacity with optimisation analysis’. Discovery Seminar, Youth Mental Health and Technology, Brain and Mind Centre, University of Sydney, October 2025.

Contents

Appendices

List of tables

Tables published in journal articles are not listed here.

List of figures

Figures published in journal articles are not listed here.

Acronyms and abbreviations

ACT	Australian Capital Territory
AI	Artificial intelligence
AU/AUD	Australian dollars
BAU	Business as usual
CHEERS	Consolidated Health Economic Evaluation Reporting Standards
DSM	Dynamic simulation model/modelling
ED	Emergency department
GRADE	Grading of Recommendations Assessment, Development and Evaluation
HHS	Hospital and Health Service
HTA	Health technology assessment
ICER	Incremental cost-effectiveness ratio
INMB	Incremental net monetary benefit
LHD	Local Health District
NMB	Net monetary benefit
PHN	Primary Health Network
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analysis
PSA	Probabilistic sensitivity analysis
SDM	System dynamics model/modelling
QALY	Quality-adjusted life year
US/USD	United States dollars

Both SDM and DSM are used frequently throughout this thesis and are not interchangeable. SDM refers to a specific modelling technique whereas DSM refers to the broader category of dynamic modelling approaches, of which SDM is one type, as discussed in detail in Chapter 1.

Abstract

The health and economic burden of mental ill-health is worsening in Australia and globally, particularly in younger age groups. The increasing incidence and persistent prevalence of mental health conditions is most likely driven by a complex causal web of social and economic factors; barriers to accessing services; and lack of personalised and measurement-based care. A shortage of transparent, accountable and evidence-based decision-making processes further limit the effectiveness and allocative efficiency of investments intended to improve population mental health.

System dynamics modelling (SDM) provides an explicit framework to account for the various influences on resource allocation decisions by combining data from a variety of sources, including expert advice, analytical and experimental evidence from scientific literature, observational data, administrative data, resources, and costs. These computer-based mathematical representations of the relationships between system components allows for forecasting and testing of scenarios in the virtual world before interventions, new policies or other changes to the system are implemented in the real world.

Economic evaluation aims to determine the cost effectiveness of new interventions or other system changes by comparing alternative courses of action in terms of their health benefits, costs and consequences. Conventional economic modelling techniques developed primarily for the purposes of health technology assessment (HTA) are usually based on static cohort, Markov health state transition approaches and linear, cause and effect processes. Dynamic modelling approaches attempt to account for the characteristics of the complex, dynamic systems in which we live. These include non-linear relationships, feedback loops that either amplify or diminish desirable or undesirable outcomes, and interactions among different components of the system. A literature review conducted for this thesis did not find any studies that used a SDM approach for economic evaluation of mental health interventions.

The objective of this PhD research project was to use SDM to conduct economic evaluation of mental health interventions, with the ambition of providing a more complete and nuanced picture of the relative cost effectiveness of a wide range of strategies that decision makers could invest in to improve youth mental health. The overarching research question was, 'Is SDM a feasible and useful approach to conducting economic evaluation of mental health interventions, and what are the unique attributes of this technique compared with conventional modelling techniques?' This was achieved through the application of the approach to three

modelling studies, each one exploring a distinct economic question facilitated by the unique characteristics of the SD framework.

The research conducted for this PhD has made significant contributions to methodological knowledge by developing applied examples that extend the capabilities of the SDM-based approach to economic evaluation that health economists, systems modellers and other researchers can adopt and build upon in the future. It has also contributed to scientific knowledge and mental health policy and planning by generating economic evidence that is useful in and of itself for guiding resource allocation decisions that aim to improve youth mental health (i.e. the cost effectiveness of new interventions).

Modelling Study 1 was a cost-utility analysis of eight interventions for youth mental health for the Australian Capital Territory. It found that Technology-enabled integrated care, Family education, an Online parenting programme and Multi-cultural informed care were cost effective. Methodological insights included the identification of synergistic effects, identification of emergent outcomes in the form of unintended consequences, the importance of mental health service capacity on the cost effectiveness of some interventions, and a user interface for stakeholders to enhance transparency and accountability of decision making.

Modelling Study 2 estimated the health benefits and economic value of improving the social determinants of mental health in the Brisbane South region. Even modest improvements in determinants resulted in material increases in health outcomes and reduction in costs. Social cohesion, childhood difficulties, substance misuse and unemployment were a set of social determinants that could be targeted for meaningful improvements in a variety of health and cost outcomes.

Modelling Study 3 used constrained optimisation analysis within a SDM framework to systematically test the cost effectiveness of seven scenarios varying existing mental health services capacity growth, new interventions targeted at youths, and budget constraints on the amount of investment funds available for new interventions. The analysis demonstrated there is health and economic value in expanding existing services and implementing new interventions concurrently to capitalise on synergistic effects; the combination of interventions that is most cost effective can be identified using systematic methods in response to changes in the budget constraint; and there are health and economic consequences to attenuated levels of investment in new interventions. The same combination of five interventions was identified as cost effective when no budget constraint was applied: Technology-enabled integrated care, Post-suicide attempt care; Youth mental health service hubs; Safety planning; and the Acute response team. The preferred combination of interventions changed as the budget constraint was intensified and the health benefits and economic value forgone due to these levels of lower investment were estimated.

Strengths of the PhD research project include the participatory systems modelling process, taking a system-level approach to mental health policy and planning, integrating best-practice methods of economic evaluation within the SDM technique, developing a framework for explicit, transparent and accountable decision making, and the adoption of both health and societal perspectives.

Overarching limitations include the dependence of model accuracy on the quality and availability of input data; the potential oversimplification of complex social and health systems in the model structure; lack of comprehensive uncertainty analysis in Modelling Study 2 and Modelling Study 3 due to time and computing constraints; the exclusion of some costs and benefits from the societal perspective to make the exercise tractable; the potential for model complexity to limit stakeholder understanding; and the take-up of the SDMs being constrained by the lack of existing structured and systematic decision-making processes.

This PhD thesis described a body of research advancing the field of economic evaluation for mental health by using SDM as the structural framework for modelling. There are several opportunities for future research to build upon the initial methods developed here, including expanding upon the decision-support tools developed here for even greater accuracy and functionality, and supporting the development of better decision-making processes within agencies that have a remit for mental health reform to have greater capacity and capability for adopting sophisticated simulation modelling techniques like the ones developed through this PhD thesis.

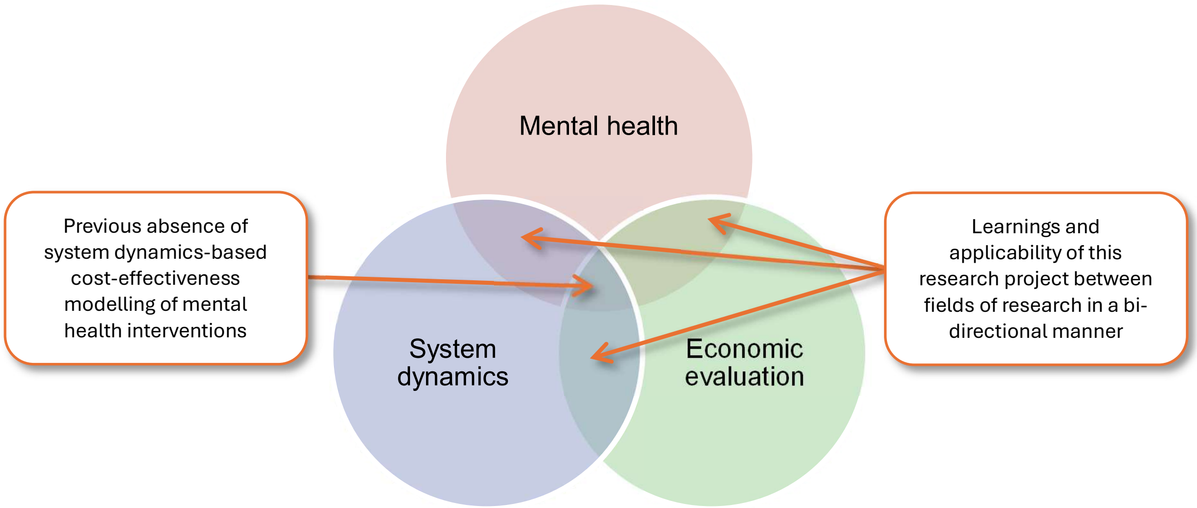
Preface to Chapter 1

Chapter 1 is an expanded and adapted version of an article published in *PharmacoEconomics*, 'Incorporating complexity and system dynamics into economic modelling for mental health policy and planning' [1]. The original article is provided as an appendix (Appendix 1). This is a narrative literature review based on the proposition that system dynamics modelling is rarely used in the field of health economics, despite the publication of guidance for this over a decade ago [2], and there are no studies investigating the cost effectiveness of mental health interventions using system dynamics modelling (SDM). A rationale is then provided for why this might be a useful economic modelling technique for mental health, forming the foundational premise of this PhD research project.

Although I have conducted and published several systematic reviews in the past, I decided this was not an appropriate method for this component of work. I was aware of several contemporary reviews already published on related and overlapping topics (discussed in this chapter), obviating the need for another systematic review. Furthermore, based on the findings of these reviews, there was a high likelihood of finding no studies meeting the research question of interest at the intersection of health economic evaluation, system dynamics modelling and mental health (Figure 1). Therefore, it was seen as a more valuable contribution to scientific knowledge to write a transdisciplinary narrative literature review focusing on high-level evidence across the three fields of research based on non-systematic searches of the literature, citation searches and relevant reference identification.

Chapter 1 starts by describing the problem of mental ill-health in Australia and globally. Dynamic simulation modelling (DSM) is introduced. Contemporary paradigms in mental health treatment and prevention are then discussed. The theoretical foundations of economic evaluation are presented, along with a summary of current economic evidence on mental health interventions, before tying these methodological frameworks together for the rationale underlying this PhD thesis. The objectives of the research, constituent research questions and outline of the thesis are presented at the end of this chapter.

Figure 1: The gap in knowledge at the intersection of three fields of research and contribution of this research project



1. Introduction and literature review

1.1. Introduction

The objective of this chapter is to outline the need for greater use of dynamic simulation modelling (DSM), with a focus on system dynamics modelling (SDM), for generating economic evidence to guide investments in mental health, particularly for children, adolescents, and young adults due to the increasing prevalence of mental health conditions in this population and the long term consequences of this. The overarching research question of the thesis is explained, along with the research questions for each individual chapter, and how the chapters interrelate methodologically and conceptually.

Advocating for greater use of DSM does not preclude the continued use of conventional approaches, such as state transition Markov models (discussed below). Rather, it adds to the repertoire of tools available for health economists to help decision makers have a more complete understanding of the potential influence of systems, complexity, and dynamics on the economic credentials of alternative courses of action.

Interest in dynamic approaches to conducting economic evaluation is growing and they suit some decision-making contexts, such as precision medicine and infectious disease, more than others [3]. This chapter seeks to provide theoretical reasons why SDM is well-placed to help fill an evidence gap at the intersection of mental health, economic evaluation, and simulation modelling research across five main sections.

Firstly, the mental health challenge is described, in terms of the health and economic burden, both in Australia and globally. Secondly, DSM is explained, including its relevance to mental health. Thirdly, I provide a summary of contemporary approaches to mental health prevention and treatment. Fourthly, fundamental economic concepts are discussed and the current state of economic evidence on mental health interventions is explored. Finally, these three fields of research are brought together to propose an integrated process of generating economic evidence for mental health using SDM.

The theoretical benefits of DSM discussed in this chapter include the ability to account for the following: the characteristics of complex dynamic systems; context-specific implementation parameters, such as reach and service capacity constraints; synergistic or antagonistic effects; unintended consequences that are not accounted for in conventional economic modelling techniques; participatory model-building processes that make cost-effectiveness analyses directly relevant to intersectoral decision makers and young people with a lived experience of mental health conditions, enhancing the likelihood of implementing cost-effective interventions; and enhancing transparency and accountability of the decision-making process. One of the objectives of this PhD research project was to explore whether these benefits could be realised in the real-world application of SDM-based economic evaluation in mental health.

Panel 1 below contains a summary of definitions of key terms.

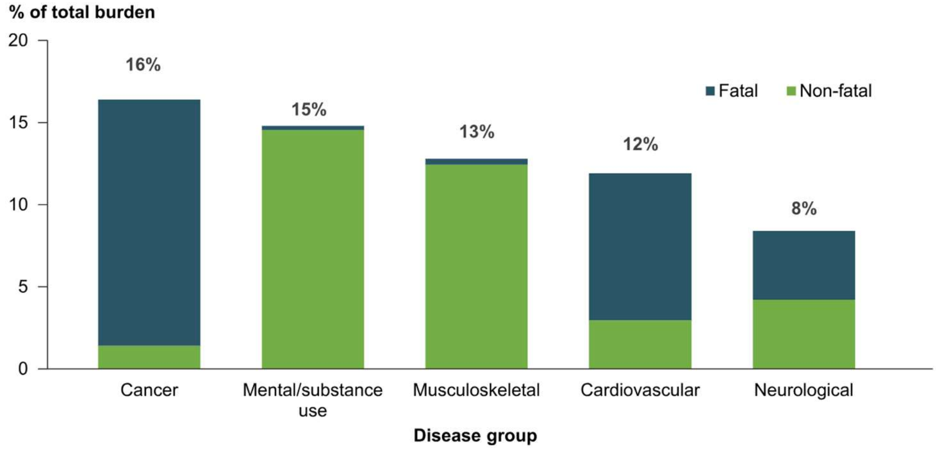
1.2. Health and economic burden of mental ill-health

1.2.1. Mental ill-health in Australia

In Australia, mental illness and substance use disorders accounted for 14.8% of total health burden in terms of disability-adjusted life years (DALYs) in 2024 (Figure 2) [4]. According to the Global Burden of Disease Study, Australia experiences the highest rate of age-standardised DALYs due to mental health compared to other countries [5]. The proportion of overall health burden attributable to mental illness has increased relative to other diseases since 2003 (Figure 3) [4].

Younger age groups experience a higher degree of burden compared with older age groups (Figure 4) [4]. Children, adolescents and young adults have experienced a greater deterioration in mental health than older adults over the past decade [6,7]. For example, a longitudinal survey (the Household, Income and Labour Dynamics in Australia Survey (HILDA)) found that the prevalence of depression and anxiety more than doubled between 2009 and 2021 in Australian young people aged 15–34 years (from 6.1% to 14.4% for males and from 12.7% to 29.3% for females) [8]. The prevalence of psychological distress also more than doubled between 2011 and 2021 in young people in Australia aged 15–24 years (from 18.4% to 42.3%) [8]. Consequently, suicide remains the leading cause of death for people aged 15 to 44 years of age [9]. Experiencing mental health challenges when younger has important implications for future trajectories of mental and physical health and participation in the labour force in adulthood [10]. Considering that around 75% of mental illness manifests before the age of 25, failure to prevent these conditions in younger people and improve the mental health care system mean the health and economic consequences are persistent for many years to come [11,12].

Figure 2: Proportion of total burden, fatal and non-fatal composition of total burden, for the leading 5 disease groups in 2024



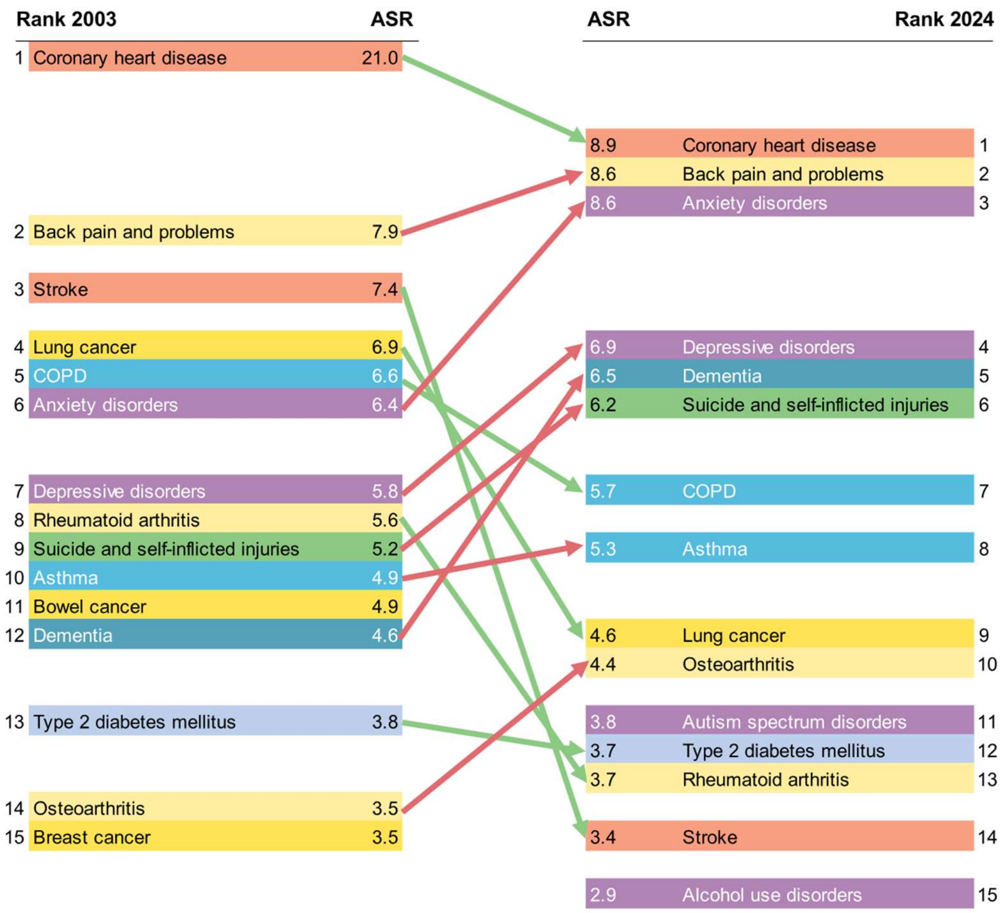
Source: AIHW – Australian Burden of Disease Study 2024 [4]

There is a socioeconomic gradient whereby people that are most disadvantaged experience anxiety disorders 40% more, and suicide and self-inflicted injuries 88% more, than people at least disadvantage [13]. The suicide rate for Indigenous Australians is double the rate than non-Indigenous Australians [13].

The prevalence of mental disorders has not decreased despite increased funding and treatment provisions in Australia over the last decade [14]. This is due to a concurrent rise in the incidence of psychological distress and disorders [15], driven by the economic, social, cultural and technological environments in which we live [16]. These increases have occurred despite greater national attention on youth mental health, suicide prevention, and recent additional funding [17,18]. However, mental health's share of total health spending (7% when the health burden is 15%) has not increased in 10 years [19]. Systems and processes that enable accountability and efficient resource allocation for mental health are also poorly developed [19,20].

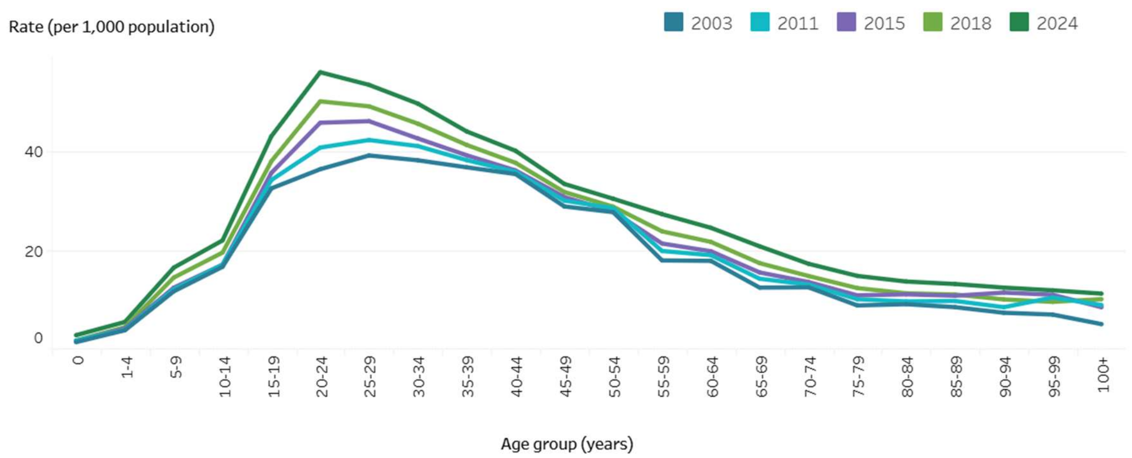
The intractability of the prevalence of mental ill-health necessitates transformed models of care [21], implementing evidence-based interventions and policies that are effective and cost-effective rather than doing more of the same thing, prevention through reforming economic and social systems [16], and potentially even the re-conceptualisation of mental suffering itself [22].

Figure 3: Change in disease ranking and age-standardised DALY rate (DALY per 1,000 population) between 2003 and 2024



Source: AIHW – Australian Burden of Disease Study 2024 [4]
ASR = age-standardised rate; COPD = chronic obstructive pulmonary disease.

Figure 4: Comparison of age-specific DALY rates for mental and substance use disorders



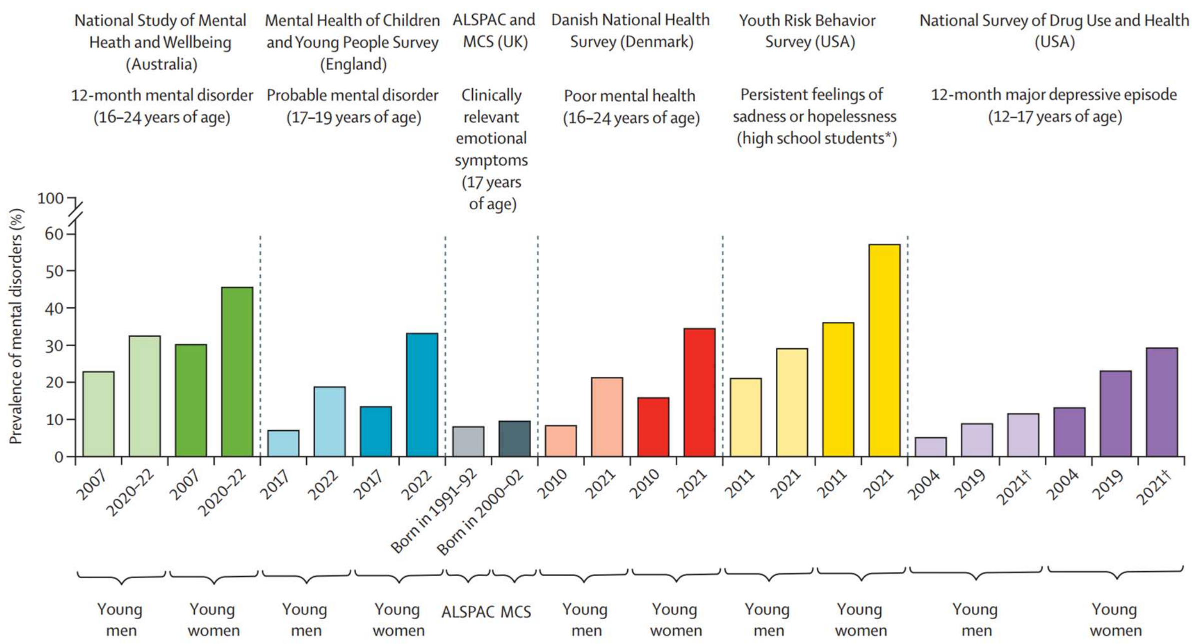
Source: AIHW – Australian Burden of Disease Study 2024 [4]
Rates were age-standardised to the 2001 Australian Standard Population

1.2.2. Global mental health

The Lancet Commission on global mental health and sustainable development states that the “collective failure to respond to this global health crisis results in monumental loss of human capabilities and avoidable suffering” [23]. Mental health conditions are among the leading causes of global disease burden, are highly prevalent in high income countries, and are gaining prominence in developing countries (Figure 6, Figure 7) [23,24]. Depressive disorders were the second-highest cause of non-fatal health burden globally in 2021, an increase of 36.5% from 2010 [24]. A population-based survey across 27 European countries found that the prevalence of current depressive disorder was 6.38% for the whole cohort, ranging between 2.58% for the Czech Republic to 10.33% in Iceland [25].

The Lancet Psychiatry Commission on youth mental health catalogued the evidence and urgency of this problem for the global youth population [26]. Similar to the Australian situation mentioned in the previous section, population-wide surveys across several countries have recorded increases in the prevalence of mental disorders in younger cohorts (Figure 5) [6,26]. The Lancet Psychiatry Commission proposes several ‘megatrends’ as the driving forces behind these changes: rising intergenerational inequality, unregulated social media, wage theft, insecurity of employment and climate change [26]. “Young people are showing the most serious warning signs and symptoms of a society and a world that is in serious trouble” [26].

Figure 5: Youth mental health trends by country and sex



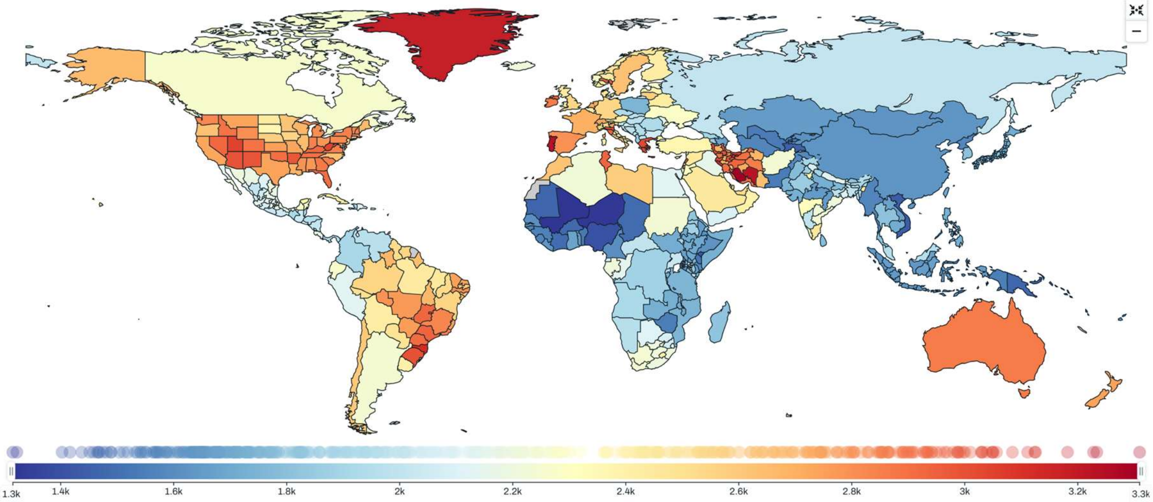
Source: Lancet Psychiatry Commission on youth mental health [26]

Another reason for the worsening health burden of mental disorders is the challenge of accessing, and being provided with, optimal treatment. For example, by analysing the prevalence and severity of anxiety disorders in Australia, and comparing shifts in severity between full access to optimal treatment (for the purposes of this study this was based on cognitive behavioural therapy and antidepressants) and without access to treatment, Santomauro et al. estimated that, globally, 12.5% of anxiety disorder burden was averted because of available treatment [27]. However, 71% "could have been averted if all people with anxiety disorders had access to optimal treatment" as it was defined in this study [27]. Affordability is another factor hindering access to mental health services [28].

The other main driver of incident cases and sustained prevalence are the social determinants of mental health [16], recognised by both Lancet mental health commissions [23,26]. These social, economic and other environmental risk factors interact with “genetic, neuro-developmental, and psychological processes” to affect biological pathways in the brain and the mental ill-health as it is experienced by an individual [23]. The social determinants of mental health are discussed in more detail in a later section of this chapter.

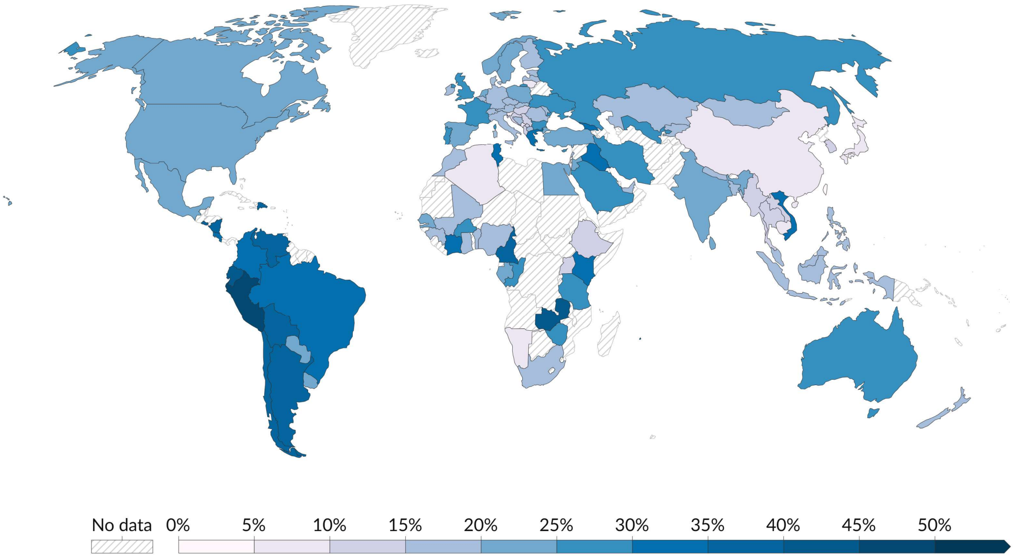
The health consequences of mental illness extend beyond the experience of the disorder itself. For example, a study of 17 countries found that mental disorders of all kinds are associated with an increased risk of developing a wide range of chronic physical conditions [29]. Although this means the increasing prevalence of mental health conditions in young people is concerning for the future prospects of population health and societal welfare, it also highlights the potential effectiveness and likely value-for-money of widescale prevention and early intervention efforts.

Figure 6: Health burden of mental disorders, both sexes, all ages, 2021, DALYs per 100,000



Source: Global Burden of Disease Study 2021 via GBD Compare [30]

Figure 7: Proportion who report lifetime anxiety or depression, 2020



Source: OurWorldinData.org/mental-health [31]; original data Wellcome Global Monitor 2021

1.2.3. Economic burden of mental health conditions

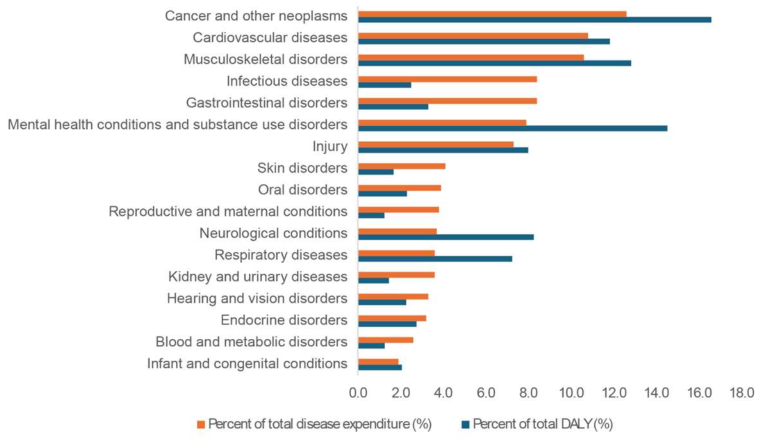
The spending on mental health-related services in Australia was $13.2 billion in 2022-23, equivalent to 7% of total health expenditure [32]. This included $8.1 billion on state and territory government specialised mental health services, $1.5 billion on Medicare mental health services and $672 million on mental health medications subsidised under the Pharmaceutical Benefits Scheme (PBS) [32]. Although spending on mental health has been increasing in absolute, real terms for at least the last 10 years, as a share of total health expenditure, it has not changed since 2013-14, at just under 7% [33]. Furthermore, the proportion of health expenditure committed to mental health each year is substantially below the proportion of health burden that mental health is responsible for (Figure 8) [33].

Mental health expenditure in other developed nations is substantial, although it accounts for only 2% of government health expenditure globally [34]. In the United States, US$166.42 billion was spent on mental disorders (6.8% of total health expenditure; excludes substance use disorders otherwise included in Australian estimates) [35]. This compares with 7.28% of the health burden in terms of DALYs that mental health is responsible for, although this excludes another 7.8% attributable to substance use disorders (which are included in AIHW's Australian mental health estimates) [30]. Expenditure on mental disorders in the US had the third-highest annual growth rate between 2010 and 2019 (after substance use disorders and 'other infectious diseases') [35].

Direct costs to the health care system are only one part of the economic burden of mental disorders. In Australia, the Productivity Commission estimated that there were an additional AU$39 billion in productivity impacts attributable to mental ill-health in 2018-19, AU$150 billion in monetised health impact and substantial out-of-pocket costs incurred by individuals that are difficult to estimate [36]. Globally, an analysis prepared for the World Economic Forum estimated that the cost of mental, neurological and substance use disorders was US$2.5 trillion in 2010, increasing to US$8.5 if a value of a statistical life is applied [37]. Another study estimated that US$5 trillion of economic value was lost globally each year due to mental disorders [38]. Much of the productivity impacts associated with mental ill-health is caused by absenteeism, presenteeism, and inability to participate in the labour force [39]. A review of Australian cost of illness studies found that young people with mental disorders had an increased risk of leaving school early, a lower probability of gaining full-time employment, and a reduced quality of life [40]. A limitation of most of the studies on the productivity impacts of mental health (and the literature on health-related productivity impacts in general) is that they focus on paid employment only, leaving the economic cost of lost unpaid work and lost social production (activities that deliver social value including volunteering, informal care and civic participation) due to poor mental health largely unknown in the scientific literature [41].

Despite the billions of dollars spent on mental health and the broader impacts on economic and societal welfare, "little data is available on the impact and efficacy of the billions of dollars invested by governments across the system each year, or the experiences and outcomes of people who receive support through the system, and their families, carers and kin", according to the Australian National Mental Health Commission [42]. Systems and processes that enable accountability for mental health are also poorly developed [19,20].

Figure 8: Spending vs. burden for each Australian Burden of Disease Group



Source: Australian Institute of Health and Welfare, Health system spending on disease and injury in Australia 2022-23 [33]

1.3. Simulation modelling, systems thinking and system dynamics modelling

1.3.1. Simulation modelling

Simulation modelling has a long history of use in non-health areas of operations research and business planning and is increasingly being used for healthcare operations and system design, medical decision making, and infectious disease transmission scenarios [43]. Resource scarcity dictates that difficult choices must be made about which interventions to fund in mental health, and simulation modelling is useful because it provides an explicit framework to account for the various influences on decision choices, establishing value-for-money and enhancing accountability and transparency [44]. Modelling combines data from a variety of sources, including expert advice, experimental evidence from literature, observational data, resources, and costs. Mathematical representation of the relationships among system variables allows for forecasting and testing of scenarios in the virtual world before interventions, new policies, or changes to the system are implemented in the real world. For the purposes of this thesis, simulation modelling is conceptualised in the broadest possible terms to encapsulate any computational model that combines data from multiple sources to compare alternative courses of action and their anticipated future impacts on one or more outcomes of interest (Panel 1). For the purposes of this thesis, simulation models can be categorised into two broad camps: conventional modelling techniques, predominantly static cohort state transition Markov models (and decision trees); and dynamic simulation modelling (DSM), encompassing system dynamics modelling (SDM), discrete event simulation (DES) and agent-based modelling (ABM).

1.3.2. Systems science

> The least obvious part of the system, its function or purpose, is often the most crucial determinant of the system's behaviour.
> A system's function or purpose is not necessarily spoken, written or expressed explicitly, except through the operation of the system.
> Purposes are deduced from behaviour, not from rhetoric or stated goals.
> One of the most frustrating aspects of systems is that the purposes of subunits may add up to overall behaviour that no one wants.
> - *Donella Meadows* [45]

Systems science emphasises the relationships that connect constituent parts of a system rather than the parts themselves [46]. Systems thinking is part of a broader view of evaluating public health interventions, distinguishing between micro analysis (of an individual for example) and macro analysis (of a societal perspective and the system) when improving public health [47]. The main properties of complex systems are emergence, feedback, and adaption. An emergent property is one that is more than the sum of its parts and cannot necessarily be predicted based on the individual elements of the system [48]. Feedback is a reciprocal relationship between two elements that can be a vicious or virtuous self-reinforcing loop or a self-correcting balancing loop [49]. Adaption is a response in behaviour by an actor or part of the system in response to a change elsewhere in the system [48].

Rutter et al. advocate for a move away from linear, causal conceptual models and towards systems thinking that accounts for all of the processes and outcomes of a system [48]. “Instead of asking whether an intervention works to fix a problem, researchers should aim to identify if and how it contributes to reshaping a system in favourable ways” [48]. Rather than relying on the randomised controlled trial as the gold standard to guide public health decisions, they argue for greater use of alternative evaluation and analytical techniques, such as systems mapping, interrupted time series analysis, natural experiment evaluations, qualitative enquiry, and simulation approaches like ABM and SDM [48]. A framework for developing and evaluating complex interventions was commissioned by the UK’s Medical Research Council and the National Institute for Health Research, providing a process for responding to the trade-off that often exists “between precise unbiased answers to narrow questions and more uncertain answers to broader, more complex questions” in complex systems research [50].

1.3.3. Dynamic simulation modelling

DSM seeks to apply systems thinking by taking a different approach to conventional economic modelling techniques such as state transition Markov modelling. DSM approaches are used to account for the characteristics of the complex, dynamic systems in which we live. These include non-linear relationships, feedback loops that either amplify or diminish desirable or undesirable outcomes, and interactions among different components of the system. Additionally, DSM incorporates mechanisms that enable system adaption, as well as emergent outcomes that may be overlooked by more linear modelling approaches [49]. DSM helps us to learn effectively in a world of dynamic complexity by performing ‘what if’ analysis, forecasting a system’s behaviour in the future under significantly different circumstances, comparing alternative strategies to find an optimal solution, and experimenting with scenarios that are infeasible in the real world [51,52]. DSM can be used across a wide variety of contexts and purposes [53]. Because of these characteristics, it has been argued that DSM is necessary for improving public health policy, particularly for complex issues like suicide and mental health, so that decision makers can better target resources to achieve contextually relevant and more meaningful population-level outcomes [54,55].

Examples of DSM include discrete event simulation (DES), agent-based modelling (ABM) and SDM (Table 1) [2,56]. DES focuses on the occurrence of events over time and the impact those events have on individuals [44]. DES typically models individual patients as they progress through care pathways, occupying and releasing resources such as hospital beds, clinicians, or equipment. The flow of patients through the system is governed by the availability of these resources and by service processes that determine how patients are prioritised and treated. DES is particularly well suited to evaluating operational and service delivery decisions, such as resource allocation, patient scheduling, and capacity planning [52]. Examples of purpose-built software solutions for DES include SIMUL8, Arena, and AnyLogic and it can also be performed in R using the *simmer* package. Agent-based modelling (ABM) focuses on the behaviours and interactions of individual entities - or 'agents' - such as patients, clinicians, or organisations - that together shape system performance [57]. Each agent has its own characteristics (e.g. age, health status, role), belongs to one or more networks (such as families, care teams, or service providers), and follows a set of behavioural rules that determine how it interacts with other agents and responds to changes in its environment. Through these interactions, system-level patterns - such as the spread of disease, uptake of interventions, or changes in service use - emerge from the bottom up. ABM is best suited to exploring how individual and organisational behaviours influence system outcomes, and to testing targeted policy or program interventions within defined sub-systems rather than across an entire health system or policy landscape [52]. Examples of software used to conduct ABM are AnyLogic and NetLogo. SDM represents the aggregate behaviour of systems using stocks (for example, the number of people experiencing a high level of distress, emergency department presentations or cumulative hospitalisation costs) and flows (for example, the rate at which people progress to higher levels of distress, the rate at which people present to an emergency department or the additional cost incurred due to hospitalisation each time period). SDM captures how these quantities evolve over time through feedback loops, delays, and non-linear relationships that drive system behaviour. It is particularly useful for understanding how changes in one part of the system – such as implementation of prevention programs, service capacity changes, or increased funding – affect outcomes elsewhere over time. SDM models are typically expressed as systems of ordinary differential equations that describe the continuous rates of change between stocks and flows over time. The section below discusses the contexts that are best suited for SDM as the focus of this thesis. Examples of purpose-built software solutions for SDM are STELLA, AnyLogic and Vensim, but it can also be performed in R.

Various frameworks and decision tools have been published to aid the choice of technique based on the decision context for mental health [44,57,58] and healthcare in general [2,49,52,56,59-63]. For example, Jin et al. survey the literature on tools that can be used to determine the most appropriate economic modelling technique and recommend an optimal model selection process [60]. Marshall et al. and Breeze et al. provide more specific guidance on how to decide whether DSM is appropriate for the decision problem, which technique is most relevant, and other practical considerations when developing DSMs in the context of health economic evaluation [49,56]. Larrain et al. define simulation types and provide guidance for selecting the most appropriate technique, with a focus on the technical capabilities of each within the context of complexity and integrated healthcare systems [61]. Table 1 provides a synthesis of this literature by summarising the distinguishing features of each approach in terms of their strengths, weaknesses and relevance to mental health.

Conceptualising the model structure in terms of stocks and flows using SDM is different to a conventional state-transition Markov model in at least two respects. Firstly, SDMs uniquely incorporate feedback loops and nonlinear relationships, allowing for a more dynamic and realistic representation of complex systems. Secondly, it extends beyond the health states of persons to incorporate any entity or system component of relevance, such as health care services or socioeconomic determinants of mental health. These features enable SDM to capture the interdependencies and cyclical behaviours within the system, providing deeper insights for policy analysis and decision-making.

Panel 1: Definition of key terms

Agent-based modelling (ABM)
A simulation modelling method in which individual agents represent the system, with each agent having their own rules of behaviour, objectives and history, determined to a large extent through its interactions with other agents and its environment.

Clinical staging
A core component of a more personalised approach to mental health care provision, which uses symptom severity, duration and functional impairment to inform treatment decisions, tailoring them to the pathophysiological mechanisms and illness subtypes of individuals at each stage of the disorder. Often used in conjunction with measurement-based case.

Complexity
Complexity is a property of the system in which an intervention operates. Complex dynamic systems exhibit feedback loops, interaction, emergent outcomes, adaption, and non-linearities, and may be composed of smaller subsystems and be part of larger systems.

Discrete event simulation (DES)
A simulation modelling method that focuses on the occurrence of events over time, including queuing processes and networks of queues.

Dynamic simulation modelling (DSM)
A group of simulation modelling methods that refers to DES, ABM, SDM or some combination of these techniques. These modelling approaches attempt to account for various aspects of complex dynamic systems using different underlying structures.

Markov cohort modelling
A simulation modelling method, also called state-transition models, where aggregate health states represent the movement of a group of homogenous people through time, with the movement of individuals between health states determined by transition probabilities. This is the primary technique falling under the banner of conventional modelling approaches for the purposes of this thesis.

Measurement-based care
The objective of measurement-based care is to provide a more personalised approach to treatment planning and greater appreciation of the client's perspective by routinely monitoring symptoms and functioning using standardised self-reported measures. This is usually facilitated by a technology platform. Can also be known as progress feedback, feedback-informed treatment or measurement feedback systems. Can be used to inform clinical staging.

Participatory systems modelling
A structured process of engaging with multidisciplinary stakeholders to create shared representations of reality using computer simulation by co-conceptualising the problem, using modelling to describe and quantify the problem, mapping the system, testing potential solutions, and informing decision-making actions. Participatory model-building is a slightly broader concept that is not necessarily restricted to DSM. Similar activities could be referred to as participatory modelling, group model-building, companion modelling or participatory simulation. Topic experts and other stakeholders are normally involved in simulation modelling, including conventional approaches, to at least some extent, although often lacking the formalised process referred to in this thesis.

Simulation modelling
For the purposes of this thesis, simulation modelling broadly refers to any computational modelling technique that seeks to aid decision making, including both dynamic and conventional approaches.

System dynamics modelling (SDM)
Simulation modelling technique that represents system-level behaviour by using aggregate stocks and flows and differential equations. Stocks are accumulations of any relevant unit (e.g. people experiencing high distress) and flows are rates of change in and out of these stocks.

1.3.4. When and how to use system dynamics modelling

SDM is effective in capturing the broader policy landscape, as it integrates feedback loops, interactions, delays, and accumulations. These elements are critical for understanding the long-term effects of policy actions, particularly in the context of strengthening complex health systems and addressing the social determinants of mental health (Table 1). SDM is especially suited for strategic policy advice because it requires less granular data compared to ABM, making it more feasible when detailed individual-level data are scarce or unavailable. Furthermore, the time horizon for SDM can be extended to decades, providing a long-term perspective that is essential for evaluating the sustainability and impacts of policy interventions over time, aligning with best practices in conventional economic modelling. Our focus on SDM is based on the need for a system-level understanding of policy implications. SDM's robust framework for incorporating economic evaluations alongside behavioural dynamics offers a comprehensive tool for decision makers to navigate the complexities of health systems. Although SDM has been applied to simulate mental health and suicide prevention strategies, these instances lack integration of cost-effectiveness analysis [15,57,64-67].

SDM is less suitable when individual heterogeneity, behavioural adaptation, or network relationships are central, as these are more effectively represented using ABM. Similarly, SDM is also not ideal for operations research and logistics problems, where DES provides a framework better suited to time-based events and queuing algorithms. DES is also better suited to capturing individual heterogeneity than SDM. For many health technology assessments (HTAs), Markov cohort modelling can be appropriate, particularly when comparing a narrow class of medicines or medical devices for a specific disease and well-defined population.

Another practical consideration is that accurately representing the system through participatory systems modelling is a key aspect of the SDM approach. Thus, gathering the varied perspectives and experiences of individuals with different levels of involvement in the system requires sufficient time and resources. This process can be useful in and of itself, with stakeholders learning about the system, interactions between sectors of the system, and effects on and from other parts of the system they may not be engaged with on a day-to-day basis.

In practice, the lines between different methods are blurred, with blended models or hybrid simulation incorporating several techniques possible in most simulation modelling software [68]. For example, queuing functionality is available in Stella Architect, DES and ABM-style microsimulation functionality is available in TreeAge, and all dynamic methods can be carried out concurrently within Anylogic, R and Python. Composite models of different approaches can also be produced by linking software programs [69]. Modern software solutions also blur the distinction made in prior literature between discrete and continuous processes, as well as deterministic and stochastic processes. Probabilistic simulations using Monte Carlo methods can now be conducted to varying degrees across different modelling approaches.

1.3.5. Existing studies of simulation modelling for mental health

There have been calls for systems approaches to the evaluation of public health interventions to take into account complexity, spillover effects and multisectoral consequences [47,48]. Contemporary approaches to mental health treatment and prevention exhibit many of these characteristics of complex dynamic systems, discussed in more detail in the next section. Several research groups have developed simulation models for suicide prevention, with a review identifying 53 interventions or hypothetical scenarios for suicide prevention that are supported by this type of analysis [57]. However, due to the absence of cost-effectiveness analysis in all of these models, it is unknown whether these interventions represent an efficient allocation of resources, or are even feasible within the current budget constraints of the relevant authority [57]. A systematic review of studies using SDM to assess the economic efficiency of innovations in the public sector found that, in some cases, cost calculations were based on the output of SDM models rather being embedded and integrated into the models themselves [70]. The review did not specify how many studies adopted this approach [70]. Another systematic review of simulation modelling in general for mental health found that Markov models were the most commonly used method, appearing in 87 out of 166 papers [71]. SDM accounted for only 6.3% of studies [71].

There is limited evidence directly comparing alternative simulation modelling techniques for the same decision-making problem and context. One study compared a conventional epidemiological approach, based on population preventive fractions, with a SDM to evaluate the effectiveness of a psychosocial therapy intervention for suicide prevention[72]. The SDM predicted a significantly lower proportion of suicides would be prevented (0.5%) compared with the conventional approach (5.4%) over the 10-year timeframe of the model, due to factors such as changes in the effect size over time, barriers to uptake, and limitations of service availability [72]. These factors are likely to hinder implementation in real-world situations. However, economic considerations were not included in this analysis [72]. Another study found that interventions designed to reduce self-harm hospitalisations and suicide deaths were less effective when evaluated using an SDM compared with the outcomes expected in existing literature based on static, linear approaches. This discrepancy was largely attributed to the inclusion of real-world factors in the SDM, such as inertia, delay, feedback loops (both vicious and virtuous cycles), implementation challenges in resource-constrained environments, and supply-demand dynamics. However, economic evaluation was not part of this analysis [73].

In summary, there is a gap in the literature on SDM for mental health that includes economic evaluations despite the theoretical usefulness of this technique for high-level strategic decisions at the population-wide level where dynamic complexity and a long-term time horizon is more relevant to the decision-making context [52].

Table 1: Key characteristics of modelling techniques

Modelling technique	When to use	Strengths	Weaknesses	Key aspects of complexity accounted for in technique	Relevance to the mental health context
Agent-based modelling (ABM)	• Well-suited to individual-level problems and the interactions that generate emergent behaviour • Instances where capturing heterogeneity is critical, such as equity challenges • Infectious diseases, epidemics	• Individual-level simulation means this method excels at capturing patient heterogeneity, individual characteristics, changes in individual behaviour and interactions with other agents	• Resource and time intensive to develop, program and run • Attempts to represent entire healthcare systems or populations can be too complex to calibrate or validate due to the heterogeneous agents and networks	• Interaction between individuals, other parts of the system and the environment • Dynamics • Non-linearity	• Transmission effects of mental health challenges among social networks • Ability to account for service capacity constraints • Ability to track individual patient medical history, behaviour and treatment response over time
Discrete event simulation (DES)	• Operational research, tactical problems and process-centred situations when events, the timing of events and the influence of queuing process are of primary interest • Well-suited to logistical and service planning contexts due to analysis of queuing processes, such as emergency departments and intensive care units based on patient flow • Shorter time horizons more appropriate, like medical treatment decisions	• Individual-level simulation means this method can capture heterogeneity in individual patient characteristics and these are traceable over time • Prior events can affect subsequent event rates • Disease progression can be represented as a continuous process • Great degree of flexibility in the functions and logic governing the flow of entities • Can be very detailed and handle great complexity • Designed to capture queuing processes and networks of queues	• Limited representation of feedback and adaption due to the assumption of fixed process structures and event sequences • Could be difficult to generalise beyond the modelled context due to the highly customised and specific service processes • Data intensive • Time and resource intensive to develop	• Dynamic changes in the probability of events over time • Non-linearity • Feedback can be accounted for • Interaction with service providers	• Effectiveness and side-effects of psychiatric medicines, including past treatment history and progression • Service planning where waiting lists are particularly relevant • Ability to account for service capacity constraints

Markov cohort modelling	• Ideally suited for the analysis of health technologies (new medicines) for well-defined conditions and relatively homogenous populations	• Well-established best practices and history of wide adoption in HTA due to relative simplicity due to the cohort approach and ubiquity of relevant software and training in this approach	• Memorylessness of the Markovian assumption (the transition to future states depends only on the present state, not preceding states) which ignores patient history and individual characteristics • Difficult to account for many aspects of complexity • Does not usually account for various constraints faced by health care delivery systems	• Limited dynamics, individual characteristics, patient history and non-linearities can be accounted for by using 'workarounds' (as opposed to being an inherent part of the approach)	• Comparison of medicines or psychotherapies for diagnosed disorders, particularly in the context of HTA provided the patient population is relatively homogenous
System dynamics modelling (SDM)	• Well-suited to strategic-level, top down and conceptual decisions where a systemwide perspective is required, and learning about long-term system behaviour would be advantageous • Also useful for operational research and other contexts where service capacity constraints are important • Less useful for detailed resource allocation problems • Epidemics, disease prevention, developing a new service and forecasting the demand for	• Modelling structure of stocks and flows clearly captures feedback loops, interactions between different parts of the system, and dynamic changes over time • The initial qualitative aspect based on causal loop or influence diagrams enhances are useful exercises in and of themselves to aid understanding of the problem, the system in which it occurs and relationships between parts of the system • Participatory systems modelling exercises can be learning experiences about	• Judgement required to draw boundary around parts of the system that will be included • As models grow in size and complexity, they can become difficult for stakeholders to interpret and engage with • Represents populations at an aggregate level, assuming homogeneity and limiting the ability to account for individual variation • Resource intensive to develop if comprehensive participatory model-building is part of the development process	• Incorporates most characteristics such as feedback loops, non-linearity, interaction, dynamics, emergent behaviour as a fundamental model structure • Optimisation analysis extends the ability of SDM to allow the identification of a set of parameter settings and/or combination of interventions that maximises health outcomes, cost reductions or net monetary benefit	• Ability to quickly test multiple scenarios of mental health interventions alone or in combination, with or without service capacity changes, for small or large populations • Interaction between demand and supply for mental health services, and the influence of service capacity constraints on intervention cost effectiveness • Ability to assist with high-level decision making and strategic resource allocation for mental health interventions

	services are examples where SDM would be useful • Useful for formalising a mental model of a problem and defining the relations between a system's structure and its behaviour	the system in and of themselves, including the influence of the system on health outcomes • Generally faster to run than ABM or DES models • Able to model large, complex systems • Range of qualitative and quantitative output can be produced • Easier to validate			

1.4. Contemporary mental health treatment and prevention paradigms

Contemporary approaches to preventing and treating mental health conditions have introduced greater complexity to the healthcare decision-making and allocation of public resources. This is due to an increased recognition of the influence of social determinants and life circumstances on mental health [6,16,26,74,75], as well as the shift towards personalised, integrated and multidisciplinary models of care for individuals requiring mental health services [21,76,77]. These developments contrast with the more traditional, binary, biomedical-based treatment approaches [22].

1.4.1. Social determinants of mental health and prevention

There is a wealth of evidence that social determinants, including the cultural, economic and political systems in which people live, have a great influence on mental health [16,78,79]. Social determinants include childhood adversity experienced during critical developmental stages, economic disadvantage, inequality, and poverty, as well as social isolation and feelings of loneliness. They also involve access to safe, stable housing, sufficient food, and clean water, along with the opportunity for meaningful employment. Discrimination and the impacts of climate change further contribute to these determinants [23,26]. For instance, reductions in the prevalence of sadness, worry and unhappiness have been linked to improvements in income, education and life expectancy more so than antidepressant prescribing [80]. Building economic systems and communities that are well-supported and equipped to thrive in the modern world requires accounting for the intersectoral complexity and dynamics involved in decision making. This entails considering bidirectional causality and multidirectional pathways between the social determinants and mental health outcomes.

1.4.2. A movement towards more personalised approaches to mental health treatment

More personalised approaches built around measurement-based care and clinical staging have been proposed for people that have mental health challenges requiring treatment provided by mental health professionals [21]. This replaces the stepped-care strategy, where the initial treatment offered is the cheapest, least intensive, and carries the most favourable risk profile with minimal side effects, before progressing to more intensive treatments [81]. Stepped care is commonly referred to as the 'fail first' approach [82]. More contemporary approaches are "stage-appropriate, transdiagnostic, effective, highly personalised and measurement-based" [82], with stratified treatment options matched to the individual needs of patients and the various dimensions of their lives [81,83]. Clinical staging uses a classification system similar to general medicine where “more advanced stages are associated with a poorer prognosis and a need for more intensive interventions with a higher risk-to-benefit ratio” [84]. This approach uses symptom severity, duration and functional impairment to guide treatment decisions, tailoring interventions to the pathophysiological mechanisms and specific illness subtypes of individuals at each stage of the disorder [23,84-87]. The multidimensional outcomes targeted in personalised treatment include social and occupational functioning, self-harm and suicidal thoughts or behaviours, alcohol and other substance misuse, physical health (including circadian rhythm disturbances) and illness trajectory [83,88]. Essentially, this means that most young people with emerging mental illness should receive dynamic, multidisciplinary, measurement-based care [76,89].

This more integrated approach is optimally supported by digital technologies that enhance communication between patients and multidisciplinary teams while tracking health outcomes [23,90-92]. Digital technologies include the use of online e-learning and psychotherapy platforms, potentially providing economies of scale and faster access to care through more tailored treatment options [93,94]. While this model has not been directly compared to stepped care, the evidence for its validity for the stratification approach is strong and supported by many clinical and neurobiological studies [83-87]. Several systematic reviews on measurement-based care, also known as measurement feedback systems or feedback-informed treatment, support the use of this use of this approach to guide treatment decisions and personalisation of care [95-97]. There is little economic evidence to support this approach. A within-trial economic evaluation of feedback-informed treatment, apparently the first in the literature, found it was cost effective on the basis that it increased the probability of reliable symptomatic improvement by 8%, with an incremental cost-effectiveness ratio of £187.40 per additional case of reliable improvement [98]. However, the difference in costs was small and not significant and quality-adjusted life years (QALYs) were not included in the analysis.

In summary, contemporary approaches to treatment and prevention of mental health conditions are more complex and dynamic because they move beyond binary approaches to diagnosis and biomedical treatments based on a single drug or psychotherapy. Conventional economic modelling techniques are well-suited to analysing single therapies but not necessarily more personalised approaches, impacts on service capacity, the influence of social determinants, and more strategic and impactful combinations of programs and initiatives [54,55]. Economic analyses that are being used to guide funding decisions need to be equipped to handle this complexity.

1.5. Economic evaluation for resource allocation and priority setting in mental health

1.5.1. Fundamentals of economic evaluation for health care

Economic evaluation

Economic evaluation is the “comparative analysis of alternative courses of action in terms of both their costs and consequence in order to assist policy decisions” [99]. This definition is often quoted because it describes the ingredients necessary to conduct a meaningful economic evaluation. There must be at least one intervention (or policy or some other change to the system) and this intervention needs to be compared to some alternative in order to evaluate whether it is an efficient allocation of resources. This comparator could be ‘do nothing’ in all its forms (for example, usual care, status quo, wait list control, watch and wait, business as usual) or another new intervention. Clearly defining the strategies being compared is essential for informing everything that follows (effectiveness, resources required for implementation, etc.). “Comparative analysis” highlights that what we are mostly interested in is the incremental differences between two or more strategies. We are also interested in both the costs to provide a new intervention and the downstream consequences, both in terms of the health benefits and cost increases or decreases. Finally, the economic evaluation is being conducted to inform a real and present policy decision that needs to be made on the allocation of resources, and this analysis is one form of evidence considered to inform that decision.

There are several types of economic evaluation, categorised by the type of health outcome being assessed and summary decision metric (Table 2). The merits and appropriateness of one type of economic evaluation over another depends on: (a) the normative foundation, (b) the decision maker’s preferences and convention, and (c) other contextual factors, biases, political inclinations and practical considerations; all of which are, in practice, interlinked and likely to remain implicit and unrecognised throughout the analytical and decision-making process. There are two main normative foundations that influence the choice of analysis, representation of health benefits and maximand to be achieved: Welfarism and Extra-welfarism. Welfarism prioritises the maximisation of societal welfare, predominantly in monetary units, thereby preferencing CBA over other types of analysis. This is the preferred approach of treasury departments in Australia [100]. However, there are practical challenges preventing widespread adoption of this approach in healthcare, the main one being the lack of valuations for the various effects and outcomes that make up an intervention beyond health (for example, timeliness of accessing treatment, value of knowledge gain, value of therapeutic relationship or social connection) that would be considered important for a true application of CBA. The goal of Extra-welfarism is to maximise health. An Extra-welfarist would prefer CUA because of the clear definition of a health metric to be maximised and the avoidance of monetising these health gains. Most HTA agencies implicitly take an Extra-welfarist normative view when specifying CUA in their reference cases. Other practical and political influences on the preferred type of analysis could take the form of, for example, a state government with primary responsibility of a tertiary health care system who prioritises a reduction in demand for hospital services as their primary objective, thereby preferencing CEA based on intermediate health outcomes (for example, mental health-related ED presentations or self-harm hospitalisation), potentially at the cost of cost-shifting demand to other parts of the healthcare system and/or subsequent reductions in more final health outcomes.

Table 2: Types of economic evaluation

Type	Health outcome	Summary measure	Decision rule *
Cost-minimisation analysis or Cost analysis (CMA)	Identical in all respects	Cumulative costs	Choose the intervention with the lowest total cost
Cost-effectiveness analysis (CEA)	'Intermediate' natural units *Examples: suicide deaths, life-years, person years lived in high distress, person years lived with disorder*	Cost per suicide death avoided Cost per life-year gained Cost per person year lived in high distress	Choose the intervention that maximises health outcomes whilst the ICER does not exceed the cost-effectiveness threshold ^ #
Cost-utility analysis (CUA)	Preference-based combined measure accounting for both length and quality of life *Examples: Quality-adjusted life year (QALY) and other multi-attribute utility instruments*	Cost per QALY gained	Choose the intervention that maximises health outcomes whilst the ICER does not exceed the cost-effectiveness threshold ^
Cost-benefit analysis (CBA)	Health outcomes converted to $ *Example: Willingness to pay for additional QALY*	Net monetary benefit	Choose the intervention with the highest net monetary benefit
Cost-consequence analysis (CCA)	Various *Examples: QALYs, suicide deaths, ED presentations*	None - various disaggregated outcomes of importance to the decision maker are presented	Decision maker uses their own judgement to trade-off disaggregated costs and benefits

ICER: incremental cost-effectiveness ratio
* Assuming all options are mutually exclusive
^ After excluding dominated and extendedly dominated alternatives
# Most economic summary measures based on intermediate outcomes are unlikely to have established cost-effectiveness thresholds

Incremental analysis

Once the analysis has been performed, incremental analysis is required to identify the most cost-effective strategy that maximises health benefits within an acceptable opportunity cost. In a context where all options are mutually exclusive, incremental analysis involves rank ordering all strategies from lowest to highest in terms of health benefits, excluding all dominated and extendedly dominated options, and choosing the option with the highest incremental cost-effectiveness ratio (ICER) up to the cost-effective threshold. An option is dominated when it has increased costs and less health benefits compared with the previously-ranked option. Extended dominance is where the ICER for an option is higher than that of the next, more effective, alternative [99]. If multiple alternatives are included in the analysis, full incremental analysis may require an iterative process as options are compared against a new alternative after dominated and extendedly dominated interventions are excluded. Although an assumption of mutual exclusivity is the norm in HTA contexts (for example, different doses and types of selective serotonin reuptake inhibitors; screening for colorectal cancer every 5 years vs. 2 years), in the modelling studies conducted for the present thesis we did not assume the interventions were mutually exclusive based on stakeholder feedback and topic expert advice that all interventions could conceivably be implemented concurrently (if the necessary funding was made available). This means that full incremental analysis was not conducted in the conventional manner described above, and ICERs and other incremental metrics for all interventions are compared with a common alternative, business as usual.

Cost-effectiveness threshold

The cost-effectiveness threshold is the ICER at which an intervention switches from being considered cost effective to not cost effective. The threshold can be valued based on either an opportunity cost (supply side) approach or a social value of a QALY (demand for health) approach [101]. The former is more appropriate for contexts of resource allocation and prioritisation within a fixed healthcare budget and HTA, such as the National Institute for Health and Care Excellence’s (NICE) guidance for the National Health Service (NHS) in the United Kingdom (UK), and the Pharmaceutical Benefits Advisory Committee (PBAC) in Australia. The demand side approach is more relevant to the contexts of flexible budget allocation, such as interventions implemented outside the health sector or those that target the social determinants, and this was the approach taken for the modelling studies of the present thesis. NICE adopts a cost-effectiveness threshold of £20,000 per QALY gained, with some discretion for advisory committees to accept ICERs towards £30,000 per QALY gained in some circumstances [102].

The appropriateness of these thresholds is contested, with some empirical research finding the threshold in the UK's NHS is actually closer to £12,500 per QALY gained based on existing services forgone [103,104]. In Australia a threshold of AU$50,000 per QALY gained is implicitly used but this has never been explicitly stated by a government agency [105], similar to the situation in Canada. What little empirical evidence does exist on the Australian context again suggests that the actual threshold is much lower than this (AU$28,033 per QALY gained) [106]. Where the social value of a QALY approach is used to value the threshold, such as in this thesis, contingent valuation is one method by which this can be elicited. Here we use the findings of Shiroiwa et al., indexed to the relevant financial year of the modelling study's analysis [105]. Best practice methods recognise that there is uncertainty around the cost-effectiveness threshold. One method of communicating the results of an economic evaluation in relation to this type of uncertainty is using a cost-effectiveness acceptability curve, where the proportion of simulation runs that fall below a threshold is plotted against a range of thresholds (for example, Modelling Study 1 of this thesis) [107].

Net monetary benefit is a conversion of health into financial units to aid the comparability of strategies and presentation of results, by multiplying QALYs by the threshold and deducting total costs [108]. Incremental NMB is the difference in NMB for an intervention compared with business as usual. Conclusions of cost effectiveness based on NMB are equivalent to those based on the ICER.

Perspective

A boundary needs to be established around the categories of costs and health benefits that are included in an economic evaluation in order for it to be tractable. Perspective is the main method by which this is achieved and this is normally defined based on the decision maker for whom the analysis is being performed. The two main perspectives are the health care perspective and societal perspective [109], and both are utilised throughout the three modelling studies performed for the thesis because of the diverse range of stakeholders involved in this research project and ongoing debate about which perspective should be adopted in the reference cases of HTA agencies [110]. Alternative perspectives could include government (state, federal or local), patient, provider, payer (potentially different to the health care perspective), employer, manufacturer/industry, family/household. An underappreciated and under-reported part of the analysis design stage, these examples highlight the important influence that a clearly defined perspective could have on the inclusion and exclusion of costs and effects.

Discounting

Discounting is the process of adjusting future costs and health outcomes to their present value. This is necessary in both health economic evaluation and CBA outside the health sector because of time preference, the opportunity cost of capital, and consistency over different time horizons [99]. Time preference is the principle that people and society generally value present consumption and benefits more highly than future ones. Financial or health benefits in the future are worse less than those received today. The opportunity cost of capital refers to money available today that could be invested to yield future returns rather than being spent now. Health interventions may have costs and benefits that occur over different time horizons so discounting allows for a consistent comparison across time by converting these metrics to the present time point.

That discounting should be applied to costs is uncontroversial [111]. What remains contentious in the health economics field is the magnitude of the discount rate that should be applied and whether it should be applied to health benefits, and if so, at the same or a different rate [111,112]. The Australian HTA review recently recommended reducing the discount rate specified in its reference case from 5% to 3.5% for both costs and health benefits, one reason being harmonisation with international HTA agencies [113]. There are ethical arguments for differential discount rates for health benefits, potentially 0%, such as intergenerational equity [114]. For example, the Global Burden of Disease Study does not discount DALYs on this basis after going through an in-depth process of consultation with ethicists, health economists and other experts and stakeholders. In the absence of clear consensus, sensitivity analysis is key, particularly where health benefits and costs accumulate many years into the future, such as with prevention.

In the modelling studies conducted for the present thesis, we adopted a discount rate of 5% for both costs and health benefits in the base case on the basis this was the reference case specified by PBAC at the time of model development [115]. Sensitivity analysis was performed using alternative discount rates where appropriate to do so.

Time horizon

In conventional economic evaluation adopting a static cohort for Markov modelling, best practice involves following this population for their lifetime (i.e. all persons are in the dead health state before stopping the model) in order to capture all relevant health and cost consequences that might be missed by a shorter time horizon. In DSM and the models used for the modelling studies described here, this approach is inappropriate because the population is dynamic and continually growing due to births and net migration (in the Australian context). The decision on time horizon in this scenario depends on what is most relevant to the decision maker and practical considerations like model run time and degree of uncertainty that would apply with estimates many decades into the future. Here we adopt 10 and 11 year timeframes based on a pragmatic balance of a time horizon that: is sufficiently long to capture a meaningful accumulation of costs and health benefits; sufficiently long to capture the non-linear impacts of different interventions and their combinations, ensuring the most effective strategies are identified over time; sufficiently short to make it politically relevant; facilitates a manageable model run time, particularly when probabilistic sensitivity analysis or optimisation analysis is run.

Other considerations

Economic evaluation is just one input into a broader process of policy making and investment planning. Several frameworks exist by which considerations that have the potential to affect the adoption of new interventions or policies, but are outside of the economic analysis, are accounted for. For example, the Assessing Cost Effectiveness (ACE) series of economic evaluation projects [116-118] specifies a set of ‘second stage filters’ or ‘implementation considerations’, the most recent being a comparison of interventions for obesity prevention in Australia [119]:

- Strength of evidence
- Equity
- Acceptability to
    - Government
    - Industry
    - Public
- Feasibility
- Sustainability

In the context of HTA, NICE describes specific methods and guardrails for considering [120]:

- Degree of uncertainty
- Net budget impact, overall and to local health economies

- Impact on health inequalities
- Knock-on effects on other NHS resources, and potential constraints
- Factors that go beyond QALYs, warranting a QALY weighting, including for disease severity or highly specialised technologies
- Technologies or populations for which evidence generation is difficult, such as rare diseases, for use in a population that is predominantly children
- Innovative and complex technologies.

In the context of developing clinical guidelines for the NHS, NICE specifies other factors like the need to prevent discrimination, promote equity, account for non-health effects and consider health inequalities [121]. Whether for clinical guideline development or HTA, these other considerations are intended to be alignment with NICE's principles that guide the development of all NICE guidance and standards [102]. There is no organisation in Australia like NICE that has responsibility for setting the principles and methods used to guide priority setting and resource allocation for the health care system as a whole (discussed further in Chapter 5).

1.5.2. Broader frameworks of priority setting and resource allocation

Economic evaluation via CMA, CEA, CUA, CBA or CCA is one type of economic evidence generation with well-established methods that have been developed predominantly through HTA contexts. Alternative processes may be required where prioritisation and resource allocation relates to a broader portfolio of interventions or public health policies, particularly those that have inter-sectoral implications. Programme Budgeting and Marginal Analysis (PBMA) involves reviewing the resources allocated to specified programs (PB) and assessing the added benefits and added costs of proposed investments, or forgone benefits and lower costs of disinvestment (MA) [122]. These are not necessarily dichotomous choices – programs could be scaled up or down. Multi-criteria decision analysis (MCDA) is "a set of methods and approaches to aid decision making, where decisions are based on more than one criterion, which make explicit the impact on the decision of all the criteria applied and the relative importance attached to them" [123]. The benefits of MCDA are that it provides support and structure to the decision-making process, it is an explicit approach and enhances consistency, transparency and legitimacy of decisions and can be used across different contexts [124]. While both PBMA and MCDA are decision-making tools used in public policy and resource allocation, PBMA focuses on optimising resource allocation within a budget constraint by evaluating the marginal benefits and costs of programs, whereas MCDA has the potential for broader use by comparing and evaluating alternative options based on multiple, often competing criteria and objectives.

CEA/CUA is complementary to these priority setting frameworks. For example, cost effectiveness can be a criterion in MCDA or be used to inform, or be considered alongside, PBMA.

In practice, most government agencies with responsibility for prioritisation and guidance development rarely compare existing and new programs and policies 'head-to-head', instead focusing on the assessment of individual new interventions.

1.5.3. Existing economic evidence on mental health interventions

Several systematic reviews have been published on the economic credentials of mental health interventions in the last five years, with most economic evaluations finding them to be cost-effective or cost saving. There are still many opportunities to generate and improve economic evidence in this area. Ha et al. conducted a systematic review including 49 studies of model-based economic evaluations for mental health prevention, with a focus on the methods used in these studies[125]. Most existing studies, covering a broad range of mental health conditions, were for indicated strategies for high-risk populations (31 out of 49), followed by universal (15 out of 49) and selective preventions (10 out of 49) [125]. Markov cohort modelling was the most common approach (26 out of 49), with no DSM approaches identified [125]. The authors noted that "a large number of papers reported little or no details of the model structures and rationale for choosing the models" [125]. Another review by Kularatna et al. also focused on methodological approaches of model-based cost-effectiveness analyses for paediatric mental health interventions [126]. It includes a thorough assessment of the use of utility instruments for children and the limitations of current evidence on the measurement of paediatric mental health-related quality of life [126].

The economic credentials of mental health-related public health interventions and promotions have also received substantial attention in the literature. Feldman et al. conducted a systematic review of public health interventions for improving mental health and reducing suicide [127]. They found that fourteen out of 22 interventions were cost effective. There was a good mix of indicated (13 out of 22 interventions) and universal interventions (9 out of 22 interventions), 14 out of 19 studies were trial-based evaluations (the remaining 5 studies were model-based evaluations), and were focused on psychological interventions at school (7 out of 19 studies), the workplace (1 out of 19 studies), within elderly care (2 out of 19 studies), the community (2 out of 19 studies), homes (1 out of 19 studies), or primary care (6 out of 19 studies) [127]. Another systematic review that focuses on interventions for mental health prevention and promotion excluded those that were directly related to treatment [128]. The authors found that many interventions were cost effective or cost saving [128]. Targeted prevention was likely to be cost effective compared to universal prevention [128]. The authors noted that "standard economic evaluation methods commonly applied to HTA may not be transferable to health promotion evaluation" and "economic evaluations with improved methods and capturing intersectoral cost and outcomes of such interventions are needed", citing services capacity constraints as one of the limitations to generalising trial-based economic evaluations to inform real-world policy implementation [128].

A systematic review of economic evaluations of treatments for depression in low- and middle-income countries, which included 17 studies on adults and 5 on children and/or adolescents, found inconsistent evidence on the cost effectiveness of antidepressants [129]. There was stronger economic evidence supporting the use of aripiprazole and task sharing with lay health workers [129].

Lastly, a systematic review of universal mental health interventions for children and adolescents identified nine studies, all but one of which were school-based programs [130]. Results on cost effectiveness were mixed, with a parenting programme, a school-based social and emotional wellbeing programme and anti-bullying interventions showing more positive results than cognitive behavioural therapy-based interventions aimed at the prevention of depression or anxiety [130]. The review confirms that these interventions have high costs and are sensitive to intervention effectiveness, delivery mode and duration, baseline prevalence and perspective [130]. None of the systematic reviews described here identified economic evaluations for mental health that used an SDM approach.

I argue that greater use of DSM is part of the solution to improving economic evidence for mental health. Many modelling methods exist that are relevant to mental health systems and the choice of model depends on context and purpose [44,59,60]. Currently, most of the evidence is based on conventional (i.e. non-dynamic) modelling techniques developed in the context of HTA where single drugs or medical devices are being compared for very specific conditions and well-defined populations, using evidence from well-controlled, clinical trial settings [131,132]. For example, most European HTA guideline manuals only mention decision trees and Markov models [133]. Exceptions are submission guidelines issued by the Canada's Drug Agency (CDA-AMC) and the Pharmaceutical Benefits Advisory Committee (PBAC) which explicitly recognise the existence of SDM, DES and ABM as options, although they expect a thorough rationale as to why these more complex approaches are required because these are not the standard reference case modelling platforms adopted for submissions [115,134]. The technique of constrained optimisation analysis further extends the relevance of SDM for economic evaluation, allowing the identification of a set of parameter settings that maximise a key objective of the decision maker within constraints often encountered in the real world, such as limitations to resources or funding [135]. This is particularly relevant for priority setting in mental health where a key objective is maximising health outcomes within budgetary constraints. Table 1 provides a summary of modelling approaches in the context of economic evaluation for mental health.

In summary, economic evaluation is critical in the healthcare sector to achieve allocative efficiency in the absence of market mechanisms [136], and much evidence already exists on the cost effectiveness of interventions that could be implemented or upscaled now to achieve improvements in population mental health. However, conventional economic modelling approaches may inadequately capture the complexity of contemporary treatment paradigms (described in the previous section), particularly those that require intersectoral collaboration or prevention interventions that seek to move upstream to affect the social determinants of health or economic systems.

1.6. System dynamics modelling-powered cost-effectiveness analysis as an enhanced decision-making tool for mental health

I propose a fully-integrated decision making and planning framework for mental health that includes SDM, cost-effectiveness analysis, and participatory systems modelling methods, including young people with a lived experience of mental health conditions, with models that are reviewed and updated over time in a circular process as new data becomes available. This framework would achieve the objectives of informing the implementation of effective and cost-effective interventions, maximising both allocative efficiency and technical efficiency, while ensuring rigour, transparency and accountability. The intersection of economic evaluation within an SDM approach provides an opportunity to inform systems-based investments that improve the lives of young people with mental ill-health while taking into account the complex nature of contemporary models of care and mental healthcare systems. This approach also aligns with the growing interest in learning health systems (LHS). LHS aims to develop an integrated, circular infrastructure for data collection, evidence generation, personalisation and monitoring to learn from each patient and continually improve the health system [137]. SDM could be a crucial element of a LHS whereby real-time data from the health system is used to update forecasts of simulation modelling to guide planning and learning.

The purpose of participatory model-building is to develop simulation models that are useful and used – useful in the sense that they are robust, valid and credible - and used meaning that end users of the model itself or its output understand and trust the process and methods that went into developing the model, and know how to extract and interpret results to inform decision making. Freebairn et al. describe seven benefits of the participatory systems modelling process as (1) contributing expertise, including lived experience, of participants to model development, (2) social learning between participants, (3) joint problem framing to ensure that the model is focused on priority policy questions, (4) production of regionally customised and socially robust solutions, (5) identification and prioritisation of evidence gaps, (6) opportunities to insert the model into policy and program decision-making dialogues, and (7) development of strategies to address communication challenges [138].

Prior to this thesis, there were no economic evaluations of mental health interventions that adopted an SDM approach. A systematic review that included 29 studies conducting economic efficiency analysis of innovations in the public sector did not identify any that related to mental health [70]. The authors concluded that "SD modelling is not currently used to its full potential to evaluate the technical or allocative efficiency of public sector innovations, particularly in health" [70]. A systematic review of model-based economic evaluations of paediatric mental health intervention identified 12 studies and all of them used conventional modelling techniques [126]. A scoping review of simulation models for suicide prevention identified 53 interventions that were supported based on health outcomes but cost-effectiveness analyses were absent from all included models [57]. The cost-effectiveness analysis described in Chapter 2 and published after these reviews represents the first use of SDM to conduct economic evaluation of mental health interventions. Another study published after these reviews, albeit not directly related to mental health, used SDM to investigate the cost effectiveness of increasing buprenorphine treatment initiation, duration and capacity among individuals who use opioids [139].

Table 1 provides a summary of the strengths, weaknesses and potential application to mental health of DSM approaches. One limitation of SDM is the level of complexity of the model structure and how this affects interpretability and transparency for decision makers and other stakeholders. As the CDA-AMC's guideline states, the choice of modelling technique "should be no more complex than is necessary to address the decision problem" [134]. Another potential limitation to broader adoption of the SDM approach to economic evaluation is the level of resources required to develop the models, conduct stakeholder workshops and process input data, and this is ideally carried out for each region where local planning needs to occur.

However, the participatory model-building processes are resource intensive regardless of the modelling approach, and other modelling techniques may require more (e.g. ABM) or less (e.g. Markov modelling) depending on a variety of factors like scope, complexity, population sub-groups etc. Another challenge is the level of data – both the variety of sources and amount of data required to populate the models and also the variety and quantity of results that are produced. While simple SDMs can be developed, when they are being tailored as a decision-support tool for a region they need to be capable of answering a broad range of questions that stakeholders want the model to answer, increasing its scope and complexity. Stakeholders need to be prepared for a greater degree of training and sense-making than they otherwise might be accustomed to in conventional modelling exercises.

1.7. Objectives of the PhD research project and overview of the thesis

The objective of the PhD research project was to leverage the unique strengths of SDM, where system elements such as social determinants of mental health, system capacity, and interactions between system components, are incorporated into simulation modelling, with the potential to influence the effectiveness and cost-effectiveness of mental health interventions. The ambition was to provide a more complete and nuanced picture of the relative cost effectiveness of a wide range of strategies that decision makers could invest in to improve youth mental health. This was achieved through the application of the approach to three modelling studies, each one exploring a distinct economic question facilitated by the unique characteristics of the SDM framework. The overarching researching question was, 'Is SDM a feasible and useful approach to conducting economic evaluation of mental health interventions, and what are the unique attributes of this technique compared with conventional modelling techniques?'

The aim of **Modelling Study 1** was to investigate the cost effectiveness of eight youth mental health interventions for the ACT (Chapter 2) [140]. This research also sought to identify any unique attributes of the SDM approach to economic evaluation compared with conventional modelling techniques.

The goal of **Modelling Study 2** was to estimate the health benefits and economic value of improving the social determinants of mental health (Chapter 3) [141]. Again, a secondary objective was to identify benefits and limitations of using SDM for this analysis.

The intention of **Modelling Study 3** was to explore the use of constrained optimisation analysis with a SDM approach to systematise the process of identifying the most cost effective combination of interventions, with and without changes to the growth rates of existing mental health services, and with and without constraints on the funding allocated to implementing new interventions (Chapter 4) [142].

Chapter 5 summarises the results and insights from these modelling studies; my interpretation of the research project's contribution to scientific knowledge; implications for policy and practice for policy makers, health economists and dynamic simulation modellers; a comment on the transferability of these results to other jurisdictions; research translation activities; overarching strengths and limitations, with a focus on overarching learnings that apply across the research project; and opportunities and enablers of future research brought to light by this project.

Given the lack of studies in the literature using a SDM approach to conduct economic evaluation of mental health interventions prior to this thesis (as demonstrated by the present literature review), the research project was purposefully designed to answer the overarching research question. Modelling Study 1 was the first demonstration of conducting CUA for mental health using SDM, and did this for eight interventions, whilst identifying the unique aspects of this approach. Modelling Study 2 extended and adapted the knowledge gained through Modelling Study 1 by broadening the scope outside treatment interventions to consider the impacts of the social determinants of mental health, expanding the contexts for which this approach could be utilised. Modelling Study 3 expanded and adapted the learnings of the prior two studies even further by leveraging ability to conduct constrained optimisation analysis within SDM-powered economic evaluation, a response to the practical challenges of maximising allocative efficiency within a resource constrained environment. Overall, the combination of these modelling studies and the PhD research project demonstrated the feasibility and usefulness of using SDM for conducting economic evaluation for mental health, whilst uncovering the unique attributes and limitations of this approach for different decision-making contexts.

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Preface to Chapter 2 (Modelling Study 1)

Chapter 2 takes the form of an article published in *The Lancet Psychiatry*, ‘Cost-effectiveness of system-level mental health strategies for young people in the Australian Capital Territory: a dynamic simulation modelling study’. This chapter contributes to addressing the overarching research question by demonstrating a cost-utility analysis using a system dynamics modelling approach, the first of its kind in the literature.

Supplementary material supporting this analysis can be found in Appendix 2.

A list of equations is available upon request by emailing Paul Crosland at paul.crosland@sydney.edu.au.

Cost-effectiveness of system-level mental health strategies for young people in the Australian Capital Territory: a dynamic simulation modelling study

Paul Crosland, Nicholas Ho, Seyed Hossein Hosseini, Catherine Vacher, Adam Skinner, Andrea N Natsky, Sebastian Rosenberg, Raphael Hasudungan, Sam Huntley, Yun Ju Christine Song, Grace Yeeun Lee, Deborah A Marshall, Jo-An Occhipinti, Ian B Hickie**

Summary

Background Regional mental health planning is a key challenge for decision makers because mental health care is a complex, dynamic system. Economic evaluation using a system dynamics modelling approach presents an opportunity for more sophisticated planning and important evidence on the value of alternative investments. We aimed to investigate the cost-effectiveness of eight systems-based interventions targeted at improving the mental health and wellbeing of children, adolescents, and young adults in the Australian Capital Territory (ACT).

Methods We assessed eight interventions for children and young people (aged ≤25 years) with low, moderate, and high-to-very-high psychological distress: technology-enabled integrated care, emergency department-based suicide prevention, crisis response service, family education programme, online parenting programme, school-based suicide prevention programme, trauma service for youths, and multicultural-informed care. We developed a system dynamics model for the ACT through a participatory process and calibrated the model with historical data, including population demographics, the prevalence of psychological distress, and mental health services provision. We calculated incremental cost-effectiveness ratios compared with business as usual for cost (AU$) per: quality-adjusted life-year (QALY), suicide death avoided, self-harm related hospital admissions avoided, and mental health-related emergency department presentation, using a 10-year time horizon for health-care and societal perspectives. We investigated uncertainty through probabilistic sensitivity analysis and deterministic sensitivity analysis, including using a 30-year timeframe.

Findings From a societal perspective, increased investment in technology-enabled integrated care, family education, an online parenting programme, and multicultural-informed care were expected to improve health outcomes (incremental QALYs 4517 [95% UI –3135 to 14 507] for technology-enabled integrated care; 339 [91 to 661] for family education; 724 [114 to 1149] for the online parenting programme; and 137 [88 to 194] for multicultural-informed care) and reduce costs ($–91·4 million [–382·7 to 100·7]; $–12·8 million [–21·0 to –6·6]; $–3·6 million [–6·3 to 0·2]; and $–3·1 million [–4·5 to –1·8], respectively) compared with business as usual using a 10-year time horizon. The incremental net monetary benefit for the societal perspective for these four interventions was $452 million (–351 to 1555), $40 million (14 to 74), $61 million (9 to 98), and $14 million (9 to 20), respectively, compared with business as usual, when QALYs were monetised using a willingness to pay of $79 930 per QALY. Synergistic effects are anticipated if these interventions were to be implemented concurrently. The univariate and probabilistic sensitivity analyses indicated a high level of certainty in the results. Although emergency department-based suicide prevention and school-based suicide prevention were not cost effective in the base case (41 QALYs [0 to 48], incremental cost $4·1 million [1·2 to 8·2] for emergency department-based suicide prevention; –234 QALYs [–764 to 12], incremental cost $90·3 million [72·2 to 111·0] for school-based suicide prevention) compared with business as usual, there were scenarios for which these interventions could be considered cost effective. A dedicated trauma service for young people (9 QALYs gained [4 to 16], incremental cost $8·3 million [6·8 to 10·0]) and a crisis response service (–11 QALYs gained [–12 to –10], incremental cost $7·8 million [5·1 to 11·0]) were unlikely to be cost effective in terms of QALYs.

Interpretation Synergistic effects were identified, supporting the combined implementation of technology-enabled integrated care, family education, an online parenting programme, and multicultural-informed care. Synergistic effects, emergent outcomes in the form of unintended consequences, the capability to account for service capacity constraints, and ease of use by stakeholders are unique attributes of a system dynamics modelling approach to economic evaluation.

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See Comment page 85

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Research in context

Evidence before this study

The need for better mental health planning has been recommended by repeated statutory and other inquiries into mental health. We searched MEDLINE via EBSCOhost from database inception to April 19, 2023, for review-level evidence in English using search terms related to economics (eg, 'cost utility'), mental health (eg, 'suicide'), and dynamic simulation modelling (eg, 'agent-based model'). Evidence exists on effective and cost-effective interventions for improving the health and wellbeing of children and young people but they are not fully implemented due to fragmentation of the mental health care system, service capacity constraints, and barriers to accessing care. Economic evidence for some treatment and prevention interventions for mental health conditions is mixed. Economic evaluation using a system dynamics modelling approach can augment traditional approaches to planning, providing planners with new information about health and cost consequences of system-wide impacts compared with conventional modelling techniques. However, no studies currently exist at the intersection between mental health interventions, health economics, and systems research.

Added value of this study

To our knowledge, this is the first economic evaluation to adopt a system dynamics modelling approach to investigate the cost-effectiveness of mental health interventions. We found that technology-enabled integrated care, family education, an online parenting programme, and multicultural-informed care were cost effective compared with business as usual. These interventions improve health outcomes and reduce costs under the societal perspective and there is a high degree of certainty in these results. There were scenarios for which emergency department-based suicide prevention and school-based suicide prevention could also be cost effective. The unique attributes of a system dynamics modelling approach compared with conventional economic modelling techniques were: the ability to identify synergistic effects for combinations of interventions; the identification of emergent outcomes in the form of unintended consequences; the capability to investigate the impact on population mental health outcomes of changes in services capacity, alone or in combination with other programmes and initiatives; and the ability for stakeholders to interact with the model, test a range of scenarios, and produce results through a user-friendly interface, enhancing transparency and accountability of decision making.

Implications of all the available evidence

The findings highlight an opportunity to improve health outcomes in the Australian Capital Territory through implementation of technology-enabled integrated care, family education, an online parenting programme, and multicultural-informed care. Implementing all four interventions concurrently is expected to optimise health outcomes and allocative efficiency. This research demonstrated that system dynamics modelling is a feasible approach for economic evaluation of mental health interventions, offering a number of distinct benefits over conventional modelling techniques. This study adds to existing evidence, including systematic reviews that indicate mental health interventions often represent good value for money.

Introduction

Repeated enquiries have called into question the effectiveness of extant approaches to mental health planning in Australia.[1] Beyond the toll on individuals and families, the cost of poor performance is clear, with AU$200 billion of wider social and productivity costs attributable to mental disorders.[1,2] Increased national attention to mental health has paradoxically failed to deliver reductions in prevalence or severity.[3] Effective and cost-effective treatment and prevention strategies exist but are not fully implemented, due to partial implementation of best practice guidelines, scarcity of resources, service capacity constraints, fragmented care, and high out-of-pocket costs.[4–9] A key missing factor in driving effective mental health reform is better planning, augmenting traditional, historical approaches to decision making in relation to the design of budgets, policies, and services. The capacity to deliver this improved planning region by region is important, given the complex and dynamic nature of mental health systems in different places. Centralised solutions are unlikely to reflect variation at the local level.[10]

Economic evaluation provides valuable analysis to inform resource allocation and priority setting. Such analysis could be better utilised to guide investments for improving mental health outcomes regionally in an evidence-based manner.[11] Economic modelling is widely used in health-care systems for health technology assessment, informing decisions on the adoption of new medicines and medical devices by combining data from various sources, extrapolating future health benefits and cost consequences beyond clinical trial data, clearly articulating and comparing alternative courses of action, and investigating and quantifying the role of uncertainty and the degree of confidence decision makers can have in results. Due to the comparison of a narrow set of similar types of treatments for a precisely defined population and disease in health technology assessments, most model-based economic evaluations adopt some variation of a static cohort Markov health state approach, even in population-wide public health and prevention contexts, when a greater degree of complexity is present. The most common type of modelling approach for the economic evaluation of mental health prevention interventions is cohort Markov modelling, but few studies provide details of the model structure and rationale.[12] A systematic review, which included 65 economic evaluations of mental health prevention and promotion interventions, noted that conventional economic evaluation methods might not be transferable to health promotion evaluation, and that economic evaluations with improved methods and capturing intersectoral costs and outcomes are needed.[5] The review also mentioned service capacity constraints as one of the limitations to generalising trial-based economic evaluations to inform real-world policy implementation.[5]

Dynamic simulation modelling encompasses a set of alternative modelling techniques (system dynamics modelling, agent-based modelling, and discrete event simulation) that attempt to take account of the inherent complexity of public health and health-care systems.[13] The characteristics of complex dynamic systems, which also make them difficult to model using conventional approaches, include the following: dynamic changes over time, self-reinforcing feedback loops, interaction between different parts of the system, behavioural adaption, and the potential for emergent outcomes or unintended consequences.[14] Given that the mental health-care system has many of these attributes of complex dynamic systems, dynamic simulation modelling, and system dynamics modelling in particular, seems to be an appropriate and promising approach for economic evaluation of mental health treatment and prevention interventions. System dynamics modelling is the most appropriate simulation modelling technique in the domain of macro health policy and forecasting; for high-level strategic decisions at the population-wide level, where aggregated data is the most available and desirable input; and for cases in which a long-term time horizon is more relevant to the decision making context.[15] However, to our knowledge, no economic evaluations of mental health interventions have adopted a system dynamics approach, as confirmed by three previous systematic reviews.[12,16,17] Although some examples of system dynamics modelling for health outcomes in mental health exist,[18–21] progress has been slow with regard to economic outcomes since the publication of a systematic review by Carey and colleagues[22] in 2015, which concluded that many opinion pieces and best practice recommendations have been written about the virtues of systems science and modelling for public health, with few examples of these recommendations actually being applied in practice.

The aim of this study was to use system dynamics modelling within a collaborative model-building approach to investigate the cost-effectiveness of eight systems-based interventions targeted at improving the mental health and wellbeing of children, adolescents, and young adults in the Australian Capital Territory (ACT). The ACT has a population of 454 500 people and the population increased by 27% between 2011 and 2021, at a faster rate than in any other Australian state. A third of the population growth observed in the past 5 years was due to migration from India and Nepal. ACT has a relatively young and educated population (median age 35 years), with 40% of the population aged between 20 and 44 years.

Methods

Model development process and structure

Reporting of methods and results follows the Consolidated Health Economic Evaluation Reporting Standards (CHEERS)[23] 2022 (the completed CHEERS checklist is available upon request from the corresponding author). Methods are described briefly here and in full in the appendix (pp 9–32). The interventions that were included in the model were identified through a participatory modelling process. Interventions were suggested by stakeholders in the workshops, and a shortlist was created through consensus by the model development group. The set of final interventions was further narrowed on the basis of the availability of high quality evidence identified in the literature through non-systematic literature searching (usually in the form of published systematic reviews with meta-analyses or controlled trials) and the ability of the model development group to define the intervention in sufficient detail as to allow identification of resources required and costs that would be required to implement the intervention (appendix pp 16–17). The interventions assessed were: technology-enabled integrated care, emergency department-based suicide prevention, crisis response service, family education programmes, online parenting programme, school-based suicide prevention programme, trauma services for youths, and multicultural-informed care (table 1). The population of interest was children and young people aged younger than 25 years with low psychological distress (Kessler 10 score[25] 10–15), moderate distress (Kessler 10 score 16–21), and high-to-very-high levels of distress (Kessler 10 score 22–50), although the entire ACT population was included in the model due to its dynamic nature.

See Online for appendix

The choice to adopt a system dynamics approach to modelling was informed by best practices available in the scientific literature. One taskforce developed an eight-point checklist (the SIMULATE tool)[13] to help researchers identify whether dynamic simulation modelling was appropriate for the decision problem. The present context of mental health treatment and prevention for young people meets each of these domains: multiple events, relationships and stakeholders that make up the system; interactions between parts of the system including non-linear relationships and outcomes that are difficult to anticipate; multilevel strategic investment opportunities affecting decision makers in health, treasury departments, hospitals, and care providers; an opportunity for better understanding of the system by having all relevant stakeholders in the one room, including people with lived experience; incorporation of feedback loops that affect future consequences; multiple stakeholders and agents that interact and change the performance of care delivery;

For more on the **Australian population from the Australian Bureau of Statistics** see https://www.abs.gov.au/statistics/microdata-tablebuilder/tablebuilder

	Overview	Effectiveness used in model
TechInt	A coordinated, multidisciplinary model of care supported by a software platform that aids communication between care providers and their patients. There are three features of the platform: a triage function including initial assessment and identification of appropriate service pathways; provision of online education materials and information; and a care coordination function. The effectiveness of the intervention is applied in the model by improving the per-service recovery rate, improving referral to specialised services, and reducing disengagement from mental health services.	Improves per-service recovery rate by 18%; improves referral to specialised services by 27%; and reduces disengagement from mental health services by 28%.
Emergency department-based suicide prevention (EDSP)	Provides universal suicide risk screening and secondary suicide risk screening by a clinician, discharge resources, and follow-up phone calls after discharge from the emergency department focused on reducing suicide risk.	Reduces repeat presentations for suicidal ideation or behaviour by 28%; duration of effect of reduced repeat presentations of 24 weeks.
Crisis response service (CRS)	Mental health clinicians travel with police officers and paramedics and work together to manage individuals in crisis requiring a specialist mental health response. Some situations are de-escalated and require no further response. Individuals requiring immediate treatment are transported to emergency department as usual. Patients with less severe symptoms are referred to community mental health services.	11% of incidents can be de-escalated by the crisis team; 52% of incidents that cannot be de-escalated are transferred to the emergency department.
FamEd	Provision of psychosocial education and support to families and carers of patients engaged with mental health services, with the aim of supporting family or carer involvement in the management of psychotic mental disorders.	Improves the per-service recovery rate by a factor of 2; reduces presentation to the emergency department by 82%.
OnlPar	Based on the Triple P intervention:[24] participants develop new skills to help raise their children and strategies to prevent problems from developing. This increases the emotional wellbeing of children, resulting in more self-sufficient and resilient young people and families. It is applied to children aged 0–11 years.	Reduces transition to higher scores on the strengths and difficulties questionnaire by 37%; the program decay rate is the fractional rate per year at which the effects of the online parenting program decline to a value of 1 (ie, no effect) after the program concludes; the default value (1) implies that the effects of reduced behavioural difficulties onset would decrease to a value of 1 in one year given the initial rate of decline.
School-based suicide prevention (SSP)	School-based mental health education and suicide prevention programme delivered to secondary school students aged 12–17 years. There are three features to the programme: universal component of curriculum-based mental health education and awareness of suicidal ideation; indicated intervention component involving brief screening and provision of cognitive therapy for students with high-to-very-high distress; and a treatment-seeking component providing assistance with barriers to seeking professional help.	Increases the perceived need for mental health services by 45%; reduces the rate of suicidal behaviour of secondary school students by 38%; no effect on the rate at which students progress to higher levels of distress.
Trauma services for youths (TSY)	Mental health service providing trauma-informed care for young people under 18 years of age who are victims of family and domestic violence.	Improves the per-service recovery rate by a factor of 2·345; duration of effect of improved recovery rate of 12 weeks.
MultCult	Provides mental health professionals with the resources and training to deliver multicultural-informed care for people from culturally and linguistically diverse backgrounds engaging with the mental health care system.	Improves the per-service recovery rate by a factor of 2·84.
TechInt, FamEd, OnlPar, and MultCult (combination intervention)	All four interventions that were identified as cost effective are implemented concurrently.	As per individual interventions.

Detailed descriptions of interventions, including references supporting each effectiveness measure, are available in the appendix (pp 9–16). TechInt=technology-enabled integrated care. FamEd=family education programmes. OnlPar=online parenting programme. MultCult=multicultural-informed care.

Table 1: **Summary of interventions**

time-dependent and dynamic transitions as interventions are progressively scaled up; and the emergence of intended and unintended consequences.[13,26]

A participatory systems modelling approach was used to develop a system dynamics decision-support tool.[27] Protocols describing this process and economic aspects are provided elsewhere.[28,29] Participatory systems modelling involved three workshops, with more focused technical model development advisory group meetings in between, and a range of stakeholders such as health agency representatives, clinicians, and people with lived experience of mental ill-health. The model is a logically consistent mathematical framework that integrates best available data and evidence sources with expert and local knowledge. The model captures population and demographic dynamics, pathways to youth mental health care, service interactions and workforce capacity, and the potentially non-additive effects of intervention combinations (appendix pp 9–32). The model was calibrated through face validity among stakeholders and by observing its ability to reproduce historical trends across observed data (ie, the model produces results over time that make sense to stakeholders given their knowledge of their local area), including, but not limited to, population demographics, prevalence of psychological distress, employment, hospital admissions for self-harm, and mental health-related emergency department presentations.

Health measures

The main health outcome of interest for this cost-utility analysis was quality-adjusted life-years (QALYs). QALYs are a composite measure of health that includes both changes in survival and quality of life, reflecting the preference-based utilities of health states. Utilities were derived by using a mapping algorithm to convert low, moderate, and high-to-very-high distress levels based on the Kessler 10 disease-specific measure to the EQ-5D multi-attribute utility instrument, applying mapped utility decrements to Australian population norms (appendix p 24).[30,31] Cost-effectiveness analyses were also conducted for several intermediate health outcomes: suicide deaths, self-harm related hospital admissions, and mental health-related emergency department presentations (appendix p 34).

Costs

Health-care costs were obtained from the Australian Institute of Health and Welfare and the Independent Health and Aged Care Pricing Authority (appendix pp 26–27). Intervention costs were developed in collaboration with stakeholders including government agencies. Productivity costs were established from a variety of sources, including the Australian Bureau of Statistics (appendix pp 29–30). Costs related to domestic violence and homelessness were obtained from a report on the cost of youth homeless in Australia, a report on the cost of homelessness and net benefit of homelessness programmes, and a report by KPMG on the cost of violence against women and their children (appendix pp 27–28).

Economic settings

The time horizon was set to 10 years to allow sufficient time for cost and health consequences to occur after intervention implementation, but short enough for model run time to be manageable for probabilistic sensitivity analysis. A 30-year timeframe was adopted in a deterministic sensitivity analysis. A conventional lifetime time horizon is not relevant due to the dynamic nature of the population, where births and positive net migration mean the population continues to grow. Costs and health consequences were discounted at 5%, based on the reference discount rate set by the Pharmaceutical Benefits Advisory Committee,[32] and varied between 0% (based on the lower bound of sensitivity analysis specified by Pharmaceutical Benefits Advisory Committee) and 7% (discount rate used by treasury departments in Australia[33] for cost-benefit analysis) in sensitivity analysis. Health-care and societal perspectives were adopted due to the diverse stakeholders and decision makers involved, and all results are presented for both perspectives. The main differences between the two perspectives are the inclusion of costs related to productivity, carers, domestic violence, and homelessness for the societal perspective.

Univariate and probabilistic sensitivity analysis

In addition to the alternative time horizons and discount rates, intervention parameters were varied within plausible ranges to test the effect of alternative values on results (appendix p 7). Probabilistic sensitivity analysis was conducted to account for the effect of varying multiple parameters simultaneously based on the distributions around those parameters (appendix p 32). Latin hypercube sampling was used to draw 200 samples.[34] Intervention parameters were allocated to either univariate or probabilistic sensitivity analysis. Probabilistic sensitivity analysis was reserved for parameters with known variability, such as CIs reported by meta-analyses or costs that are expected to vary between providers (eg, consultation fees). All other intervention parameters were allocated to univariate variation.

Economic summary measures

Economic summary measures were used to compare the trade-off between health benefits and cost consequences. The incremental cost-effectiveness ratio (ICER) is the difference in costs divided by the difference in health units for the intervention compared with business as usual. The business-as-usual scenario assumes that existing policies and programmess remain in place, and that services capacity continues to grow at the current rate. This is not the same thing as assuming stasis; the system remains dynamic, changing over time with the changing size and age structure of the population, increasing health services provision, and trends in social determinants. Lower ICERs indicate greater value for money because greater health benefits are achieved at lower cost. The denominator can be any health measure, such as QALYs, suicide deaths avoided, or hospital admissions avoided. Cost per QALY is the most common economic summary measure because of the ability to compare ICERs within and between disease areas without the need to monetise health outcomes. In this analysis, the cost-effectiveness threshold, the point above which a positive ICER is no longer considered to be cost effective, was set at AU$79 930, based on the findings of a contingent valuation survey of willingness-to-pay for a QALY in Australia, indexed to 2019–20.[35] All results are given in 2019–20 AU$.

Dominant and dominated were used instead of negative ICERs because they could result from a reduction in costs and increase in health, or an increase in costs and reduction in health. Dominant indicates the intervention is expected to result in better health and lower costs than business as usual. Dominated indicates the intervention is expected to result in poorer health and greater costs than business as usual. Net monetary

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benefit is a conversion of health into financial units to aid the comparability of programmes and presentation of results. Net monetary benefit was calculated by multiplying QALYs by $79 930 (the specified cost-effectiveness threshold) and then subtracting costs. Incremental net monetary benefit (INMB) is the difference in net monetary benefit for an intervention compared with business as usual. A positive INMB indicates it is cost effective compared with business as usual. Although conclusions about value for money based on the INMB are identical to those based on the ICER, the INMB provides information about the absolute degree of cost-effectiveness, in addition to the relative cost-effectiveness conveyed by the ICER.

Role of the funding source

The study funder had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

Results

For the health-care perspective, technology-enabled integrated care, the online parenting programme, and multicultural-informed care had positive ICERs of $666, $7, and $572 per QALY gained, respectively, which were below the willingness-to-pay threshold of $79 930, indicating they would be cost effective (table 2). The ICER for family education was dominant, meaning it would result in an improvement in health and reduction in costs (ie, highly cost effective). The combination of technology-enabled integrated care, family education, online parenting programme, and multicultural-informed care was dominant. The ICERs for emergency department-based suicide prevention and trauma services for youths were $104 373 and $910 584 per QALY gained, respectively, exceeding the willingness-to-pay threshold, indicating they would not be not cost effective. Additionally, the crisis response service and school-based suicide prevention would not be cost effective because of their dominated ICERs. Technology-enabled integrated care had the highest INMB ($358 million [95% uncertainty interval (UI) 274 to 1227]), followed by the online parenting programme ($58 million [8 to 92]) family education ($31 million [11 to 57]), and multicultural-informed care ($11 million [7 to 16]). The combination intervention (technology-enabled integrated care, family education, online parenting programme, and multicultural-informed care) had an INMB of $460 million (–191 to 1317). The INMBs for the emergency department-based suicide prevention, crisis response service, school-based suicide prevention, and trauma services for youths were negative.

Conclusions were similar for the societal perspective, although the economic summary measures for most interventions improved due to the inclusion of more cost

	Health-care perspective				Societal perspective		
	Incremental QALYs, n (95% UI)	Incremental cost, $ (95% UI)	ICER, $ per QALY	INMB, $ (millions; 95% UI)	Incremental cost, $ (95% UI)	ICER, $ per QALY	INMB, $ (millions; 95% UI)
TechInt	4517 (–3135 to 14 507)	3 010 603 (–44 957 580 to 23 838 721)	666	358 (–274 to 1227)	–91 413 339 (–382 749 074 to 100 679 961)	Dominant	452 (–351 to 1555)
Emergency department-based suicide prevention (EDSP)	41 (0 to 48)	4 279 961 (1 459 889 to 8 209 666)	104 373	–1 (–8 to 2)	4 149 495 (1 207 883 to 8 209 535)	101 191	–1 (–8 to 3)
Crisis response service (CRS)	–11 (–12 to –10)	8 418 138 (5 671 599 to 11 599 186)	Dominated	–9 (–12 to –7)	7 847 305 (5 115 180 to 11 092 826)	Dominated	–9 (–12 to –6)
FamEd	339 (91 to 661)	–3 850 479 (–4 702 339 to –3 214 492)	Dominant	31 (11 to 57)	–12 756 804 (–20 951 987 to –6 584 630)	Dominant	40 (14 to 74)
OnlPar	724 (114 to 1149)	4992 (–518 751 to 747 628)	7	58 (8 to 92)	–3 598 303 (–6 272 572 to 183 597)	Dominant	61 (9 to 98)
School-based suicide prevention (SSP)	–234 (–764 to 12)	73 049 096 (56 494 717 to 89 901 876)	Dominated	–92 (–134 to –70)	90 337 441 (72 195 855 to 110 935 957)	Dominated	–109 (–171 to –75)
Trauma service for youths (TSY)	9 (4 to 16)	8 386 113 (6 853 200 to 10 111 422)	910 584	–8 (–9 to –6)	8 290 298 (6 805 566 to 9 994 830)	900 180	–8 (–9 to –6)
MultCult	137 (88 to 194)	78 437 (–65 667 to 203 150)	572	11 (7 to 16)	–3 087 025 (–4 532 990 to –1 849 115)	Dominant	14 (9 to 20)
TechInt, FamEd, OnlPar, and MultCult (combination intervention)	5732 (–2149 to 15 672)	–1 711 595 (–53 851 348 to 20 088 994)	Dominant	460 (–191 to 1317)	–112 053 074 (–402 131 433 to 85 792 094)	Dominant	570 (–256 to 1661)

All figures are cumulative over 10 years between 2023 and 2032 for the entire population of the Australian Capital Territory and discounted at 5%. All costs are in 2019–20 AU$. Interventions were assumed to be non-mutually exclusive therefore all incremental costs and QALYs were compared with business as usual. Although the combination intervention was mutually exclusive with the corresponding individual interventions, the comparison with business as usual was retained rather than undertaking separate incremental analysis to maintain tractability of results. A willingness-to-pay threshold of $79 930 per QALY was used to calculate net monetary benefit. 95% UIs were not provided for ICERs due to the challenging nature of calculating and correctly interpreting variability across all four quadrants of the cost-effectiveness plane for a large number of interventions. Identical conclusions are garnered from the uncertainty intervals for INMB. ICER=incremental cost-effectiveness ratio. QALY=quality-adjusted life-year. INMB=incremental net monetary benefit. UI=uncertainty interval. TechInt=technology-enabled integrated care. FamEd=family education programmes. OnlPar=online parenting programme. MultCult=multicultural-informed care.

***Table 2:* Cost-utility analysis results of interventions compared with business as usual**

categories, such as productivity. For the cost-effective interventions, family education and the combination intervention remained dominant but the online parenting programme, technology-enabled integrated care, and multicultural-informed care were also dominant interventions. The INMBs were higher for the cost-effective interventions for the societal perspective than for the health-care perspective. The interventions that were not cost effective for the health-care perspective were also not cost effective for the societal perspective. The additional costs accrued for the societal perspective compared with the health-care perspective are largely driven by health outcomes. Interventions that resulted in a large number of incremental QALYs were also associated with a large reduction in costs for the societal perspective compared with those same interventions for the health-care perspective. Interventions that had little impact or negative impact on QALYs had little or negative impact on incremental costs for the societal perspective. INMBs for the societal perspective over time are shown in figure 1.

Outcomes for several alternative scenarios are provided in the appendix (p 7). The base case set of results based on deterministic analysis, where the default values were used without taking into account joint probability of probabilistic sensitivity analysis, are shown in the appendix (p 2). The conclusions regarding cost-effectiveness in the deterministic analysis (appendix p 2) were the same as for the probabilistic sensitivity analysis (table 2). Data on costs per suicide death avoided, intentional self-harm hospitalisations avoided, and mental health-related emergency department presentations avoided are in the appendix (appendix pp 3–5). Whether interventions would be cost effective based on these

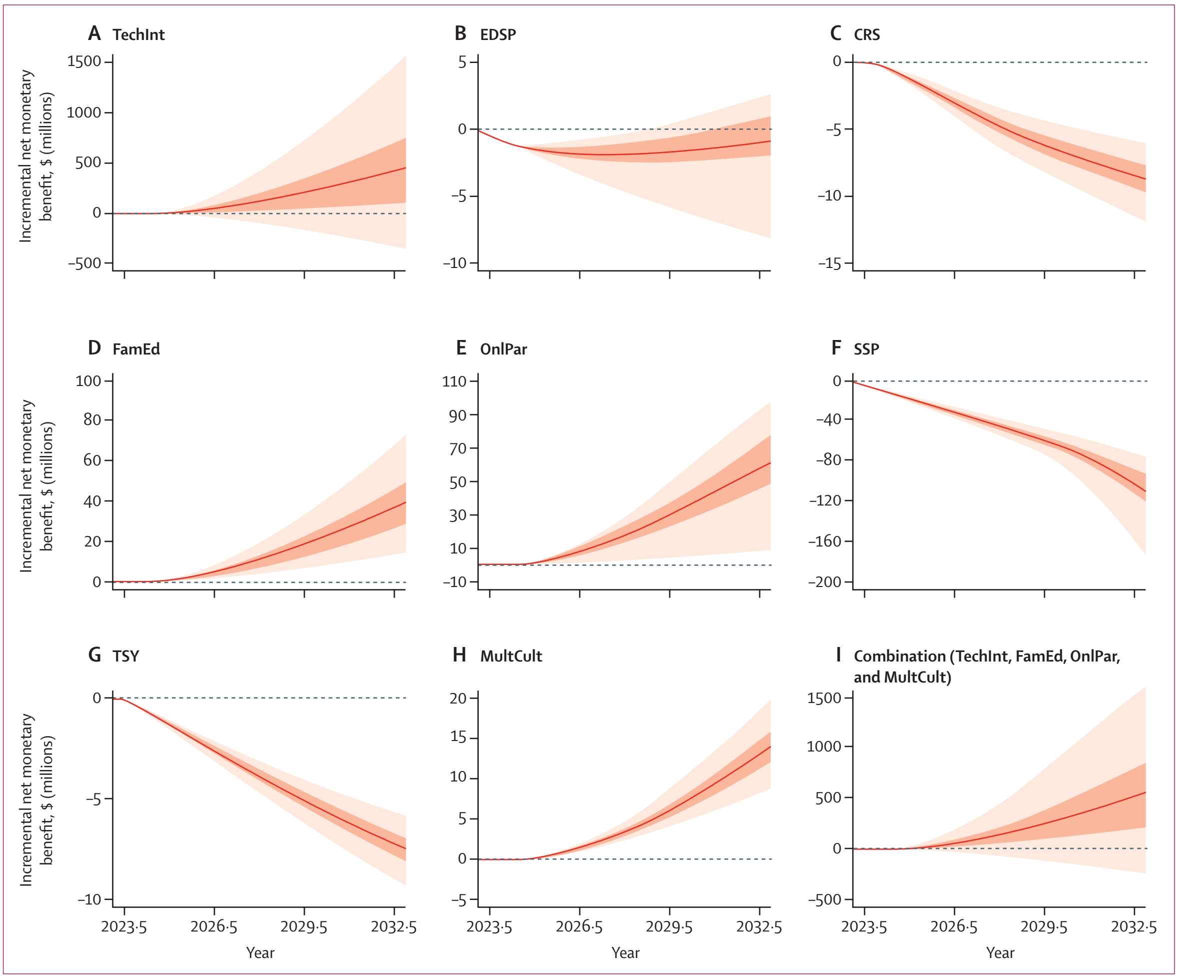

Figure 1: **Incremental net monetary benefit over time from the societal perspective**
Cumulative incremental net monetary benefit of mental health interventions between January, 2023 and December, 2032, compared with business as usual. A willingness-to-pay threshold of $79 930 per QALY was used to monetise health benefits. Costs and QALYs are discounted at 5%. The solid line indicates the expected mean incremental net monetary benefit, darker shading represents the 50% uncertainty interval, and lighter shading indicates the 95% uncertainty interval. Positive incremental net monetary benefit indicates cost-effectiveness compared with business as usual. TechInt=technology-integrated care. EDSP=emergency department-based suicide prevention. CRS=crisis response service. FamEd=family education programmes. OnlPar=online parenting programme. SSP=school-based suicide prevention. TSY=trauma service for youths. MultCult=multicultural-informed care.

measures depends on willingness-to-pay per unit of health outcome avoided, with the exception of cases where the ICER are dominated or dominant, in which case the findings are unambiguous. These results generally supported the base case conclusions on cost-effectiveness, with the exception of emergency department-based suicide prevention, which had the potential to be considered cost effective by a decision maker at higher thresholds. Disaggregated cost impacts by category are in the appendix (p 6). For example, the combination intervention would involve an investment of $15 million and is projected to deliver health-care cost savings of $11·6 million, domestic violence and homelessness cost savings of $1·8 million, carer cost savings of $24·6 million, and productivity improvements of $76 million using the 10-year time horizon.

The results of univariate sensitivity analysis for selected parameters are in the appendix (p 7). Most results are robust to changes of parameters within plausible ranges, with three exceptions. Emergency department-based suicide prevention would be considered cost effective for both the health-care and societal perspectives, if the duration of effect on the ACT population was 36 weeks (rather than 24 weeks) or the annual budget was reduced by 20%. School-based suicide prevention would be considered cost effective, if it was effective at reducing the rate at which students in the ACT progressed to higher levels of distress by 20% (no effect in the base case, based on a 2006 randomised controlled trial).[36] Conclusions on cost-effectiveness were robust to changes in time horizon and discount rate (appendix p 8). One exception was emergency department-based suicide prevention, which became cost effective for both the health-care and societal perspectives when the timeframe was extended to 30 years (in comparison to the default of 10 years) or the discount rate was lowered to 0% (where the default was 5%).

The cost-effectiveness acceptability curve is another tool for investigating the impact of uncertainty by reporting the proportion of simulations considered cost effective at varying levels of willingness-to-pay. On the basis of the parameters included in the probabilistic sensitivity analysis (table 2), we can be fairly certain that the interventions that are cost effective in the base case remain cost effective across a wide range of willingness-to-pay thresholds and vice-versa for interventions that are not cost effective (figure 2). One exception is emergency department-based suicide prevention, which is more likely to be cost effective at higher thresholds.

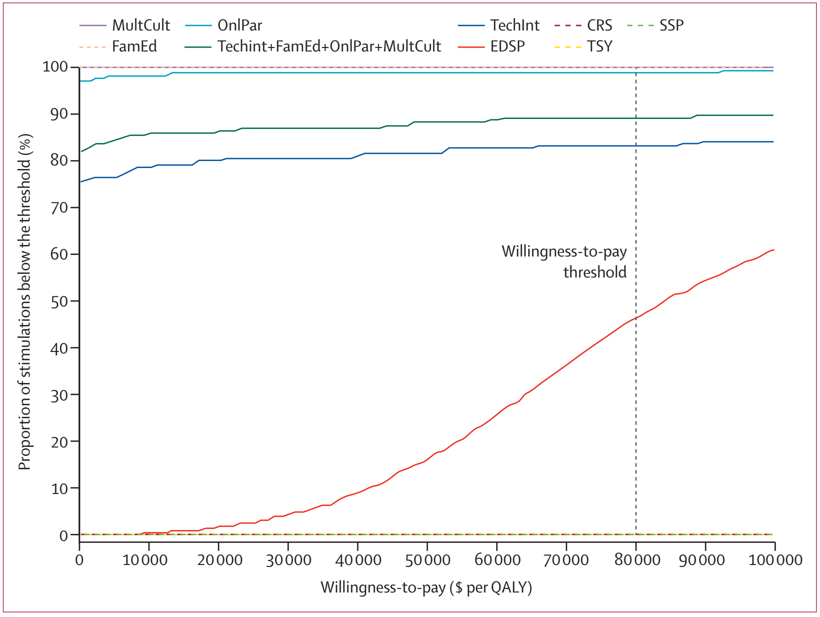

Figure 2: **Cost-effectiveness acceptability curve for cost-utility analysis (QALYs) from the societal perspective**
Each cost-effectiveness acceptability curve indicates the proportion of simulations considered to be cost effective at varying willingness-to-pay thresholds for a QALY. Cost-effectiveness thresholds are conventionally applied to modelling exercises where a closed cohort has been adopted. The business as usual comparator for each intervention has been omitted from the graph. QALYs=quality-adjusted life-years. MultCult=multicultural-informed care. FamEd=family education programmes. TechInt=technology-integrated care. OnlPar=online parenting programme. EDSP=emergency department-based suicide prevention. CRS=crisis response service. TSY=trauma service for youths. School=school-based suicide prevention programme.

Discussion

The interventions technology-enabled integrated care, family education, online parenting programme, and multicultural-informed care were found to be cost effective because they were dominant (improved health benefits and reduced overall costs) or had ICERs that were below the willingness-to-pay threshold. There was a high degree of certainty in these findings based on one-way deterministic and probabilistic sensitivity analysis. Four interventions were not cost effective in the base case: emergency department-based suicide prevention, the crisis response service, trauma services for youths, and school-based suicide prevention. However, probabilistic sensitivity analysis highlighted less certainty in this finding for emergency department-based suicide prevention and scenarios were identified in which it would be considered cost effective, such as extending its duration of effectiveness, reducing the cost of the intervention, adopting a lower discount rate, and extending the time horizon of the model to 30 years. School-based suicide prevention was sensitive to whether it was effective at reducing the rate at which students progressed to higher levels of distress.

The combination of all cost-effective interventions was found to be dominant, resulting in a large improvement in health outcomes and a reduction in costs, particularly for the societal perspective. Synergistic effects were identified, suggesting greater systemic benefits when all four interventions were operating concurrently. When all four interventions were implemented together, the health benefits in terms of QALYs and INMB were higher than a simple summation of the effects of individual interventions alone. The expected incremental QALYs for the combination was 5732 compared with 5717 for the summation of individual interventions. The expected INMB was $2 million higher for the combination than with individual interventions summed for both the health-care and societal perspectives. The combination also provided an additional $1 million of cost savings compared with the summed interventions alone.

Several unique attributes of adopting a system dynamics modelling approach for economic analysis compared with conventional economic modelling were identified. First, synergistic effects, in terms of both health benefits and overall economic value, were identified for the combination of cost-effective interventions. It is only through modelling the dynamic relationships and interactions between different parts of the system that such an outcome can be identified. It cannot be assumed that combining interventions will always result in synergistic effects since interventions operate on different parts of the system. The simulation needs to be run for any combination of interest to identify any synergistic or antagonistic effects. Second, emergent outcomes in the form of unintended consequences were uncovered for some interventions, predominantly caused by health service capacity constraints. For example, school-based suicide prevention resulted in negative QALYs because of its effectiveness in driving services engagement in addition to the improvement it had on suicidal behaviour. Compared with business as usual, 45% more adolescents would engage with the mental health system under this intervention, placing substantial demand on services and increasing waiting times for services. The additional time that people spend at higher levels of distress results in fewer QALYs accumulated over the 10-year period of the model (compared with business as usual). Third, scenarios testing changes to services capacity growth could be performed, alone or in combination with interventions. This function is not usually included in conventional economic modelling, which simply assumes that any adoption of a new intervention is absorbed by the health-care system without quantifying the additional sources from which these resources might be obtained. Fourth, a user-friendly interface was available to enable stakeholders to interact with the model, test interventions and scenarios, alone or in combination, and produce results themselves to enhance the transparency and accountability of decision making.

The findings of this analysis add to existing literature on the cost-effectiveness of mental health interventions. For integrated, collaborative care for depressive disorders, 11 of 13 studies in a systematic review found the interventions were cost effective but the maximum time horizon was 2 years and the most recent study was for a population in 2011.[37] The degree to which technology was used as a central component of these studies is unknown.[37] A cost-effectiveness analysis of the ED-SAFE intervention in the USA found that universal screening in the emergency department and after-discharge follow-up resulted in an ICER of US$5020 per averted suicide attempt or suicide death. Although the economic analysis was restricted to the 12-month period of the trial, it did not estimate health outcomes in terms of QALYs and did not include costs outside the direct health-care costs of the intervention. The findings are broadly consistent with our analysis, demonstrating that there are circumstances in which emergency department-based suicide prevention would be considered cost effective.[38] A 2012 evaluation of the Police Ambulance Clinical Early Response service in the state of Victoria (Australia), similar to the crisis response service intervention modelled in our study, found that the Police Ambulance Clinical Early Response model was less costly than usual service, but data limitations prevented firm conclusions about cost-effectiveness. Health outcomes were not included in that evaluation, limiting comparability with the present analysis.[39] A cost-effectiveness analysis published in 2004 found that three types of family interventions were cost effective with ICERs of AU$2 000 per DALY averted and below, consistent with the finding of the present analysis that family education was cost effective.[40] A cost-effectiveness analysis of the Triple P parenting programme for conduct disorder, similar to the online parenting programme, found ICERs of $1013 and $20 498 per DALY averted for group and individual formats, respectively, consistent with the present study, which found that the online parenting programme was cost effective.[41] A comprehensive systematic review of mental health prevention and promotion cost-effectiveness analyses found mixed evidence on school-based suicide prevention programmes. One study in the USA context reported cost savings, one in the Australian context was found to be cost effective, and a trial-based cost-effectiveness analysis across ten European countries found them not to be cost effective.[5] This suggests that further research is required on the cost effectiveness of school-based mental health programmes, the specific design of such programmes is an important determinant of their cost effectiveness, and evaluation findings are not necessarily generalisable to another programme or context.

This analysis has limitations. The inclusion of a single combination of interventions, and the inclusion of the four cost-effective interventions in that combination, is somewhat arbitrary. Other combinations were tested, whereby interventions that were not cost effective were included with the main cost-effective combination to identify any unanticipated effects, but they were found to be antagonistic as expected (reduced INMB compared with the cost-effective combination alone; appendix p 33). Other combinations might be worthy of exploration depending on the priorities of decision makers. Although we did comprehensive univariate and probabilistic sensitivity analyses, structural uncertainty was not examined due to time and resource constraints. Therefore, the impact on the results of adopting alternative modelling approaches and assumptions about the underlying mental health-care system in the ACT is unknown. Another important consideration is that the results relate to the modelled interventions described in this Article. Whether the results are generalisable to a specific programme or change to model of care depends on how similar that programme or model of care is to the present modelled intervention.

Technology-enabled integrated care, family education, online parenting programme, and multicultural-informed care were found to be cost effective and the economic evidence generated by this analysis supports their implementation, preferably concurrently to take advantage of synergistic effects to maximise population health outcomes. System dynamics modelling was found to be a useful modelling approach for resource allocation and priority setting contexts involving complex dynamic systems often encountered in public health, such as the mental health care and prevention systems. System dynamics modelling could become part of the regular toolkit used by mental health planners, with the aim of making regional mental health systems more efficient, effective, and equitable.

Contributors

All authors contributed to review and editing of the manuscript. PC wrote the original draft, advised on the integration of economic components to the model and extracted and interpreted economic output, and directly accessed and verified the underlying data reported in the manuscript. NH developed the model; sourced, cleaned and integrated data to the model; and directly accessed and verified the underlying data reported in the manuscript. SHH, CV, and AS contributed to development of the model. AS advised on visualisation, data curation, and software. ANN and RH advised on economic input data and interpretation of economic results. SH and GYL managed project administration. SR and DAM provided supervision and methodology advice. YJCS, JO, and IBH led the project conceptualisation and funding acquisition. All authors confirm that they had full access to all the data in the study and accept responsibility to submit for publication.

Declaration of interests

JO is head of systems modelling, simulation and data science at the Brain and Mind Centre at the University of Sydney and is managing director of Computer Simulation and Advanced Research Technologies. SH is a member of the Hunter New England Central Coast Primary Health Network's Community Advisory Committee. IBH is the co-director of Health and Policy at the Brain and Mind Centre at the University of Sydney, which operates early-intervention youth services at Camperdown under contract to Headspace; has previously led community-based and projects supported by the pharmaceutical industry (Wyeth, Eli Lily, Servier, Pfizer, AstraZeneca, Janssen, Cilag), focused on the identification and better management of anxiety and depression; and is the Chief Scientific Advisor to, and a 3·2% equity shareholder in, InnoWell, which aims to transform mental health services through the use of innovative technologies. PC, NH, HH, CV, AS, AN, RH, YJCS, SR, PM, EM, GYL, and DM declare no competing interests.

Data sharing

Data collected for the study will not be made publicly available. We did not collect original data for this study and because it is a modelling exercise, input data are either publicly available or provided in confidence by an organisation as per the sources cited in the appendix (pp 9–32). Model output data are available on request to the corresponding author, with publication, for non-commercial purposes. No additional related documents will be made available. Protocol papers have been published previously and are cited in the manuscript.

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Preface to Chapter 3 (Modelling Study 2)

Chapter 3 takes the form of an article published in *Nature Mental Health*, ‘Modeled estimates of the health outcomes and economic value of improving the social determinants of mental health’. This chapter contributes to addressing the overarching research question by demonstrating the ability of system dynamics modelling to move outside a treatment-based paradigm and health sector perspective by considering the economic credentials of improving the social determinants of mental health.

Supplementary material supporting this analysis can be found in Appendix 3.

A list of equations is available upon request by emailing Paul Crosland at paul.crosland@sydney.edu.au.

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Analysis

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Modeled estimates of the health outcomes and economic value of improving the social determinants of mental health

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The prevalence and burden of mental disorders have worsened despite increased community awareness. Enhanced access to treatments alone is unlikely to deliver improvements in population mental health, so more attention needs to be paid to social and environmental influences. Here we estimate the health benefits and economic value of improving the social determinants of mental health within Brisbane South, a diverse population of 1.2 million people, in Australia. The incremental net monetary benefit (combining costs and monetized health outcomes) derived from 5% improvements in the average yearly change of social cohesion, childhood difficulties, substance misuse and unemployment over 11 years from 2024 to 2034 was projected to be AUD$146.64 million, AUD$234.50 million, AUD$281.67 million and AUD$100.43 million, respectively. Quality-adjusted life years, suicide deaths, emergency department presentations and self-harm hospitalizations were also improved. This study demonstrates the health and economic value of investing in the social determinants of mental health.

Despite greater community awareness about mental health, the prevalence and burden associated with mental disorders are deteriorating[1–4]. Depressive disorders were the second-highest cause of nonfatal health burden globally in 2021, an increase in years lived with disability of 36.5% from 2010[5]. Anxiety disorders were the sixth-highest cause of nonfatal burden[5]. Young people, in particular, have experienced a serious deterioration in mental health in the past 14 years. For example, a longitudinal survey found that the prevalence of depression and anxiety more than doubled between 2009 and 2021 in Australian young people aged 15–34 years (from 6.1% to 14.4% for males and from 12.7% to 29.3% for females)[6]. The prevalence of psychological distress also more than doubled between 2011 and 2021 in young people in Australia aged 15–24 years (from 18.4% to 42.3%)[6]. Suicide was the leading cause of death among people aged 15–44 in 2022 in Australia[7]. Although the decline in the mental health of younger age groups has been underway for more than a decade, the coronavirus disease 2019 pandemic and associated lockdowns have influenced these estimates in recent years[8]. Increases in the provision of mental health care have been outweighed by a concurrent increase in the incidence of high to very high levels of distress, as demonstrated by simulation modeling[9]. The Australian experience is replicated across most high-income countries[10,11] and is also an emerging threat in developing nations[12].

There are long-term consequences of young people experiencing mental disorders, for individuals and their families, for communities and for the whole economy. These disorders are a risk factor for a wide range of chronic physical illnesses[13] and affect their ability to participate

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in the labor force later in life[14]. Some of this burden could be averted if young people had full access to optimal treatment[15]. However, expanding access to mental health treatments alone is insufficient to reduce the burden of poor mental health due to the rising incidence of disorders[9,16], which occur in—and interact with—the context of wider social, economic, commercial and environmental factors. More meaningful, long-term, intergenerational reductions in mental illness are thus likely to be achieved by 'moving upstream', targeting the 'causes of the causes' and preventing mental ill health before it develops[17,18]. This could be achieved by a more intentional approach to choosing mental health and well-being as a key policy objective (which can be formally conceptualized as Mental Wealth[19]) and designing and implementing evidence-based economic and social systems and environments that foster this objective as the norm[17,20].

Economic implications are interwoven through the causes and consequences of mental disorders. The global economic burden of mental disorders was estimated to be between US$2.5 trillion and US$8.5 trillion in 2010 depending on the methodological approach used to monetize health impacts[21]. The more conservative approach is expected to reach annual costs of US$6 trillion by 2030[21]. In the USA, more health expenditure is dedicated to treating mental health disorders than any other disease area[22]. The persistent nature of mental health and substance use disorders in the USA, and other countries, suggests this expenditure is not currently allocated efficiently. Furthermore, most of the economic burden of poor mental health is incurred outside the health care system[23]. For example, the Australian Productivity Commission estimated there were AUD$39 billion in productivity costs associated with poor mental health and suicide in 2018–2019 compared with AUD$16 billion of mental health-related healthcare expenditure[24]. Estimates of the economic burden of mental illness are a part of the prioritization problem facing decision-makers (that is 'How big is the problem?'); another is economic evidence supporting interventions (that is, 'What can be done about it?'). Although much evidence exists on the cost-effectiveness of treatments[25,26] and the prevention of mental ill health and promotion of mental health[27,28], many gaps still exist[29–31], including strategies that target the social determinants of mental health. Evidence on the economic credentials of current expenditure is also lacking[32], and accountability in mental health decision-making and planning is poor[33]. Generating more and better economic evidence is critical for guiding better investment decisions and helping decision-makers prioritize the areas and strategies that can have the biggest impact for improving mental health[34].

The Lancet Commission on Global Mental Health and Sustainable Development recognized that treatments alone are unlikely to achieve sufficient improvements in population mental health and that more attention needs to be paid to social and environmental influences, particularly during important developmental periods in the early life course, childhood and adolescence[12]. The social determinants of mental health refer to the social, economic and physical environments that directly influence the incidence, prevalence and severity of mental illness[35,36]. Examples of the structural risk factors that influence mental health include low educational attainment, unemployment and underemployment, poverty, food insecurity, unstable housing, social isolation and loneliness, discrimination, early life and childhood adversity and trauma, neighborhood social and physical conditions, and access to best practice and affordable health care[37,38]. These determinants can play out in regionally specific ways to impact population mental health and well-being. They often have a bidirectional relationship with mental health and are interlinked and dynamic, interacting with each other in a complex causal web, highlighting the importance of systems thinking when developing strategies to overcome them[17]. Most of these risk factors are associated with a social gradient based on socioeconomic disadvantage and inequality, whereby "the greater the inequality the higher the inequality in risk"[35]. There is also increasing awareness of the role of 'global megatrends' in harming the mental health of young people[11] as well as the ongoing shadow cast by the coronavirus disease pandemic. These megatrends are broader concepts than social determinants, referring to long-lasting societal upheaval in environmental, social, economic, political or technological domains. Nevertheless, they overlap with the social determinants discussed here.

Evidence exists supporting the causal link between social determinants and later mental health outcomes[37]. The importance of different social determinants varies across the life course[37]. An umbrella review of 46 meta-analyses found that numerous social determinants, such as midlife unemployment, homelessness and interaction with the criminal justice system, had consistent associations with suicide-related outcomes[39]. Another umbrella review included 289 systematic reviews on the evidence for potential mechanisms by which social determinants affect mental health conditions[16]. This evidence was mapped to the United Nations Sustainable Development Goals using five domains: demographic, economic, neighborhood, environmental events, and social and cultural domains[16]. The World Health Organization recently issued new guidance on mental health policy and strategic action plans that has a strong emphasis on social and structural determinants[40]. Despite this evidence, social determinants of mental health are rarely addressed within child and youth health policies and services planning[41], and the social determinants of mental health are either not improving or getting worse over time[11,32]. Investing in child and youth mental health has the potential to optimize the return on investment of scarce healthcare resources, given the potential for major intergenerational impacts that stretch into adulthood and beyond.

The Lancet Psychiatry Commission on Youth Mental Health specify enhancing awareness and advocacy of the social and economic determinants of mental ill health as the first key element of optimal youth mental health care[11]. However, in the context of scarcity and budgetary constraint, decision-makers require guidance on which social determinants should be prioritized, and what specific interventions can be implemented to improve them. This is one of the reasons why prominent reviews of the social determinants of mental health call for the generation of more economic evidence in this area[36,42].

The objective of this Analysis was to estimate the health benefits and economic value of improving the social determinants of mental health for the Brisbane South region in Australia using system dynamics simulation modeling. To enhance the validity, transparency and usability of the Analysis, participatory model-building processes were followed, including meaningful participation of young people with lived experience of mental health conditions. This makes the Analysis relevant to the multifaceted nature of the problem, which involves diverse stakeholders engaging with the issue in real-world contexts. Results were reported for a variety of health outcomes and economic summary measures, and the cost impacts were disaggregated by payer. Only a selection of social determinants have been included in this Analysis. These were priority determinants identified by stakeholders of the region as key drivers of youth mental health outcomes and where sufficient data could be obtained.

Results

All costs are reported in 2020–2021 Australian dollars. All estimates relate to all ages of the Brisbane South Primary Health Network region, a population of 1.2 million people (4% of the Australian population), and are cumulative over the 11-year time horizon of the model (2024–2034) unless otherwise specified. Estimates are incremental compared with business as usual. Costs and quality-adjusted life years (QALYs) were discounted at 5%. Table 1 contains a definition of each social determinant and the specific changes that were applied for each scenario of improvement. 'Improvement' in this context could mean a reduction in the rate at which people develop substance misuse disorder or an increase in social cohesion, for example (Table 1).

The greatest increase in health outcomes in terms of QALYs was attained by a 5% improvement in childhood difficulties (2,621 QALYs),

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Table 1 | Defining the social determinants and scenarios of improvement

Social determinant	Description as defined for the present model	Source of historical data	What a '5% improvement' means for each scenario (additional detail provided per age group provided in Supplementary Information part B)
Social cohesion	Based on the Scanlon–Monash Index of Social Cohesion, this represents the willingness of members of society to cooperate with each other in order to survive and prosper. There are five domains this index seeks to capture: belonging; worth; social justice and equity; political participation; and acceptance and rejection[75]. The five domains are transformed to a single composite index using factor analysis and assigning weights to each indicator, with 2007 as the reference year assigned the starting index of 100. Further detail on the methods used by the Scanlon–Monash research group can be found in a report by Markus et al.[76], and https://www.monash.edu/mapping-population. The average annual decline between 2011 and 2023 in the Scanlon–Monash Index was by 0.788 units, and this was assumed to continue each year of the model timeframe in a linear fashion as part of the business-as-usual scenario.	Scanlon–Monash Index of Social Cohesion[75]	The social cohesion index continues to decline in future years but at a reduced rate by applying a multiplier of 0.95 to the baseline average annual rate of change from January 2024 onward. Each year, the index will decrease by 0.7486 (0.788×0.95).
Early life and childhood behavioral and emotional difficulties (shortened to 'childhood difficulties' in text, tables and figures)	Childhood difficulties (early life and childhood behavioral and emotional difficulties) refers to the outcome of a brief screening questionnaire (SDQ) that measures behavioral and emotional difficulties in children and young people[67]. In our model, the population aged less than 12 years is partitioned to one of three levels of distress: 'close to average', 'slightly raised' or 'high' SDQ levels. Higher levels of SDQ can be an indicator of early life difficulties, adverse experiences or trauma. Rates by which people flow between the three levels of SDQ are dependent on age, rates of engagement with the mental health services system, rates of treatment and the population levels of social cohesion.	The Longitudinal Study of Australian Children, Growing up in Australia[77,78]	The rate at which children transition to higher levels of SDQ was reduced by applying a multiplier of 0.95 from January 2024 onward.
Homelessness	Following the Australian Bureau of Statistics (ABS), homelessness refers to a state in which an individual does not have a permanent living arrangement, no fixed place of residence, and no suitable or adequate accommodation alternatives[79]. People aged 15 and older enter homelessness at rates that are dependent on age, levels of psychological distress, unemployment and substance misuse. For people under the age of 15 years, rates of entering homelessness are dependent on age.	ABS[80]	The rate at which people enter homelessness was reduced by applying a multiplier of 0.95 from January 2024 onward.
Unemployment	Following the ABS, unemployment is defined as a state in which an individual who is of working age and ability, and who is actively seeking and available for work, is not employed in any paid work or self-employed work. People can transition between the states of being sufficiently employed, underemployed, unemployed or not-in-the-labor-force.	ABS[81–83]	The rates at which people enter unemployment from being sufficiently employed or underemployed was reduced by applying a multiplier of 0.95 from January 2024 onward.
Discontinue secondary education	Discontinuing secondary education refers to when a student enrolled in any high school grade between grade 7 and 12 withdraws their enrollment. Rates of discontinuation are dependent on levels of psychological distress in the population aged 12–17 years.	Australian Curriculum, Assessment and Reporting Authority (ACARA)[84]	The rate at which students discontinue secondary education was reduced by applying a multiplier of 0.95 from January 2024 onward.
Discontinue tertiary education	Discontinuing tertiary education refers to when an individual attending education for a qualification at certificate III or above withdraws their enrollment. Rates of discontinuation are influenced by psychological distress.	ABS[83,85]	The rate at which students discontinued tertiary education was reduced by applying a multiplier of 0.95 from January 2024 onward.
Substance misuse	We followed the ABS' definition of 12-month substance use disorder, and here, we refer to this as substance misuse. Substance misuse refers to the use of alcohol and other drugs in a way that produces harm to the consumer of the substance and others. Harm associated with substance misuse can include a deterioration of an individual's mental and physical health, financial state, social connectedness, education and employment. The rate at which people develop substance misuse is dependent on homelessness, levels of young people aged 15–24 not in education nor employment, levels of psychological distress and recovery from substance misuse treatment services.	ABS[86,87]	The rates at which people developed 12-month substance use disorder was reduced by applying a multiplier of 0.95 from January 2024 onward.
Underemployment	Based on the ABS' definition, underemployment refers to a state in which an individual is employed in paid work but has indicated that they would prefer to work more hours. People can transition between the states of being sufficiently employed, underemployed, unemployed or not-in-the-labour-force.	ABS[81–83]	The rates at which people transition from being sufficiently employed into underemployment were reduced by applying a multiplier of 0.95 from January 2024 onward.

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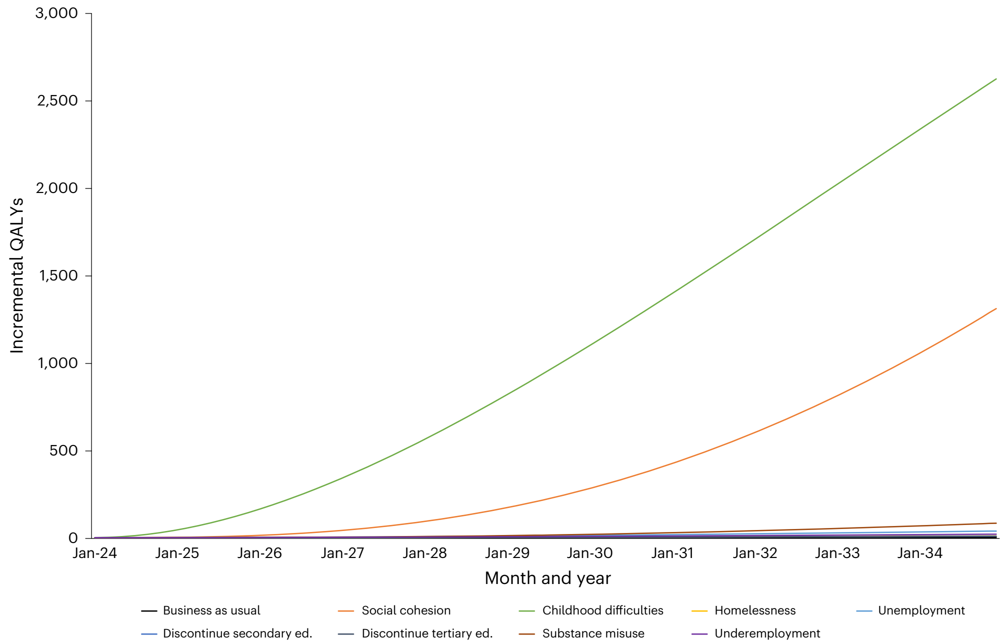

Fig. 1 | Incremental QALYs, 5% improvement in social determinants versus business as usual. Cumulative QALYs over 11 years, 2024–2034, discounted, versus business as usual.

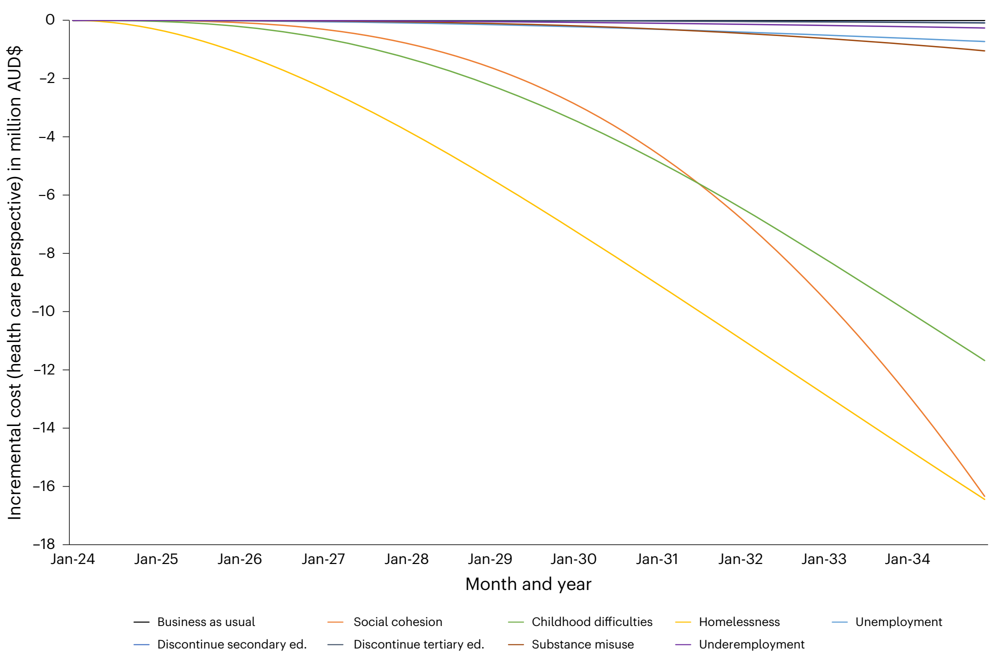

Fig. 2 | Incremental cost (health care perspective), 5% improvement in social determinants versus business as usual. Cumulative costs over 11 years, 2024–2034, discounted, 2020–2021 Australian dollars versus business as usual. ed., education.

followed by social cohesion (1,309 QALYs) and substance misuse (82 QALYs) (Fig. 1; Supplementary Table 3 in Supplementary Information part B). A 5% improvement in the other determinants was also associated with an increase in QALYs but to a lesser extent. Reducing substance misuse and improving social cohesion individually resulted in the greatest number of suicide deaths avoided (Supplementary Table 3 in Supplementary Information part B). Reducing substance misuse, improving social cohesion and reducing childhood difficulties individually realized the greatest number of avoided self-harm hospitalizations. Improving childhood difficulties and social cohesion avoided the greatest number of mental health-related emergency department presentations.

Improving the social determinants of mental health substantially reduced downstream costs. For the health care perspective, the greatest reduction in costs was achieved by a 5% improvement in homelessness ($16.4 million), followed by social cohesion ($16.3 million) and childhood difficulties ($11.7 million) (Fig. 2; Supplementary Table 1 in Supplementary Information part B). A 5% improvement in substance misuse resulted in $1 million of downstream cost savings. Improvements in unemployment, underemployment and discontinuation of secondary or tertiary education resulted in cost reductions less than this.

For the societal perspective, the greatest reductions in costs were seen by 5% improvements in substance misuse ($274.8 million),

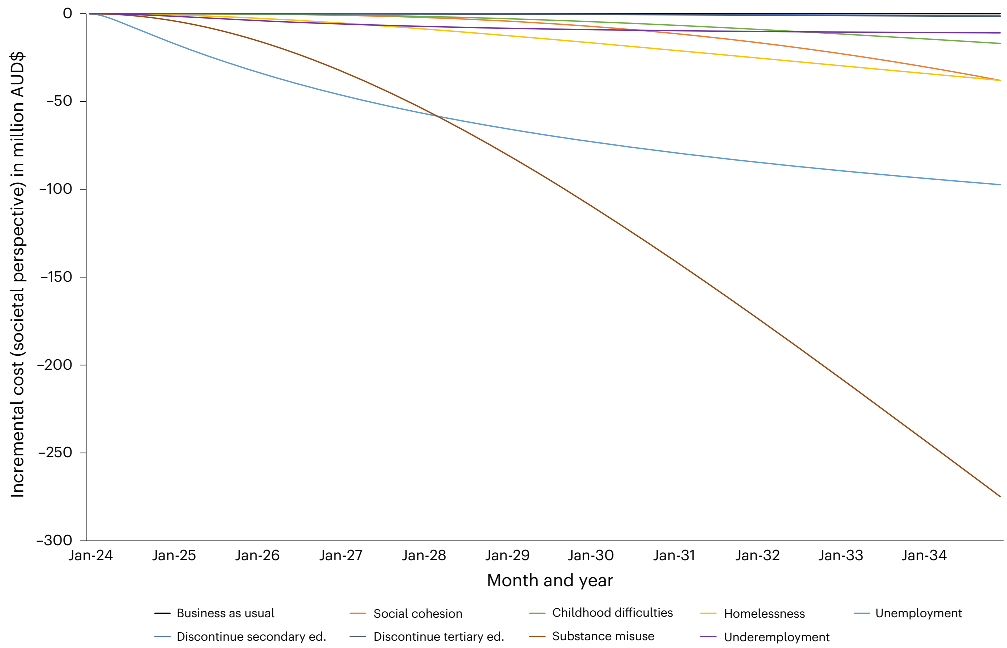

Fig. 3 | Incremental cost (societal perspective), 5% improvement in social determinants versus business as usual. Cumulative costs over 11 years, 2024–2034, discounted, 2020–2021 Australian dollars versus business as usual. ed., education.

unemployment ($97.3 million), social cohesion ($38 million) and homelessness ($38 million) (Fig. 3; Supplementary Table 1 in Supplementary Information part B). The downstream cost savings were attributed largely to a reduction in lost productivity. These productivity savings amounted to $157.3 million for substance misuse, $95 million for unemployment, and $20.6 million for social cohesion, for the societal perspective.

When analyzing cost impacts by payer for the societal perspective, homelessness ($13.6 million), substance misuse ($10.4 million) and social cohesion ($7.3 million) were the most important determinants for the Australian (National) Government. Five percent improvements in substance misuse ($107.8 million), homelessness ($19.1 million), social cohesion ($16.3 million) and childhood difficulties ($11.5 million) achieved the greatest reductions in costs for the Queensland (State) Government. Homelessness was the only determinant that reduced costs for nongovernment payers, which predominantly consists of individuals in the form of out-of-pocket costs. Improvements in all other determinants increased costs for nongovernment payers. (This was mainly due to a reduction in welfare payments received by this group. Changes in these transfer payments result in a decrease in costs to government and zero net impact on total costs. We have not included employment income, nor income tax, in this Analysis, which would be expected to more than offset the reduced welfare payments for individuals.) For reductions in the cost of lost productivity incurred by the general economy, improvements in substance misuse ($157.3 million), unemployment ($95 million), social cohesion ($20.6 million) and underemployment ($10.8 million) achieved the greatest changes.

For all social determinants except social cohesion, the estimated incremental total costs that flowed from a 10% improvement in social determinants were slightly greater than simply doubling the estimates for a 5% improvement (Supplementary Table 1 in Supplementary Information part B).

When costs and QALYs were combined with a willingness to pay per QALY of $83,004 to derive incremental net monetary benefit (INMB) compared with business as usual (a full explanation of these terms and methodology is available in the Methods), a 5% improvement in substance misuse resulted in an INMB of $281.67 million, childhood difficulties $234.50 million, social cohesion $146.64 million and homelessness $38.75 million (Fig. 4; Supplementary Table 2 in Supplementary Information part B). A comparison between 3-year and 11-year time horizons reveals that taking a long-term view would enable decision-makers to exponentially capitalize on the full extent of the net benefit anticipated from improving the social determinants of mental health. For example, for the societal perspective, the INMB for a 5% improvement in social cohesion was $3.99 million at 3 years and $146.64 million at the end of 11 years. Similar findings reinforcing the importance of a long-term view were found for health outcomes (Supplementary Table 3 in Supplementary Information part B). For example, a 5% improvement in social cohesion achieved a reduction of 648 mental health-related emergency department presentations over 11 years, but this was only 12 by the end of 3 years.

Univariate sensitivity analysis found that varying utility values, homelessness costs and substance misuse costs did not change the rank ordering of social determinants based on INMB for the societal perspective (Supplementary Information part B).

Discussion

System dynamics modeling (SDM), including a participatory model-building process, was used to demonstrate the health and economic benefits of improving eight social determinants of mental health. We observe from the model that even modest improvements in determinants resulted in material increases in health outcomes and reductions in costs for both the health care and societal perspectives. This simulation model was developed in collaboration with a diverse group of local stakeholders for a region of 1.2 million people, a process that could be replicated and customized for other regions.

This Analysis provides quantitative support for 'moving upstream' to target the underlying causes of a large portion of distress and mental health challenges[17,43,44]. A decision-maker contemplating how to prioritize the allocation of scarce resources towards improving mental health via social determinants could utilize these estimates by first identifying what their most important objectives are. If their main objective is to maximize the improvement of mental health outcomes in terms of QALYs, then social cohesion and childhood difficulties would be the primary determinants to target. If their main objective is to reduce suicide deaths, targeting substance misuse and social cohesion

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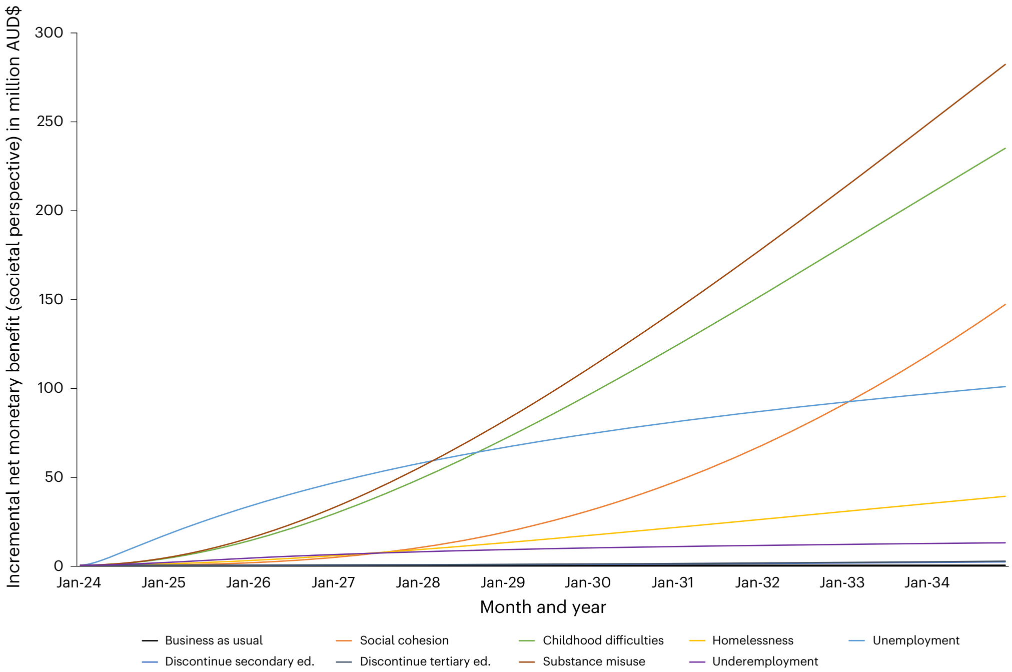

Fig. 4 | INMB (societal perspective), 5% improvement in social determinants. Cumulative costs over 11 years, 2024–2034, discounted, 2020–2021 Australian dollars versus business as usual. ed., education.

would maximize this outcome. If their objective is reducing pressure on health care services, improving social cohesion and childhood difficulties achieves the greatest reductions in mental health-related emergency department (ED) presentations, and reducing substance misuse attains the greatest reduction in self-harm hospitalizations.

The greatest reductions in costs for the health care perspective were attained by reductions in childhood difficulties and homelessness. When this perspective was expanded to account for costs incurred outside the health care sector and lost productivity for the societal perspective, reductions in substance misuse and unemployment realized the greatest downstream cost savings.

Ideally, a decision-maker would seek to maximize allocative efficiency through consideration of both health benefits (in this case, in terms of QALYs) and costs by using the INMB, which also accounts for the willingness to pay for a QALY. The ranking based on the highest INMB over 11 years for the societal perspective was (1) substance misuse, (2) childhood difficulties, (3) social cohesion and (4) unemployment. Caution should be applied when interpreting the INMB estimates in this Analysis, as these exclude the cost of interventions normally included in the calculation of INMB .

Overall, social cohesion, childhood difficulties, substance misuse and unemployment are a group of social determinants that could be prioritized on the basis that they were forecast to improve a variety of final (QALYs and suicide deaths) and intermediate (hospitalizations and ED presentations) health outcomes and/or reduce costs for the societal perspective. This adds to, and is consistent with, existing literature on the link between unemployment and suicide[45,46], the influence of early life circumstances on mental disorders in later life[47–49], the importance of social connection for mental health and well-being[39,50–53], and the association between substance misuse and mental health challenges[54,55]. Given the limitations of universal prevention in mental health[4], this Analysis provides quantitative support for targeting more specific, underlying causes. Box 3 provides a summary of systematic review-level evidence of interventions targeting the social determinants of mental health.

The findings of this study highlight the importance of taking a long-term view when considering whether the social determinants of mental health warrant the investment of scarce resources. When comparing the estimates produced here between 3 years and 11 years, much more value, in terms of both health benefits and costs, became apparent by 11 years. The choice of 11 years as the maximum time horizon is itself arbitrary, and the model timeframe could be extended to multiple decades. This would allow a more comprehensive capture of health benefits accrued by people who are younger at the start of the simulation as they age, as well as the potential for intergenerational prevention effects. The ranking of social determinants based on total cost reductions for both the health care and societal perspectives changed over the 11-year timeframe (Figs. 2 and 3) and may change beyond this time horizon.

Taking a societal perspective was useful for analyzing the economic impact of improving the social determinants of mental health, with cost estimates much larger for the societal perspective than for the health care perspective. This was due to the inclusion of additional cost categories, such as lost productivity, the criminal justice system, and non-health care social services for homelessness and substance misuse. There have been calls for greater use of the societal perspective[56], or at least reporting both the health care and societal perspectives in economic evaluations[57]. Perspective can alter the conclusions in economic evaluations for mental health. For example, a systematic review of economic evaluations for depression found that the results in 24% of studies changed quadrant of the cost-effectiveness plane (representing positive or negative differences in costs or health outcomes) when the societal perspective was taken and 5% of studies changed conclusions of whether the intervention was cost-effective or not[58]. In the case of this Analysis, a societal perspective helps to highlight a more comprehensive picture of benefits available from targeting the social determinants of mental health.

There are a number of limitations to this Analysis. First, only a selection of the social determinants of mental health have been included in this Analysis. These were identified as priority determinants thought to be driving youth mental health outcomes in the region. Some important determinants were not modeled owing to a current lack of data. Examples of excluded determinants include level of income, measures of relative socioeconomic advantage/disadvantage, food security, loneliness,

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BOX 1

Lived experience perspective

Economic arguments are sometimes portrayed as being at odds with lived/living experience frameworks as ways to guide mental health investment and public health policy. Lived/living expertise is highly experiential and highly personal—it speaks to a first-person perspective rather than a population approach to understanding community need. However, lived/living experience also provides a clear rationale for why better economic evidence and a strong approach to reducing the burden of social determinants is so necessary. Most young people, when asked to reflect on how or why they came to experience a mental health or substance use challenge, will not say that they experience a neurochemical imbalance or that they inherited an epigenetic characteristic from their parents. They will say things like: "I had a rough childhood," or "I can't find a job, so I'm stressed about rent every week" or "I don't know what the future looks like for me after I spent high school in lockdown." Understanding the impact of social determinants on the widening mental health and well-being divide between younger generations and older ones is essential to begin to curb the downward trend in youth mental health. Similarly, young people with lived experience will also tell you that the current approach of investing in hospital-based and community service provider models, even at an individual level, doesn't work well for most people. Better economic evidence is necessary to guide a social response to mental health and substance use challenges to ensure investment is placed where it will have the most impact. Tailoring this evidence to respond to the local context of a region is also in line with lived/living experience frameworks—this approach allows for the nuances, complexity and dynamism of a specific community to guide the knowledge production that sits behind the evidence. This study speaks to a particular region that has particular needs and constructs a clear rationale for evidence-based investment in the social determinants driving distress in that region. It is a fantastic blueprint for better decision-making, with young people with lived experience at the center of the process.

by Jordan van Rosmalen

BOX 2

Systems perspective

The findings of this Analysis reinforce the need to take a wider perspective on mental illness in their context of the daily lives of young people—in their families and communities, interacting with systems as well as natural, built and digital environments. This ecological approach has been adopted by The Nest[88], Australia's well-being framework for children and young people up to 24 years old. It conceptualizes well-being as six interrelated domains: feeling valued, loved and safe; being healthy, learning; participating; having material basics; and possessing a strong sense of identity and culture. To have the best possible well-being, a young person needs to be adequately resourced in all six domains at an individual level as well as within their family, community and wider society including online. Enhancing social determinants as a means of preventing and/or alleviating youth mental illness (as well as fostering well-being in its own right) is therefore the responsibility of many, and requires a multifaceted systems approach[89]. The results of this study clearly demonstrate the importance and cumulative effect of such an approach, especially when a timeframe beyond the typical duration of funding or political cycles is applied. They provide a clear, compelling argument for policymakers and funders to adopt, articulate, appropriately resource and collaboratively enact a proactive, long-term, cross-sectoral vision to interrupt the prevalence and impact of youth mental illness. Doing so will also enhance the conditions that will enable our young people—and their social networks, including future generations—a better chance to thrive.

by Sophie Morson

discrimination and inequalities experienced by marginalized groups (for example, First Nations peoples, LGBTQ+, migrants, and culturally and linguistically diverse people). Although all of these are captured to a degree by the composite measure of social cohesion included in this Analysis (Table 1), analyzing these individually would provide a more nuanced picture to a decision-maker to aid their prioritization of scarce resources to particular areas. Second, the choice of 5% and 10% improvements in the social determinants is arbitrary and hypothetical. Five percent was used as the focus for results as something that could be attainable and set as a target by a policymaker. Related to this, we cannot say whether these improvements in social determinants are cost-effective as the cost of the interventions or policy changes required to achieve them is unknown. The cost of implementation would need to be compared with the reported cost offsets and health benefits to determine cost-effectiveness through simulation modeling. Third, although we have estimated cost impacts by payer, the Australian funding system is complex, and no attempt has been made in this Analysis to account for the impacts on original funding sources. Fourth, the capacity for homelessness and substance misuse to have more of a dramatic impact on cost reductions than their increase in QALYs would suggest is because a large portion of their costs is linked directly with that determinant rather than being mediated through levels of distress (which determines QALYs). For example, criminal justice costs are incurred for both substance misuse and homelessness, and any proportional reduction in the prevalence of these determinants has an equivalent reduction in criminal justice costs, regardless of their association and effect on levels of distress or suicide deaths. The same consideration applies to unemployment and underemployment and the productivity impacts linked to employment status. Fifth, we have not included all costs that might be relevant for the societal perspective. One example of this is the increase in earnings that would be received by healthier or newly employed people (represented here by the payer category of 'nongovernment including individuals'), offsetting the reduction in welfare payments to this group. This has been excluded due to our focus on productivity-related costs. Another example would be carbon emissions and other environmental impacts. These were excluded due to time and resource constraints on the model development process. Another limitation is that only limited univariate sensitivity analysis was carried out, including the two different levels of improvement to determinants (of 5% and 10%) and two different time horizons (3 years and 11 years) (Supplementary Information part B). The main reason for this was the exclusion of defined and costed interventions from the analysis (that is, cost-effectiveness analysis has not been performed). One-way and probabilistic sensitivity analyses are useful for cost-effectiveness analyses because they reveal the circumstances for which the conclusions about cost-effectiveness might change and deriving the uncertainty intervals around economic summary measures. For the present Analysis, decision rules based on the incremental cost-effectiveness ratio, for example, are irrelevant due to the exclusion of interventions. One-way sensitivity analysis of the discount rate, for example, would only serve to change the magnitude of estimates. The limited sensitivity analysis that was performed found that varying

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BOX 3

Interventions targeting the social determinants of mental health

Although we have not included specific interventions in this Analysis, some evidence exists for various programs and services that could be implemented to move toward these hypothetical improvements. Here, we describe several systematic reviews that summarize this evidence and identify gaps that can be filled by future research. The objective of this section is to provide pointers to high-level evidence in the field for interested readers, rather than a thorough, systematic assessment of effectiveness for each individual type of intervention.

An umbrella review (systematic review of reviews) included 101 reviews of interventions targeting social determinants of mental disorders[42], mapping them to the United Nations Sustainable Development Goals and grouping them across five domains following the framework set out by Lund et al.[16]: demographic, economic, environmental events, neighborhood and sociocultural. This umbrella review serves as a useful resource covering a vast range of interventions[42]. A small sample of interventions identified by this review that could be prioritized for investment based on existing evidence includes: digital and brief advocacy for female intimate partner violence survivors; cash transfer programs for low- and middle-income countries; and investment in psychosocial support for vulnerable individuals following environmental events. However, the authors found important gaps in current evidence, at least in terms of review-level evidence. No reviews were found that met their inclusion criteria on: interventions to address income inequality or employment precarity; increased access to or completion of education; or interventions targeting climate change, vulnerable ecosystems or disaster preparedness[42]. This review did not look for cost-effectiveness analyses.

Another umbrella review, of interventions for reducing loneliness specifically, included 211 studies and found that social support, social cognitive training and meditation or mindfulness interventions decreased loneliness[90]. This review did not look for economic evidence on loneliness interventions.

Kirkbride et al., in the context of a broad review of the social determinants of mental health, argue for the prioritization of three kinds of intervention for improving the social determinants of mental health: (1) those that target the early life course (prenatal, childhood and adolescence) to interrupt intergenerational transmission between social determinants and mental health problems; (2) those that impact multiple domains such as physical, mental and social outcomes; and (3) those that focus on alleviating poverty because this is often a root cause related to many social determinants and poor mental health[37]. Examples of interventions that target the early life course are online parenting programs and school-based suicide prevention programs. The Triple P online parenting program is supported by evidence on its effectiveness[91] and cost-effectiveness, using both conventional[92] and dynamic modeling techniques[93]. The Thrive by Five International Program empowers parents with co-designed and place-based psychoeducational information coupled with practical activities that easily integrate into daily routines to support the health social, emotional and cognitive development in early childhood[94,95]. School-based suicide prevention programs[96–98] are more effective than school-based mindfulness, well-being, anxiety or depression programs[99–102], but the few cost-effectiveness analyses that exist report mixed conclusions on their value for money[25,27,93,103]. This suggests that country of implementation, context of the school and population, design of the intervention, side effects[104] and accounting for broader systemic impacts (for example, productivity of teachers and demand for mental health services) are important determinants of the economic credentials of school-based interventions.

Examples of interventions that focus on alleviating poverty include the employment program Individual Placement and Support (IPS), as well as direct economic support, such as universal/guaranteed incomes or cash transfers[38]. Systematic reviews with meta-analysis have found that IPS is effective in terms of vocational outcomes but has only indirect effects on nonvocational outcomes, such as quality life and mental health[105,106]. The cost effectiveness of IPS depends on the country of implementation, intervention design and the underlying level of unemployment based on reviews of economic literature[107,108]. A systematic review and meta-analysis of the effects of changes in income on mental health found that lifting individuals out of poverty was associated with an improvement in mental health measures and well-being[109]. Although effect sizes were modest, they were also consistent and likely to have a large impact at the population health level, particularly when targeted at lifting people out of poverty. Subgroup analysis revealed no consistent evidence that effect size was influenced by income source. The authors compared these results with antidepressants and cognitive behavioral therapy (CBT) and concluded that "interventions that move people above the poverty line might be roughly half as effective in improving mental health as antidepressants and a quarter as effective as CBT". However, because "these treatments are primarily studied in individuals at high-risk rather than general population samples, the potential impacts of anti-poverty interventions at a population mental health level could be substantial"[109].

To summarize the review-level evidence on interventions for improving the social determinants of mental health, there is sufficient evidence to support greater implementation of certain interventions now, but this is an area where much more research could be conducted, particularly evaluations of real-world implementation and generation of economic evidence, both within-trial and modeled cost-effectiveness/cost-benefit analyses. One limitation of the studies mentioned here is that they are review-level evidence. If a review has not been conducted on a particular topic, that does not mean there is no evidence supporting its effectiveness. Similarly, studies may have been published since the review was conducted, or they did not meet the inclusion criteria of a particular review. Thorough analysis of each individual type of intervention is outside the scope of the present Analysis.

utility values, homelessness costs and substance misuse costs did not change the rank ordering of social determinants based on INMB for the societal perspective. Another limitation is that we have included some costs related to carers but not changes in quality of life of carers due to time and resource constraints. This will be included in a future iteration of the model. Adding QALYs to the model for carers would be expected to enhance the value of improving the social determinants of health.

Although specific interventions have not been included in this Analysis, the results reported here do provide some guidance for decision-makers considering investing in interventions that target the social determinants of mental health. For example, if an intervention is expected to achieve a 5% improvement in social cohesion (as defined in Table 1), it could cost up to approximately $16 million over 11 years (discounted) and still be considered cost saving for the health care perspective based on the figures provided in Supplementary Table 1 (Supplementary Information part B) as well as the health benefits specified in Supplementary Table 3 (Supplementary Information part B). For the societal perspective, as long as the intervention cost less than $38 million over 11 years (discounted), it would be considered cost saving. Specific strategies are likely to be context dependent, and policymakers, academics and local communities could work together to both identify contextually appropriate interventions and develop models that can accurately evaluate them to reduce implementation barriers.

Future research directions could include using a similar modeling approach to investigate the cost-effectiveness of interventions targeted at improving the social determinants of mental health based on those that are supported by evidence of effectiveness. This would enable more specific policy actions by estimating the cost of implementing the intervention in a particular region and using the best available evidence to inform its anticipated effectiveness. Future iterations of this modeling could also seek to include an expanded set of benefits and costs that fall in the societal perspective, such as measures of well-being or environmental impacts, as relevant to the intervention and decision context being analyzed. Future research could also investigate the value of improving several social determinants concurrently or combinations of interventions concurrently.

Planning to respond to mental health is often health focused, and typically bound by the realities of funding limitations. While these limitations persist, the modeling approach outlined here vastly expands our capacity to better identify opportunities to respond to community mental health priorities, transcending the health system to more fully account for other key areas of concern, such as employment and housing. This increases our understanding of the relative utility of different interventions and their material impact on people's lives and on the broader community.

Methods

The Consolidated Health Economic Evaluation Reporting Standards (CHEERS) 2022 were followed when reporting the results and methods of analysis[59]. The completed CHEERS checklist is available as Supplementary Information. Protocols related to this project have been published on the SDM approach[60], economic analysis[61] and participatory model-building process[62]. More detailed methods area available as Supplementary Information.

Model development process

A participatory systems modeling process was undertaken to develop a system dynamics simulation model to estimate the health and economic consequences of three types of system change aimed at improving mental health outcomes for young people: (1) increasing or decreasing the growth rates of health services capacity; (2) implementing or upscaling evidence-based interventions; and (3) changing various social determinants of mental health. The present Analysis was focused on the third group of system changes. The participatory systems modeling component of the project included three in-person workshops with attendance from a range of stakeholders including mental health professionals, primary care physicians, allied health service providers, young people with a lived experience of mental health conditions and their carers, and health agency representatives.

- In workshop 1, participants identified outcomes of interest, mapped the youth mental health service system in the geographical catchment of Brisbane South Primary Health Network,and identified programs and initiatives of interest, as well as the social determinants that were most important to youth mental health in their region.
- In workshop 2, the research team presented the basic structure of the model based on the workshop 1 systems mapping exercise to participants for feedback. Participants also provided detailed advice on what new interventions would look like if implemented in their region.
- In workshop 3, a draft, interactive version of the model was provided to participants for user testing and exploration of key policy and planning insights. This process facilitated 'sense-checking' of the model output and identification of bugs or unanticipated findings.

Regular meetings were held with a model development advisory group between the workshops for more detailed components of the model development process. Where model inputs or development decisions were informed by expert advice, this could be informed through any of the workshops, model development group meetings or personal communication with subject matter experts from any of the following roles, noting that these categorizations are somewhat arbitrary and individual participants are likely to span multiple roles and identities:

- Young people with a lived experience of mental health conditions and their carers.
- Clinician subject experts such as psychiatrists, psychologists and general practitioners.
- Academic researchers including health economists, systems modelers, data scientists and research support personnel.
- Policy, health administration and management representatives, including those from the Primary Health Network and State Department of Health.
- Representatives from nonhealth sectors such as education and housing.

Research evidence and data were used to parameterize the model, and historical time series data were used to calibrate the model. With regard to searching the literature for mechanisms of effectiveness, a rapid review approach was used, relying where possible on systematic reviews. Parameter values that could not be derived directly from these sources were estimated or calibrated via constrained optimization, using historical time series data for a wide range of sociodemographic and health-related outcomes, including participation and unemployment rates, the prevalence of moderate to very high psychological distress, intentional self-harm hospitalization and suicide mortality rates and rates of mental health service usage. Powell's method was used to obtain the set of optimal parameter values minimizing the mean of the absolute differences between the observed time series values and the corresponding model outputs, where each difference was expressed as a percentage of the observed value[63].

Model structure overview

SDM was chosen for this Analysis owing to its potential for capturing complexity, interactions, dynamics and broader systemic effects relevant to mental health planning[34]. The model is a logically consistent mathematical framework that integrates best available data and evidence sources with expert and local knowledge (including the expert knowledge of those with a lived experience of mental health conditions and their carers). The model captures population and demographic dynamics, pathways to youth mental health care, service interactions and workforce capacity, and the potentially nonadditive effects of intervention combinations. The model was validated through face validity among stakeholders and by observing its ability to reproduce historic trends across observed data in the region from 2011 to 2022.

The sectors included in the model are:

- Population, which models the resident population divided into six age brackets (0–4-year-olds, 5–11, 12–14, 15–17, 18–24, and 25 and older),

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- Education, which models students enrolled in primary, secondary and post-secondary education, and people with different levels of highest qualifications,
- Labor force, which models unemployment, underemployment and participation rates,
- Not in education, employment nor training (NEET), which models the youth population aged 15–24 years not in education, employment nor training,
- Homelessness, which models the population experiencing homelessness,
- Substance misuse, which models the prevalence of 12-month substance misuse disorder and substance misuse closed treatment episodes,
- Psychological distress/disorder, which models the prevalence of low psychological distress and the prevalence of moderate to very high psychological distress based on the Kessler Psychological Distress Scale (K10)[64]. The population with moderate to very high psychological distress is further dichotomized by whether nor not they meet the criteria for any 12-month mental disorder,
- Strengths and difficulties (used as the measure of childhood difficulties), which models the prevalence of behavioral and emotional difficulties among children aged 0–11 years as measured by the Strengths and Difficulties Questionnaire (SDQ),
- Social cohesion, which models the population level of social cohesion according to the Scanlon–Monash Index of Social Cohesion,
- Suicidal behaviors, which models the rates of suicide attempts and suicide deaths, and
- Mental health services, which models mental health services delivered by health professionals and online mental health services.

Supplementary Fig. 1 in Supplementary Information part A provides an overview of the sectors and the causal connections between them. Supplementary Information part A also contains a detailed description of each sector, including its structure, sources of input data and calibration graphs.

Hypothetical improvements in each social determinant of 5% and 10% were chosen as attainable but meaningful levels of improvement that could be set by a policymaker as targets to strive toward. Table 1 contains further details of each determinant and what the levels of improvement mean for each scenario. Additional detail is provided in Supplementary Information part B, where the projection for each social determinant is provided over the 11-year time horizon along with the expected changes with 5% and 10% improvements.

Costs

Supplementary Information part B contains a detailed itemization of each unit cost, its source and derivation methods (Supplementary Tables 4 and 5). In brief, the cost of health services was obtained from the Australian Institute of Health and Welfare and the Independent Health and Aged Care Pricing Authority. Costs associated with homelessness and substance misuse were obtained from gray literature reports estimating the associated economic burden. Employee earnings used in the calculation of productivity estimates were obtained from the Australian Bureau of Statistics.

Health measures and QALYs

The detailed sector descriptions in Supplementary Information part A describe the calculation methods by which key health outcomes are estimated: suicide deaths, ED presentations and self-harm hospitalizations. The QALY is an additional measure of final health outcomes that is useful because it is a composite measure of health that includes both changes in survival and quality of life, reflecting the preference-based utilities of distress-related health states. The prevalence of people experiencing higher levels of distress is a key driver of accumulated QALYs over the timeframe of the model. Because the K10 measure is used to quantify levels of distress in the model, utilities for people aged 12 years and over were derived by using a mapping algorithm to convert low, moderate, high and very high distress levels based on the K10 to the EQ-5D multiattribute utility instrument[65], applying mapped utility decrements to Australian age-based population norms[66] (Supplementary Table 6 in Supplementary Information part B). Distressed health states for children aged 11 years and younger were based on the SDQ[67]. A mapping algorithm developed by Sharma et al., with a study population of Australian children, was used to transform SDQ scores to CHU9D utilities (Supplementary Table 7 in Supplementary Information part B)[68]. The CHU9D has strong psychometric performance in both mental health[69] and general pediatric[70] populations. A recent systematic review confirmed this was the most recent and relevant mapping algorithm with the SDQ as the starting measure[71].

Other economic methods

The time horizon was set to 11 years to allow sufficient time for cost and health consequences to play out after a change to a social determinant but short enough to minimize the uncertainty in future states of the world beyond this timeframe. Sensitivity analysis using a time horizon of 3 years was also conducted and reported here for health outcomes and INMB. A conventional lifetime time horizon is not relevant due to the dynamic nature of the population, where births and positive net migration ensure the population continues to grow. Costs and health consequences were discounted at 5%, based on the reference discount rate set by the Pharmaceutical Benefits Advisory Committee[72]. Both health care and societal perspectives were adopted due to the diverse stakeholders and decision-makers involved in the participatory model building process, and all results are presented for both perspectives. The societal perspective is broader than, and fully incapsulates, the health care perspective. One of the key differences between the two perspectives is the inclusion of productivity costs in the societal perspective. Costs incurred by nonhealth sectors are also included in the societal perspective. The costs that apply to each perspective are detailed in Supplementary Information part B. Neither univariate nor probabilistic sensitivity analyses were carried out for this Analysis (beyond alternative timeframes, degrees of improvement, utility values and costs related to homelessness and substance misuse). Our choice to exclude sensitivity analysis is predominantly due to the hypothetical nature of the improvements to social determinants. In conventional cost-effectiveness analysis where specific, defined interventions are included, the primary purpose of the sensitivity analysis is to establish the degree of uncertainty around summary economic measures based on the joint probability of all relevant uncertain parameters (probabilistic), or to what degree conclusions may change when individual parameters are varied within plausible ranges, that is, to establish the degree of confidence in whether the binary choice of implementing an intervention represents allocative efficiency. For the present Analysis, the degree of improvement in a social determinant is arbitrary, so the choice of distribution around this would also be arbitrary. Similarly, any univariate change in a parameter would only serve to change the magnitude in anticipated health or cost consequences.

One way sensitivity analysis was conducted on a select group of parameters expected to have the most influential impact on the rank order of social determinants: utility values for ages 12+ varied ±10%; utility values for ages 0–11 varied ±10%; costs related to homelessness varied ±20%; costs related to substance misuse varied ±20%. Results for this sensitivity analysis are reported in Supplementary Information part B.

Economic summary measures

Net monetary benefit (NMB) is a conversion of health into financial units to aid the comparability of strategies and presentation of results.

NMB is given by multiplying QALYs by the willingness to pay for a QALY, AUD$83,004, then subtracting costs. The willingness to pay per QALY was obtained from Shiroiwa et al.[73] and indexed to the 2021–2022 financial year. We adopted the social value of a QALY (demand for health) approach for valuing the threshold rather than an opportunity cost (supply side) approach[74]. This is relevant for the present context because the social determinants operate outside the health care sector, so any intervention or policy change would be happening at a broader level than the health sector that is not constrained by the health care budget. Using a willingness to pay for a QALY value from the literature gives us the added benefit of using a threshold based on empirical evidence, rather than an arbitrary threshold (usually AUD$50,000 per QALY in Australia, although this has never been publicly set by a government agency in Australia). INMB is the difference in NMB for a scenario of change compared with business as usual. Although INMBs reported here cannot be interpreted in the conventional manner because the costs of interventions have not been accounted for, they do provide useful estimates of the collective economic value of both health and cost consequences in a single figure.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

This simulation model used data from a variety of sources, all of which are referenced in the Supplementary Information.

Code availability

The model file is not available online; however, we welcome sharing of our models and methods with interested researchers who wish to collaborate with us. One of the reasons for a collaborative approach to sharing our models is the ability to provide training and support to users.

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Author contributions

P.C.: conceptualization, methodology, software, formal analysis, investigation, writing—original draft, writing for Box 3, visualization. N.H.: methodology, software, formal analysis, investigation, data curation, writing—review and editing. K.-H.N.: validation, writing—review and editing, investigation. K.T.: validation, writing—review and editing, investigation, data curation. S.H.H.: methodology, software, data curation, writing—review and editing. C.V.: methodology, software, investigation, writing—review and editing. AS: writing—review and editing, supervision. J.v.R.: writing for Box 1, writing—review and editing. S.R.: writing—review and editing. F.I.: writing—review and editing. V.L.: writing—review and editing. O.I.: investigation, writing—review and editing. S.P.: writing—review and editing. Y.J.C.S.: conceptualization, supervision, project administration, funding acquisition and resources. S.M.: writing for Box 2, writing—review and editing. J.M.G.P.: writing—review and editing. A.C.: writing—review and editing. D.A.M.: writing—review and editing, supervision. I.B.H.: conceptualization, writing—review and editing, supervision, funding acquisition. J.-A.O.: conceptualization, resources, supervision, project administration, funding acquisition, writing—review and editing.

Competing interests

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Additional information

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Our web collection on statistics for biologists contains articles on many of the points above.

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Policy information about availability of computer code

Data collection	This simulation model used data from a variety of sources, all of which are referenced in the supplementary material.
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Reporting on sex and gender	This simulation model does not distinguish between sex or gender.
Reporting on race, ethnicity, or other socially relevant groupings	Not applicable - the present analysis does not distinguish between these subpopulations.
Population characteristics	The simulation model structure disaggregates the modelled population by age, level of distress and mental health diagnostic category as described in the supplementary material.
Recruitment	Not applicable. The modelled population is a simulated group of people based on the population characteristics of the region.
Ethics oversight	Sydney Local Health District / Royal Prince Alfred Hospital - X21-0151 & 2021/ETH00553

Note that full information on the approval of the study protocol must also be provided in the manuscript.

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All studies must disclose on these points even when the disclosure is negative.

Study description	System dynamics simulation modelling in Stella Architect informed by participatory model-building processes
Research sample	Simulated population of Brisbane South Primary Health Network region
Sampling strategy	Not applicable
Data collection	Variety of sources were used to inform the quantitative aspects of the simulation model as described in supplementary material.
Timing	Historical data based on 2011 to 2023 and modelled forecasts from 2024 onwards
Data exclusions	Not applicable. Model sectors included fully described in supplementary material.
Non-participation	Not applicable
Randomization	Not applicable

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Methods

n/a	Involved in the study
☒	☐ ChIP-seq
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☒	☐ MRI-based neuroimaging

Preface to Chapter 4 (Modelling Study 3)

Chapter 4 takes the form of an article published in *Value in Health*, ‘The health and economic benefits of youth mental health system reform: exploring the optimal mix of interventions and service capacity through simulation modelling’. This chapter contributes to addressing the overarching research question by demonstrating the ability of a system dynamics-based modelling framework to conduct constrained optimisation analysis whilst providing insight on the cost effectiveness of both new interventions and mental health service capacity improvements, moving beyond what is normally available in conventional economic modelling techniques.

Supplementary material supporting this analysis can be found in Appendix 4.

A list of equations is available upon request by emailing Paul Crosland at paul.crosland@sydney.edu.au.

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Economic Evaluation

The Health and Economic Benefits of Youth Mental Health System Reform: Exploring the Optimal Mix of Interventions and Service Capacity Through Simulation Modeling

Paul Crosland, MHEcon, Seyed H. Hosseini, PhD, Nicholas Ho, BSc, Adam Skinner, PhD, Kim-Huong Nguyen, Sebastian Rosenberg, PhD, Yun J.C. Song, PhD, Deborah A. Marshall, PhD, Ian B. Hickie, PhD,* Jo-An Occhipinti, PhD,* and the Right Care, First Time, Where You Live group

ABSTRACT

Objectives: To help address the youth mental health crisis affecting many countries, there is an opportunity for planners to use formalized priority-setting frameworks and sophisticated modeling tools to guide their investment decisions. The objective of this study was to explore how different types of system constraints affected the optimal configuration of existing services and new interventions and to estimate the downstream health and cost consequences for each of the scenarios.

Methods: Constrained optimization analysis was used within a system dynamics modeling framework to systematically test the cost effectiveness of seven scenarios varying existing mental health services capacity growth, new interventions targeted at youths, and budget constraints on the amount of investment funds available for new interventions. Incremental net monetary benefit was the outcome selected to be optimized. Both healthcare and societal perspectives were adopted, and costs were in 2020 to 2021 Australian dollars.

Results: Allowing existing services to expand beyond their long-run average growth rates and implementing 5 of the interventions resulted in the following outcomes accumulated over 11 years compared with business as usual: 16 139 quality-adjusted life-years gained, 294 (13%) suicide deaths avoided, 41 663 (30%) mental-health related emergency department presentations avoided, and 5869 (17%) self-harm hospitalizations avoided. Combined with an investment of AUD$36.6 million in new interventions, total cost savings (societal perspective) were AUD$731.3 million, and incremental net monetary benefit (ie, overall economic value, societal perspective) was AUD$2.07 billion.

Conclusions: The estimates of overall economic value provide a rationale and support for greater investments in mental health and guidance for the implementation of regional mental health system reform.

Keywords: constrained optimization analysis, cost-effectiveness analysis, system dynamics modeling, youth mental health.

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Highlights

- Most economic evaluations for youth mental health focus on the cost-effectiveness of a single intervention, providing insufficient guidance to decision makers who need to consider combinations of interventions, their interactions, and budget constraints.
- Constrained optimization analysis found that there is health and economic value in expanding existing services and implementing new interventions concurrently; the combination of interventions that is most cost effective can be prioritized depending on the budget constraint; and there are health and economic consequences to different levels of investment in new interventions.
- System dynamics-based optimization analysis can inform joint regional planning for mental health performed by local stakeholders and governance groups.

Introduction

The prevalence and health burden of mental disorders have worsened in many countries over the last decade, particularly in children and young people.[1-3] Despite the economic consequences, only 2% of government health expenditure globally is committed to improving mental health.[4,5] For governments that are seeking to implement systemic reform and make greater investments in prevention and treatment of mental health conditions, economic evidence is crucial for ensuring that resources are allocated efficiently and health outcomes are maximized given the level of invested funds.

Australia is an OECD country with 27.5 million people with a mixed public private system, for both service provision and financing. The “Better Access” initiative provides subsidized consultations with eligible mental health service providers for up to 10 individual and 10 group services per calendar year for people with a diagnosed mental disorder.[6] This scheme is administered through Medicare, the main funder of Australia’s universal healthcare system. Service providers can charge more than the subsidized amount per consultation, and patients can access more than 10 consultations, but Medicare will not cover more than the specified subsidy amount or number of consultations.[6] Australia’s health system continues to face a range of

*Ian B. Hickie and Jo-An Occhipinti are joint last authors for this work.

Table 1. Optimization methods, rationale, and settings by scenario.

Scenario	Description	Rationale and objective	Optimization method	Optimization settings
Business as usual	Services capacity growth rates were set to their short-term average that applied to the previous 2 or 3 years, as appropriate for the input data. For all services, this involved adopting multipliers less than 1, where 1 was the long-run average, because of the reduction in growth rates in recent years. The exception was online services which was assumed to not be under the same staff capacity constraints as other services and retained at 1 for BAU. No interventions were implemented.	The current and future state of the world if no changes are made to the system or interventions implemented. This is the comparator that scenarios are compared with.	Not applicable	Not applicable
1. Services only	Services can vary between no growth (multiplier of zero) and long-run average (multiplier of 1), with no interventions.	To see if the optimization algorithm preferred some services over others based on the trade-off between improvements to health and cost, to what degree the algorithm saw value in returning services capacity back to their long-run average, and to estimate what the health benefits and cost consequences of these changes were expected to be compared with BAU.	Differential evolution	Mutation type: rand Scaling factor: 0.6 Crossover type: bin Tolerance: blank Generations: 75 Population size: 40 Crossover rate: 0.2 k/rand probability: blank Convergence achieved after 61 generations
2. Interventions only	Services fixed to BAU growth with any combination of interventions. Interventions are on or off for the entire time horizon. No budget cap on intervention costs.	To identify the most cost-effective combination of interventions without the influence of any change to services capacity by systematically testing every combination of interventions.	Grid	Search type: exhaustive This tested all 64 possible combinations of interventions.
3. Services and interventions	Services can vary between no growth (multiplier of zero) and long-run average (multiplier of 1), plus any combination of interventions. No budget cap on intervention costs.	To combine scenarios 1 and 2 to see if the added flexibility to services capacity growth changed the most cost-effective combination of interventions, and to see if the implementation of new interventions affected the priority placed on existing services. To estimate the health and economic value of combined investments in both new interventions and existing services capacity.	Differential evolution	Mutation type: rand Scaling factor: 0.6 Crossover type: bin Tolerance: blank Generations: 155 Population size: 85 Crossover rate: 0.2 k/rand probability: blank Convergence achieved after 98 generations
4. Expanded services and interventions	Services could vary between no growth and 50% greater than long-run average (multiplier of 1.5), plus any combination of interventions. No budget cap on intervention costs.	To see if the relative importance of services and the combination of interventions changed when services growth was permitted to expand beyond their long-run average. Although this is the most unconstrained scenario, services growth cannot exceed beyond 50% of the long-run average. To investigate the health benefits and overall economic value of large-scale investments in both existing mental health services and new interventions.	Differential evolution	Mutation type: rand Scaling factor: 0.6 Crossover type: bin Tolerance: blank Generations: 155 Population size: 85 Crossover rate: 0.2 k/rand probability: blank Convergence achieved after 151 generations
5. Interventions only with $30m budget cap	Services fixed to BAU growth, any combination of interventions, $30 million budget limit on intervention costs	To see how applying a light budget constraint on total, cumulative intervention costs affected the optimal combination of interventions.	Grid	Search type: exhaustive This tested all 64 possible combinations of interventions.

continued on next page

Table 1. Continued

Scenario	Description	Rationale and objective	Optimization method	Optimization settings
6. Interventions only with $20m budget cap	Services fixed to BAU growth, any combination of interventions, $20 million budget limit on intervention costs	To investigate how applying a moderate budget constraint on intervention costs affected the optimal combination of interventions. To estimate the loss in health benefits and overall economic value of lower investment funding for new interventions.	Grid	Search type: exhaustive This tested all 64 possible combinations of interventions.
7. Interventions only with $10m budget cap	Services fixed to BAU growth, any combination of interventions, $10 million budget limit on intervention costs	To investigate how applying a more severe budget constraint on intervention costs affected the optimal combination of interventions. To estimate the loss in health benefits and overall economic value of much lower investment funding for new interventions.	Grid	Search type: exhaustive This tested all 64 possible combinations of interventions.

challenges that hamper the realization of timely, equal access to low-cost care based on need.[7,8] Less than 20% of young people with a diagnosable mental disorder receive at least minimally adequate treatment.[9] Mental illness and substance use disorders accounted for 14.8% of total health burden in terms of disability-adjusted life-years in 2024[10] but receive only around 7% of the total health budget.[11] Australia experiences the highest rate of age-standardized disability-adjusted life-years because of mental health compared with other countries.[12] The proportion of overall health burden attributable to mental illness has increased relative to other diseases since 2003.[10] Younger age groups experience a higher degree of burden compared with older age groups.[10] Children, adolescents, and young adults have experienced a greater deterioration in mental health than older adults over the past decade.[13] For example, a longitudinal survey found that the prevalence of depression and anxiety more than doubled between 2009 and 2021 in Australian young people aged 15 to 34 years (from 6.1% to 14.4% for males and from 12.7% to 29.3% for females).[2] The prevalence of psychological distress also more than doubled between 2011 and 2021 in young people in Australia aged 15 to 24 years (from 18.4% to 42.3%).[2] Consequently, suicide remains the leading cause of death for people aged 15 to 44 years of age.[14]

Government reviews of mental healthcare and suicide prevention systems promote devolved decision making through enhanced regional governance.[15-17] Their intent is to reduce fragmentation and better integrate services, clarify responsibilities and accountability, and promote joint regional planning between primary and secondary health providers.[15,16] Importantly, such reviews also find inherent weakness in the capacity of mental health systems to implement change and reform. There is an urgent need to develop better tools to help local planners and funders with decision making

There is an opportunity to move from implicit, unstructured and historical decision-making processes to formalized priority-setting frameworks[18] utilizing sophisticated modeling tools that leverage a variety of data inputs, evidence of effectiveness, and the trade-off between upfront costs and downstream health benefits and cost savings (ie, economic evaluation).[19,20] Many examples exist of cost-effectiveness analysis of mental health interventions,[21-25] but there may be circumstances where this approach provides insufficient guidance to decision makers, because they fail to systematically consider all possible combinations of interventions, or their interactions, when an intervention involves a large portion of the healthcare budget, or when nonfinancial resource constraints are important.[26]

Constrained optimization is a set of computational methods for systematically identifying which solution from a range of alternatives best achieves a single, clearly defined objective (eg, maximizing quality-adjusted life-years, minimizing hospitalizations), subject to parameter constraints.[27] Constrained optimization methods can be applied to problems in healthcare, such as capacity management, facility location, efficient delivery of supplies, patient scheduling, and logistics.[27,28] It can also be used in a strategic way to identify the optimal allocation of resources when choosing between interventions, moving from the hypothetical problem implied by conventional cost-utility analysis (ie, “What is the average cost effectiveness of an intervention, assuming its implementation will involve marginal changes to the healthcare system?”) to the practical problem faced by decision makers (ie, “What is the best combination of new interventions to invest in, given the budget constraint?”).

In the context of mental health system reform, we used optimization analysis within a system dynamics modeling approach to systematically test all combinations of 6 interventions to find the most-cost-effective combination, identify the best mix of existing mental health service growth rates and estimate the value of expanding these services, explore the best mix of both existing service growth rates and new interventions when the flexibility of changing both was permitted, and explore how applying a financial constraint in the form of a budget cap on new intervention spending affected the most-cost-effective combination of interventions and what impact this budget constraint had on downstream health and cost consequences.

Methods

Methods reporting follows the Consolidated Health Economic Evaluation Reporting Standards 2022.[29] The populated Consolidated Health Economic Evaluation Reporting Standards checklist is available in Supplemental Materials. The selection of the optimization model and reporting follows guidance by Crown et al.[27] Protocols are available on the program’s system dynamics modeling (SDM) approach,[30] economic principles,[31] and participatory model-building process.[32] A brief summary of the methods is provided here, with more detailed methods available in Supplemental Materials.

Optimization Analysis

Optimization seeks to maximize a system’s desirable properties while minimizing its undesirable properties.[33] In simulation modeling, this is operationalized through an objective function,

Table 2. Optimal configuration of services and interventions within limitations set by each scenario.

Scenario	Services (multiples of long-run average)							
	GPs	Specialist MH services	Online services	CMHC	CYMHS	Psychiatric hospital	headspace	AOD
Business as usual	0.68	0.97	1	0.07	0.41	0.08	0.58	0.77
1. Services only	1	1	1	1	1	0	1	1
2. Interventions only	0.68	0.97	1	0.07	0.41	0.08	0.58	0.77
3. Services & interventions	1	1	1	1	1	0	1	1
4. Expanded services & interventions	1.5	1.5	1.5	1.5	1.5	0	1.5	1.5
5. Interventions only with $30m budget cap	0.68	0.97	1	0.07	0.41	0.08	0.58	0.77
6. Interventions only with $20m budget cap	0.68	0.97	1	0.07	0.41	0.08	0.58	0.77
7. Interventions only with $10m budget cap	0.68	0.97	1	0.07	0.41	0.08	0.58	0.77

AOD indicates alcohol and other drug treatment services; BAU, business as usual; CMHC, community mental health care for adults; CYMHS, child and youth mental health services; GPs, general practitioners; MH, mental health.

which specifies the problem's objective to be minimized or maximized (the optimization outcome) through the selection of an appropriate set of system parameters (the decision variables).[34] Table 1 provides detail on optimization types and settings for each scenario.

The final cumulative value of incremental net monetary benefit (INMB) for the societal perspective (economic measures are described in detail below) was selected as the optimization outcome. In other words, the objective of each scenario was to configure the decision variables related to services and interventions in such a way as to maximize INMB over the course of the 11-year time horizon. INMB was selected as the optimization outcome because it is a composite measure that includes the cost of interventions, the cost of services, downstream cost consequences, and health benefits in terms of quality-adjusted life-years (QALYs), with QALYs monetized using empirical evidence on the willingness to pay for an additional QALY. Other maximands may be of interest to a decision maker, such as suicide deaths avoided, emergency department presentations avoided, or health service cost savings. In this analysis, they are interrelated "side benefits" achieved in the pursuit of maximizing INMB.

The decision variables were the service capacity growth rates for the 8 mental health service types and the 6 interventions (described below). The interventions are either implemented (yes) or not (no) in any combination for the entire 11-year time horizon commencing in January 2024 until December 2034, whereas multipliers are used to set the rate of growth of services from January 2024 onward, representing the ratio relative to historical growth rates from 2011 to 2022.

Different constraints were applied to the services and interventions across 7 different scenarios. Table 1 contains full descriptions and the rationale for each scenario.

Model Development Process

A SDM was developed to estimate the health and economic consequences of 3 types of system changes aimed at improving mental health outcomes for young people: (1) increasing or decreasing service capacity growth rates for 8 types of mental health services, (2) implementing or upscaling 6 new interventions or programs, (3) changing various social determinants of mental health. The first 2 categories serve as the focus of the present article, with an article pertaining to the third published elsewhere.[35]

The target population was adolescents and young people between the ages of 15 and 25 residing in the geographical catchment of Brisbane South Primary Health Network. This region has a population of 1.2 million people, approximately 4% of the Australian national population, with broad multicultural diversity and a range of socioeconomic advantage and disadvantage.[36] Results are reported for the entire population of the region to capture impacts as younger people age and effects on other parts of the system.

Model Structure Overview

Business as usual (BAU) represents the baseline projection in which no new interventions are introduced, and the system continues to evolve under existing feedbacks and policy settings. Existing regional programs and initiatives are assumed to remain in place, and service capacity is assumed to continue following its recent observed growth trajectory. Further details are provided in Tables 1 and 2.

Eight types of mental health services are represented in the model (Supplemental Material Part A).

- General Practitioners
- Specialist mental health services (psychiatrists, psychologists, and allied health)
- Online mental health services
- Community mental healthcare
- Child and youth mental health services
- Psychiatric hospitalization
- headspace (youth-specific primary care services)
- Alcohol and other drug treatment services

Table 2. Continued

Interventions (implemented or not implemented)					
Tech-enabled integrated care	School-based suicide prevention	Post-suicide attempt care	Youth MH service hubs	Safety planning	Acute response team
no	no	no	no	no	no
no	no	no	no	no	no
yes	no	yes	yes	yes	yes
yes	no	yes	yes	yes	yes
yes	no	yes	yes	yes	yes
yes	no	no	no	yes	yes
yes	no	no	yes	no	no
no	no	no	no	yes	no

The model contains 6 interventions. Supplemental Material Part B contains a detailed description of each intervention, including its mechanism of effectiveness, supporting evidence, and model structure.

- Technology-enabled integrated care
- School-based suicide prevention program
- Post-suicide attempt care
- Youth mental health service hubs
- Safety planning for youths at risk of suicide
- Acute response team for youth

Each intervention's direct effects were informed by empirical evidence from the published literature. Combined intervention effects were not assumed to be additive but emerged dynamically from the model's feedback structure, reflecting how interventions act simultaneously on shared and interdependent system components.

Costs

Supplemental Material Part B contains a detailed itemization of each unit cost, its source, derivation methods, and assumptions, including the cost of interventions (Appendix Tables 5-7 in Supplemental Materials.

Economic Measures and Settings

Net monetary benefit (NMB) is a conversion of health into financial units to aid the comparability of strategies and presentation of results. NMB is given by multiplying QALYs by the willingness to pay for a QALY, AUD$83 004, then subtracting costs. The willingness to pay per QALY was obtained from a study by Shiroiwa et al[37] and indexed to the 2021 to 2022 financial year. INMB is the difference in NMB for a scenario of change compared with BAU.

The time horizon was set to 11 years to allow sufficient time for cost and health consequences to be realized after a change to the system. Costs and health consequences were discounted at 5%, based on the reference discount rate set by the Pharmaceutical Benefits Advisory Committee at the time of analysis.[38] Both healthcare and societal perspectives were adopted because of the diverse stakeholders and decision makers involved in the participatory model building process, and all results are presented for both perspectives. The societal perspective is broader than, and fully incapsulates, the healthcare perspective. One of the key differences between the 2 perspectives is the inclusion of productivity costs in the societal perspective. Costs incurred by nonhealth sectors are also included in the societal perspective. The costs that apply to each perspective are detailed in Supplemental Material Part B. Neither univariate nor probabilistic sensitivity analyses were carried out because of the computational demands and model run-time across multiple scenarios of the analysis. This limitation is discussed in more detail in the Discussion section.

Results

All costs are reported in 2020 to 2021 Australian dollars. All estimates relate to all ages of the population residing in the geographic region of the Brisbane South Primary Health Network and are cumulative over 11 years (2024 to 2034) unless otherwise specified. Estimates are incremental compared with BAU (ie, the cumulative difference between each scenario run and BAU). Figure 1 reports cumulative incremental QALYs for each scenario compared with BAU over time, in which the 0 line represents BAU. Figure 2 reports cumulative incremental costs for each scenario compared with BAU. Figure 3 reports INMB (societal perspective) for each scenario compared with BAU.

For Scenario 1-Services only, the configuration of services that the optimization analysis chose that maximized INMB for the societal perspective involved returning all growth rates to their long-run average, the maximum allowed under this scenario, except for psychiatric hospitalization (Table 2). By allowing services capacity growth rates to return to their long-run average, compared with the lower growth experienced over

Figure 1. Incremental quality-adjusted life-years vs business as usual. Incremental outcomes are reported here representing the cumulative difference between each scenario run and business as usual.

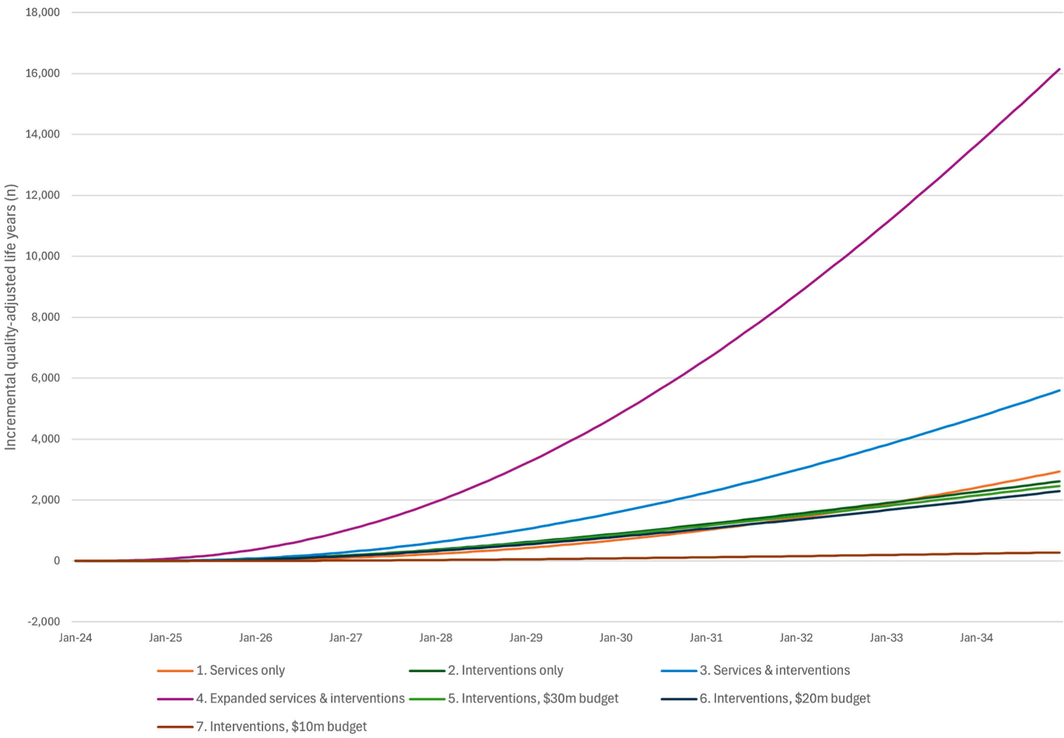


Figure 2. Incremental total cost vs business as usual, societal perspective. Incremental outcomes are reported here representing the cumulative difference between each scenario run and business as usual.

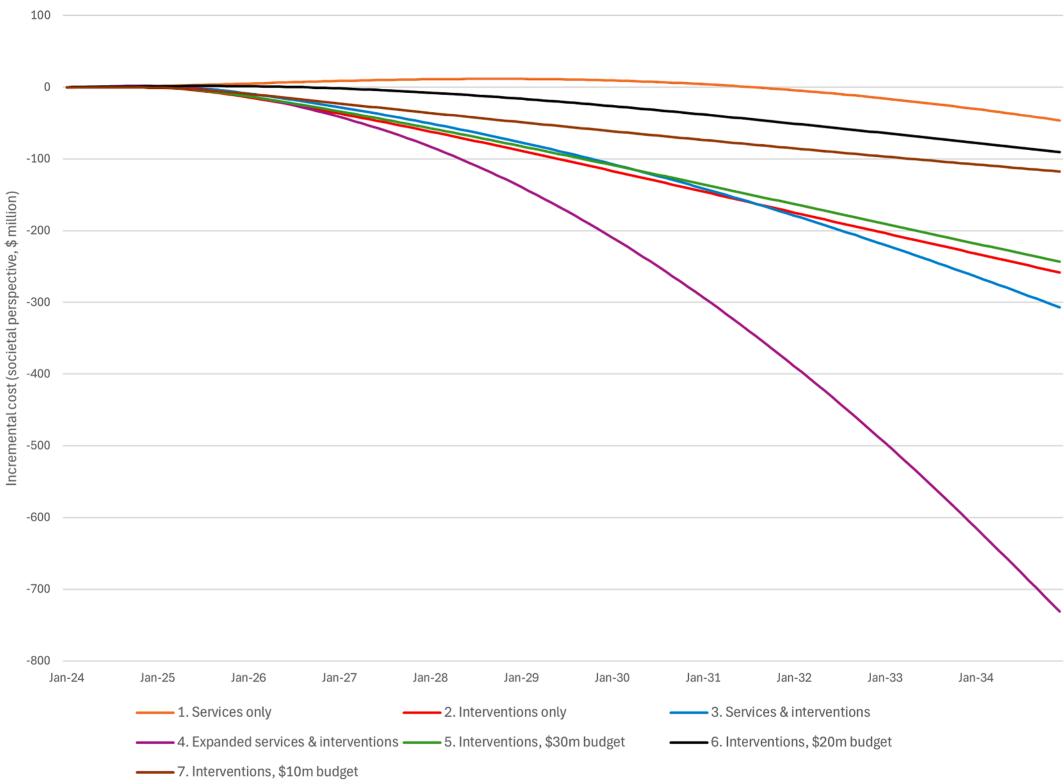
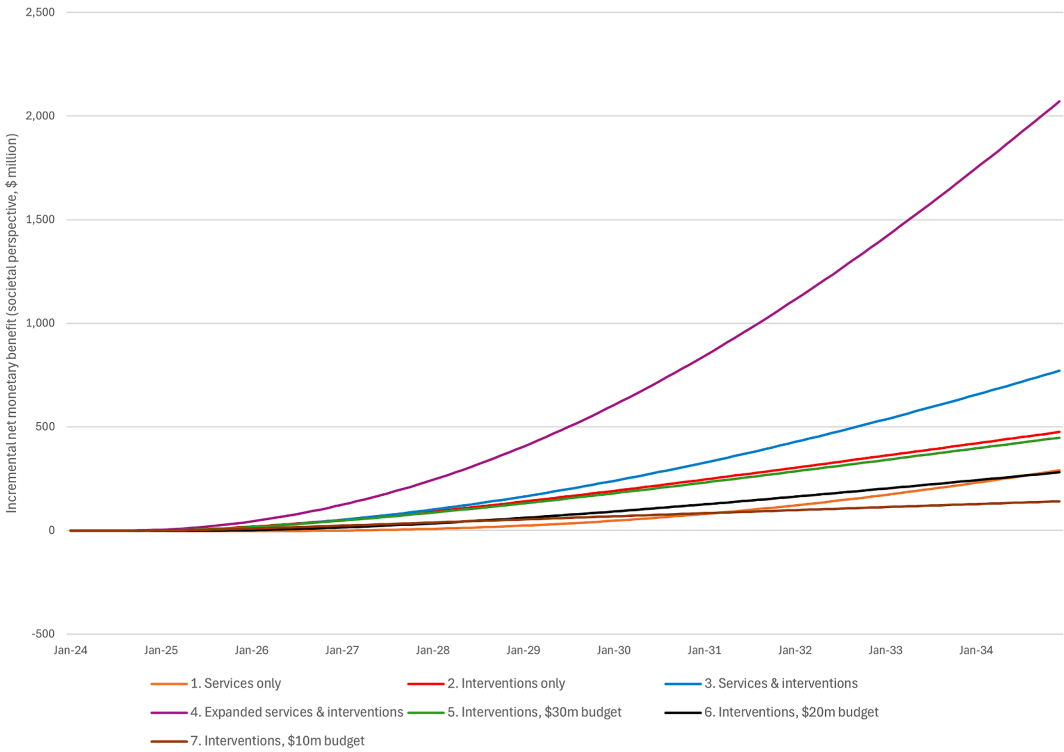


Figure 3. Incremental net monetary benefit vs business as usual, societal perspective. Incremental outcomes are reported here representing the cumulative difference between each scenario run and business as usual.



recent years, there were 2937 QALYs gained (Fig. 1), 17 suicide deaths avoided, 10 560 mental health-related emergency department (ED) presentations avoided, and 296 self-harm hospitalizations avoided (Table 3). There was an increase in incremental healthcare costs for the healthcare perspective of $68.34 million, because of the cost of expanding existing services being greater than the cost offsets accrued in later years because of a healthier population. For the societal perspective, additional cost savings achieved outside the health sector (such as productivity costs, homelessness services, and criminal justice costs) resulted in incremental cost savings of $46.30 million (Fig. 2, Table 3). The INMB was $175.45 million for the healthcare perspective and $290.09 million for the societal perspective (the outcome being optimized), indicating that this strategy was cost-effective compared with business as usual, regardless of perspective (Fig. 3, Table 3).

For Scenario 2-Interventions only, the combination of interventions that the optimization analysis chose that maximized INMB (societal perspective; ie, the most cost-effective combination out of all possible combinations) was Technology-enabled integrated care, Post-suicide attempt care, Youth mental health service hubs, Safety planning following a suicide attempt, and the Child and adolescent acute response team (Table 2). These interventions were found to be cost-effective individually for the societal perspective before the optimization analysis (Appendix Table 1, Supplemental Material Part B.

For Scenario 3-Services and interventions, the optimization algorithm identified the same configuration of services and interventions as scenario 1 and scenario 2, respectively. That is, all mental health services, except for psychiatric hospitalization, increased to their long-run growth rates and the same combination of 5 cost-effective interventions. Synergistic effects were observed for this scenario. When the outcomes achieved for scenario 3 are compared with the summation of scenario 1 and scenario 2, there are 40 more QALYs, greater cost savings for both the healthcare ($3.42 million) and societal ($2.24 million) perspectives, and greater INMBs ($6.76 million and $5.58 million for the healthcare and societal perspectives, respectively) (Table 3). Antagonistic effects (the opposite of synergistic, the outcomes of the combination are less than the sum of its parts) were observed for suicide deaths avoided, ED presentations avoided, and self-harm hospitalizations avoided.

Scenario 4-Expanded services and interventions, achieved the greatest degree of health benefits and cost savings. The optimization algorithm again maximized all mental health service capacity growth rates, except for psychiatric hospitalization, up to the constraint specified for this scenario, 50% greater than the long-run average. The same combination of 5 interventions as scenario 2 and scenario 3 was identified as maximizing INMB (societal perspective).

The remaining scenarios applied some level of budget constraint to the amount of funds that can be invested for interventions, with all mental health service capacity growth rates fixed to their BAU, short-run average default multipliers. For scenario 5-Interventions only with $30 million budget cap (over 11 years), the optimization analysis excluded 2 interventions that were included in scenarios 2-4 to maximize INMB (societal perspective) without exceeding the constrained intervention cost: Post-suicide attempt care and Youth mental health service hubs. For an intervention cost of $27.78 million, 3 interventions were included: Technology-enabled integrated care, Safety planning, and the Acute response team. By reducing intervention investment by $12.2 million compared with scenario 2, $27.46 million in INMB (societal perspective) was forgone, along with 1146 ED presentations avoided and 912 self-harm hospitalizations avoided (bottom of Table 3). Scenario 6 and scenario 7 demonstrate similar

Table 3. Health, cost, and net benefit outcomes for each scenario and set of optimized services and interventions.

Scenario	Incremental health effects (*n*)			
	QALYs gained	Suicide deaths avoided	ED presentations avoided	Self-harm hospitalizations avoided
Business as usual	n/a	n/a	n/a	n/a
1. Services only	2937	17	10 560	296
2. Interventions only	2615	234	13 605	4926
3. Services & interventions	5592	248	24 158	5155
4. Expanded services & interventions	16 139	294	41 663	5869
5. Interventions only with $30m budget cap	2466	212	12 459	4014
6. Interventions only with $20m budget cap	2289	11	2134	189
7. Interventions only with $10m budget cap	280	181	3342	2977
Synergistic & antagonistic effects of implementing new interventions combined with service capacity growth increases				
Scenario 3 vs. Scenario 2 + Scenario 1	40	−3	−7	−67
Forgone value because of budget constraint				
Scenario 5 vs. Scenario 2	−148	−22	−1146	−912
Scenario 6 vs. Scenario 2	−325	−223	−11 472	−4737
Scenario 7 vs. Scenario 2	−2334	−53	−10 263	−1949

*The outcome being optimized for is incremental net monetary benefit for the societal perspective. Although intermediate health effects (e.g. hospitalizations) are reported here, they are a byproduct of configurations of services and/or interventions that aim to maximize incremental net monetary benefit.

trade-offs between investments in new interventions and downstream health benefits and cost consequences.

Discussion

In this article, we conducted constrained optimization analyses to identify the best combination of new youth mental health interventions and/or service capacity growth rates that maximized INMB from the societal perspective. The analysis used a SDM developed to forecast the anticipated health and cost consequences of implementing new services in the South Brisbane region. Different types and degrees of constraints were applied to the optimization analysis across 7 scenarios. A variety of insights were found for each scenario compared with BAU and between scenarios. The analysis demonstrated that there is health and economic value in expanding existing services and implementing new interventions concurrently (scenario 3). The combination of interventions that is most cost-effective can be prioritized depending on the available budget. There are health and economic consequences to different levels of investment in new interventions (scenarios 5-7).

Key Insights

The first insight was that it was cost-effective to support existing mental health services to return to their higher, long-run growth rates compared with the reduced growth rates seen in recent years, with the exception of psychiatric hospitalization (scenarios 1 and 3). This was due to the benefits estimated across all 4 health measures (QALYs, suicide deaths, ED presentations, and self-harm hospitalizations) and cost savings accrued outside the health sector (in the form of productivity improvements and cost reductions related to substance misuse and homelessness). There was an expected cost increase within the health sector, but that was outweighed by sufficient health benefits to make the change cost effective (ie, positive INMBs). This finding was consistent when new interventions were introduced to the system (scenario 3). When service capacity growth rates were higher than the long-run average, greater health benefits and cost savings were identified by the optimization analysis (scenario 4). This supports the notion that greater investment in existing services is required to meet the higher prevalence of mental disorders. The exception of psychiatric hospitalization was due to a higher cost per episode of care relative to other mental health services. Psychiatric hospitalization is a vital part of the mental health care system for reasons other than maximization of QALY-based INMB. This insight should be considered alongside the caveat of service costs that were included and excluded in the limitations section below.

The second insight was that the usefulness of optimization analysis was to systematically test all intervention combinations and configurations of mental health services, accounting for any synergistic or antagonistic effects. The same combination of five interventions was identified as cost-effective when no budgetary constraint was applied (scenarios 2-4): Technology-enabled integrated care, Post-suicide attempt care, Youth mental health service hubs, Safety planning, and the Acute response team. This is consistent with what would be expected because the modeled interventions were found to be cost-effective alone when analyzed individually outside of the optimization analysis (Supplemental Material Part B). When more austere budgetary constraints were applied in scenarios 5-7, different combinations of interventions were identified by the optimization algorithm because it weighed up the trade-off between intervention costs,

Table 3. Continued

Incremental costs ($ million)						Incremental net monetary benefit ($ million)	
Intervention	Health care	Homelessness & substance misuse	Productivity	Total health costs	Total societal costs	Health care perspective	Societal perspective (Optimized outcome*)
n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
0.00	68.34	−27.97	−86.67	68.34	−46.30	175.45	290.09
39.98	−105.52	−1.80	−190.95	−65.55	−258.29	282.57	475.32
36.95	−37.57	−29.76	−276.45	−0.62	−306.84	464.77	770.99
36.60	−200.12	−68.36	−499.41	−163.52	−731.30	1503.16	2070.93
27.78	−100.50	−1.56	−168.85	−72.72	−243.14	277.44	447.86
19.66	−66.68	−2.60	−40.94	−47.02	−90.56	237.05	280.59
7.99	−14.59	0.32	−111.27	−6.60	−117.55	29.88	140.83
−3.03	−0.39	0.01	1.17	−3.42	−2.24	6.76	5.58
−12.20	5.03	0.24	22.10	−7.18	15.16	−5.13	−27.46
−20.32	38.84	−0.80	150.01	18.53	167.74	−45.52	−194.73
−31.98	90.93	2.12	79.67	58.95	140.74	−252.69	−334.48

QALYs, and cost consequences in a systematic manner. The School-based suicide prevention program was not included in the combination of cost-effective interventions in any scenarios (discussed further below). The incremental cost, and therefore incremental cost-effectiveness ratio (ICER), for this intervention increases for the societal perspective because of the time cost (productivity impacts) related to the increased burden on teachers. This is also the costliest intervention by some magnitude included in this analysis, with or without teacher-related productivity impacts.

The third insight was that both synergistic and antagonistic effects were identified depending on type of outcome measure when greater services growth and new interventions were implemented concurrently (scenario 3), demonstrating the value of different system changes working in tandem.

The fourth insight was that reduced investment in new interventions substantially tempered anticipated health benefits and cost impacts otherwise available in more large-scale system reform, albeit still more effective and cost-effective than BAU (scenarios 5-7). In contrast, greater investment in both new interventions and an expansion of existing mental health services beyond their long-run average yielded substantial health benefits and cost savings (scenario 4).

Comparison With Existing Evidence

Here, we compare the findings of the optimization analysis and the cost-effectiveness of modeled interventions with existing studies from the scientific literature.

There is little existing evidence on the cost-effectiveness of technology-enabled integrated care for mental health. In a systematic review of cost-effectiveness analyses of collaborative care for depressive disorders, 11 out of 13 studies that reported incremental costs per QALY found that the interventions were cost-effective, but it is unknown to what degree the technology platforms were used as a central component in these studies.[39] There is 1 economic evaluation of feedback-informed treatment that found an ICER of £187.40 “per additional case of reliable improvement.”[40] QALYs were not included in this analysis. A trial-based cost-utility analysis found that an online social therapy platform for maintaining treatment effects from first-episode psychosis services was dominant when health effects were based on social functioning but a central estimate of less costs and less health when health effects were based on QALYs, with much uncertainty around estimates.[41]

There are few studies with mixed conclusions on the economic credentials of school-based suicide prevention programs in the literature. A comprehensive systematic review of mental health prevention and promotion cost-effectiveness analyses found 3 studies and mixed evidence, including 1 study in the US context that found cost savings, 1 in the Australian context that was found to be cost-effective, and a European study with QALY-based ICERs that may exceed what is considered cost-effective.[22] Another systematic review confirms the paucity of evidence in this area and concludes "few studies were found, which limits the possibility of drawing strong conclusions about cost effectiveness.”[25] Another review takes a more positive, contrasting view, concluding that “there is a strong economic evidence base regarding universal and indicated school-based psychological interventions aimed to improve the mental health of children and adolescents.”[23] However, this conclusion is referring to the broader body of 6 economic studies of school-based psychological interventions in general, rather than the few relating specifically to suicide prevention.

We are not aware of any economic evaluations of post-attempt care or specialist mental health service hubs for youths. A cost-effectiveness analysis of ED-based suicide prevention and safety planning, similar to post-attempt care, found an ICER of US$5020 per averted suicide attempt or suicide death.[42] Some economic evidence exists in support of acute response teams, but they fall short of being full economic evaluations.[43]

This study represents a convergence of several fields of specialist research and can be compared with a varied landscape of existing literature in those fields. Guidance promoting greater use of dynamic simulation modeling (DSM) for economic evaluation in health was published in 2015[44,45] and again in 2023[46]; however, there has been little use of DSM for analyzing the cost-effectiveness of mental health interventions.[20] Two examples have been published by this research team.[21,47] These 2 studies focused on individual cost effectiveness of the included interventions, with service capacity growth rates remaining fixed and no limit to intervention costs, consistent with the implied assumption in conventional cost-utility analysis that new interventions can be adopted at the margin.[26] There was no systematic comparison of all intervention combinations. As this analysis has revealed, this function becomes particularly relevant when a budget constraint is applied to ensure that health outcomes are maximized within that constraint, while accounting for any synergistic or antagonistic effects.

Looking more broadly to existing literature that uses a conventional modeling approach to cost-effectiveness analysis rather than DSM, there are prior examples of using a standardized cost-effectiveness protocol to assess a panel of mental health interventions. Most recently, the National Mental Health Commission in Australia commissioned an analysis of “best buys” to analyze the return on investment of 10 mental health promotion and prevention interventions.[48] Before this, the ACE-Prevention study used a standardized economic model to compare the cost effectiveness of 11 interventions in Australia.[49,50] Examples outside Australia include a Markov model that calculated the return on investment for 12 prevention and treatment interventions for adolescents,[51] DepMod, a Markov model that includes budget impact for the prevention and treatment of depressive disorder, and the World Health Organization’s WHO-CHOICE methodology and OneHealth Tool.[52,53] These examples focus on global or national estimates in contrast to this analysis, which was tailored to a local region and the needs of that community.

Limitations

There are a number of limitations to this analysis. These are discussed in more detail in Supplemental Material Part B.

First, in some respects, this is a relatively simplistic application of constrained optimization methods, adopted for strategic-level decision making within the context of an existing dynamic simulation model. An alternative model with more detailed service specifications could allow a more thorough application of constrained optimization could take into account actual individual resource constraints, such as number of staff and physical facilities, now and expected into the future, with any changes to service capacity growth and implementation of new interventions operating within these constraints; however, this was outside the scope of this project.

The second limitation is the extra-welfarist normative judgement to select INMB (societal perspective) based on QALYs as the outcome to be optimized. This does have the advantage of utilizing a measure of health that captures changes to both length and quality of life, combined with an empirical valuation based on willingness to pay for a QALY to monetize these health benefits. However, a disadvantage to this approach is overlooking other outcomes that may be relevant to the decision-making context. One example is suicide deaths averted, to the extent that this is not already captured by life-years gained via the QALY. For example, the school-based suicide prevention intervention was excluded from all scenarios, despite it achieving the third-highest number of suicide deaths avoided when modeled individually (Appendix Table 2, Supplemental Material Part B. With an incremental cost per suicide death avoided of $1.1 million, this intervention would probably be considered cost-effective when compared with the value of a statistical life.[54]

The third limitation is the lack of uncertainty analysis in the form of univariate, multivariate, or probabilistic sensitivity analysis. This was excluded because of the combinatorial load and prohibitive amount of time it would take to run this type of analysis across all 7 scenarios using currently available software. Future iterations of the model could take advantage of alternative software and advances in high-performance computing solutions to address this limitation of our analyses.

A fourth limitation is that only the current cost per service-contact is used to inform changes in the cost of services capacity growth rates. This is likely to be an accurate representation of the cost of small changes in service volume, but larger changes may be subject to threshold effects, such as the need for more physical space for clinics to operate from and large-scale recruitment programs for more medical staff to provide the services.

The fifth limitation is that the effectiveness of services and interventions hinges on the strength of evidence informing each parameter and mechanism of effect, which is variable across interventions and studies. Importantly, this includes evidence on the effectiveness of the numerous combinations of interventions, which is not available from the literature. Here, we have assumed that the effect sizes of individual interventions are the same when combined with other interventions. In practice, they could be more or less effective when combined with other interventions depending on the mechanisms of effect and other nuances of implementation. Another aspect of this limitation is that the effectiveness of some interventions was informed by evidence that was generalized from other settings to this context.

The sixth limitation is that no differential timing of intervention implementation or changes to service capacity growth rates was applied. Interventions were either implemented or not for the entire 11-year time horizon, as were the multiplier settings for the services capacity growth rates.

Finally, the choice of (1) multiplier constraints set for service capacity growth rates and (2) budget caps applied to intervention costs were essentially arbitrary. The figures in question were chosen here to demonstrate the effect of these parameters on the configuration of intervention combinations and services and the subsequent effects on health and cost consequences. The wide range of options available to a decision maker when setting these optimization constraints highlights the importance of modeling exercises such as this being supported by participatory model-building processes.

Conclusions

This research demonstrates the usefulness of combining constrained optimization with system dynamics modeling and participatory model-building processes to generate economic evidence to inform joint regional planning for mental health performed by local stakeholders and governance groups. The estimates of overall economic value provide rationale and support for greater investments in mental health system reform.

This kind of approach can also inform and guide more structured implementation of regional mental health reform over time, with the capacity to review and assess the impact of changes against expectations. This is a critical factor currently missing in the way Australia responds to mental illness.

Author Disclosures

Author disclosure forms can be accessed below in the Supplemental Material section.

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5. Discussion and conclusion

5.1. Introduction

The overarching research question this thesis sought to answer was whether SDM was a feasible and useful approach to conducting economic evaluation of mental health interventions. The research project also sought to identify the unique attributes of this technique compared with conventional modelling approaches. This was achieved by way of three modelling studies, each harnessing a unique technique enabled by the SDM framework. All three analyses were developed in collaboration with a broad range of stakeholders, enhancing the applicability and transferability of research findings into mental health system reform and investment planning. The applied examples demonstrate the capability of SDM-based economic evaluation for informing priority setting and resource allocation in mental health. The remainder of this chapter discusses the research project's contribution to scientific knowledge, summarises the key findings of each study, explores the implications for policy and practice, describes the strengths and limitations of the research, and explains future research opportunities.

All financial amounts are in Australian dollars unless otherwise specified.

5.1.1. Contribution to scientific knowledge

The research conducted for this PhD has made significant contributions to methodological knowledge by developing applied examples that extend the capabilities of the SDM-based approach to economic evaluation that health economists, systems modellers and other researchers can adopt and build upon in the future. It has also contributed by generating economic evidence that is useful in and of itself for guiding resource allocation decisions that aim to improve youth mental health (for example, the cost effectiveness of new interventions). The learnings through both lenses are discussed in more detail for each of the modelling studies below.

The thesis began by identifying an absence in the scientific literature of SDM-based cost-effectiveness analysis (CEA) for mental health [1]. Chapter 1 outlined the worsening problem of mental illness in Australia and globally, particularly for young people, in terms of both health and economic burden. It described the promise of contemporary mental health treatment and prevention paradigms, including a better recognition of the necessary role of improving the social determinants in any broad-scale improvement in population mental health. The theoretical foundations of economic evaluation and dynamic simulation modelling as complementary decision-analytic modelling tools were explained. The theoretical rationale for greater use of SDM-based economic evaluation for mental health was presented as the foundational premise for this PhD research project.

The first modelling study was a cost-utility analysis (CUA) of eight interventions for youth mental health for the Australian Capital Territory, the first SDM-based CEA for mental health interventions to be published in the literature [2]. The second application of SDM estimated the health benefits and economic value of improving eight social determinants of mental health for the Brisbane South region [3]. This analysis of hypothetical changes represents an initial foray into motivating greater action on social factors, moving outside the bounds of treatment-based CEA restricted to the health sector perspective. The third modelling study sought to enhance the practical applicability of economic evaluation by using constrained optimisation analysis within a SDM framework to identify the most cost-effective combinations of interventions at differing levels of budget and service capacity constraint [4].

In summary, the studies have made a significant contribution to scientific understanding by accomplishing the following tasks:

1. proposed an opportunity for greater use of SDM-based economic evaluation to better account for complexity and dynamics in the mental health care system;
2. developed an approach to integrating CUA into SDM to examine the economic credentials of mental health interventions, the first of its kind to appear in the literature, whilst also identifying the unique attributes of this approach compared with conventional economic modelling techniques;
3. generated economic evidence on targeting the social determinants of mental health by broadening the SDM-based approach, the first of its kind to appear in the literature; and
4. demonstrated the ability of constrained optimisation analysis to systematise the identification of intervention combinations that maximise health outcomes within a given budget constraint, the first of its kind to appear in the literature.

5.2. Summary of key findings

Here I focus on the key findings from the three modelling studies. Each modelling exercise provides insights on both (a) the economic credentials of the interventions or system strategies, and (b) the methodological approaches and how they can be used to inform resource allocation in mental health.

5.2.1. Modelling study 1 – cost-utility analysis of eight interventions for youth mental health

The first modelling example investigated the cost effectiveness of eight systems-based interventions targeted at improving the mental health and wellbeing of children, adolescents and young adults in the Australian Capital Territory (ACT) [2]. It found that Technology-enabled integrated care, Family education, an Online parenting programme and Multi-cultural informed care were cost effective with incremental cost-effectiveness ratios (ICERs) of $666, dominant, $7 and $572 per quality-adjusted life year (QALY) gained respectively for the health care perspective compared with business as usual (BAU). All four interventions were dominant for the societal perspective. Emergency department (ED) -based suicide prevention, the Crisis response service, School-based suicide prevention and Trauma services for youths were not cost effective for the base case. One-way sensitivity analysis revealed ED-based suicide prevention was sensitive to the duration of effect, annual budget, discount rate and time horizon, with plausible scenarios in which it became cost effective, with positive ICERs below the threshold. Probabilistic sensitivity analysis (PSA) revealed a high degree of certainty in the findings on cost effectiveness, except for ED-based suicide prevention. Implementing the four cost-effective interventions concurrently was expected to yield $570 million in incremental net monetary benefit (INMB), consisting of 5,732 QALYs gained and $115 million in cost savings compared with BAU. ED-based suicide prevention would likely be recommended for implementation as well, given its potential cost effectiveness uncovered in sensitivity analysis.

This was the first study to be published in the literature using a SDM approach for CUA of mental health interventions and there were four main methodological insights ascertained from this analysis. Firstly, synergistic effects, in terms of both health benefits and INMB were identified for the combination of cost-effective interventions. It is only through modelling the dynamic relationships and interactions between different parts of the system, and the different mechanisms of action by which the interventions affect the system, that such an outcome can be identified. Secondly, emergent outcomes in the form of unintended consequences were uncovered for some interventions, predominantly caused by health service capacity constraints. That is, large increases in demand for mental health services caused by substantial referrals from the implementation of a new intervention across a broad population (School-based suicide prevention) results in more people spending more time waiting for care at higher levels of distress, attenuating or reducing QALYs. Again, it is only by including the dynamic relationships and interactions between different parts of the system that the impact of service capacity constraints on health outcomes can be examined. Thirdly, scenario testing changes to services capacity growth could be performed, alone or in combination with interventions. Fourthly, a user-friendly interface was available to enable stakeholders to interact with the model, test interventions and scenarios, and produce results to enhance the transparency and accountability of decision making.

5.2.2. Modelling study 2 – improving the social determinants of mental health

The second modelling exercise estimated the health benefits and economic value of improving the social determinants of mental health in the Brisbane South region [3]. Even modest improvements in determinants resulted in material increases in health outcomes and reductions in costs for both the health care and societal perspectives. The INMB anticipated from 5% improvements in the average yearly change of social cohesion, childhood difficulties (an indicator for early life exposure to adverse experiences), substance misuse and unemployment over 11 years from 2024 to 2034 was projected to be $146.64 million, $234.50 million, $281.67 million and $100.43 million, respectively. Five percent improvements to social cohesion and childhood difficulties achieved 1,309 and 2,621 QALYs gained respectively, 74 and 31 fewer self-harm hospitalisations respectively, and 648 and 814 fewer ED presentations respectively compared with BAU. Limited one-way sensitivity analysis produced estimates for 10% improvements in social determinants, a three-year time horizon, varied utilities, and varied costs for substance misuse and homelessness, finding no change in the ranking of social determinants based on INMB for the societal perspective. This analysis provides quantitative support for moving upstream to target the underlying causes of a large portion of distress and mental health challenges, adding to existing modelled evidence on the health benefits of improving social cohesion [5].

The first methodological insight from this analysis was the importance of the societal perspective for capturing meaningful contributions to economic value outside of the health sector, such as criminal justice costs, homelessness services and productivity. Although the benefits of a societal perspective are known [6,7], it is often not prioritised for inclusion in economic evaluation, and there is ongoing debate in the field about the appropriateness and methodological quandaries when implementing this perspective [8], particularly in contexts like health technology assessment (HTA) where the analytical focus is on impacts to the health care sector [9] (discussed in more detail later in this chapter). In the context of analysing social determinants and their impact on widescale population mental health, a broader perspective capturing interactions between determinants, mental health services, mental health outcomes and the costs attached to these components becomes more relevant. This modelling study, and the societal perspective it adopts, provides a useful foundation for future iterations of this type of modelling investigating the cost effectiveness of interventions targeting social factors because the costs related to implementing these interventions would normally be incurred outside of the health sector.

The second methodological insight from this study was the importance of a SDM framework for enabling an analysis of social factors. Dynamic simulation modelling (DSM) methods, such as SDM, inherently facilitate the inclusion of aspects of complexity into the model structure, such as interactions between social factors and with mental health outcomes and services, dynamic changes in population attributes over time, and non-linear impacts on services and outcomes. By incorporating social determinants within the SDM-based evaluation, this research demonstrates how intersectoral investments can be appraised within a unified dynamic economic framework, providing a methodological pathway for cross-sectoral policy assessment.

5.2.3. Modelling study 3 – constrained optimisation analysis

In the third modelling study, constrained optimisation analysis was used within a SDM framework to systematically test the cost effectiveness of seven scenarios varying existing mental health services capacity growth, new interventions targeted at youths, and budget constraints on the amount of investment funds available for new interventions [4]. Using INMB as the outcome to be optimised allowed for information on the health benefits, intervention costs, downstream cost consequences and the willingness-to-pay for a QALY to be accounted for in the optimisation algorithm using a single measure. The insights were many and varied across the seven scenarios exploring the impacts of different kinds of constraints on health and economic outcomes. Overall, the analysis demonstrated there is health and economic value in expanding existing services and implementing new interventions concurrently to capitalise on synergistic effects; the combination of interventions that is most cost effective can be identified using systematic methods in response to changes in the budget constraint; and there are health and economic consequences to attenuated levels of investment in new interventions. The same combination of five interventions was identified as cost effective when no budget constraint was applied: Technology-enabled integrated care, Post-suicide attempt care; Youth mental health service hubs; Safety planning; and the Acute response team. The preferred combination of interventions changed as the budget constraint was intensified.

The first main methodological insight was that optimisation analysis within a SDM framework can be used to inform the practical question faced by decision makers when investing funds for mental health, which is, 'What combination of new interventions is most cost effective within the parcel of money I have to spend on implementing new interventions?'. Optimisation analysis systematises and automates this process. The second methodological insight was that a mix of synergistic (for QALYs, costs and INMB) and antagonistic effects (for suicide deaths, ED presentations and hospitalisations) were identified when existing services were expanded and new interventions were implemented concurrently. It is only by accounting for dynamic complexity in a DSM model like this that such emergent outcomes can be observed. The third methodological insight was that this analytical approach allows the value forgone due to lower levels of investment in new interventions to be estimated, in terms of health benefits, cost savings, or INMB, whilst still identifying the most cost-effective combination of interventions within each level of budget constraint.

5.2.4. Synthesising the insights between modelling studies

Overall, this program of research integrated economic evaluation with SDM, providing a new theoretical foundation for decision-analytical approaches within the context of a complex adaptive system like mental health. This is a step in the direction of using economic modelling for assessing and changing dynamic systems rather than static efficiency exercises.

Modelling Study 1 demonstrated that SDM could be utilised to conduct cost-utility analysis of several interventions within the same decision-support tool and revealed unique attributes that differentiate the technique from conventional economic modelling approaches. However, investigating the economic credentials of combinations of interventions was limited to a single combination, leaving unanswered questions as to how the modelling framework could be better utilised to systematically test the whole range of available combinations. In addition, this analysis did not take into account any fiscal constraints, essentially assuming that the decision maker would be able to afford any interventions found to be cost effective, nor did it factor in any changes to services capacity alongside the implementation of interventions in a systematic way. Modelling Study 3 directly responded to these limitations by using optimisation analysis to systematically test combinations of interventions, with or without budget constraints, and with or without changes to service capacity growth rates. Modelling Study 3 demonstrates the extended capabilities of SDM-based economic evaluation, using systematic methods to respond more directly to the needs of decision makers who have to contend with budget constraints and implementing several interventions concurrently. This analysis also provided estimates of the health and cost consequences of attenuated levels of investment in mental health, in terms of both new interventions and existing services.

Modelling Study 2 set aside the focus on intervention-based cost-utility analysis to investigate the value of 'moving upstream' to target the social determinants of youth mental health. This work responds to recent reviews [10-12] and the Lancet Psychiatry Commission on Youth Mental Health [13], a growing recognition in the field that doing more of the same thing is not a solution to the mental health crisis, and that broad-based, long-term improvements to mental health will only come by reforming social and economic systems to prevent mental illness before it occurs. Although Modelling Study 2 does not include defined and costed interventions, it does move beyond deficit-based cost-of-illness studies that only serve to highlight how big a problem is, to estimate the health and economic value of improved social determinants in the future using attainable targets of improvement. A decision maker could compare the cost of a social determinant intervention they are considering implementing to the cost offsets estimated in this analysis, alongside evidence on the intervention's effectiveness. Modelling Study 2 complements the intervention-based insights of the other two studies by taking a broader view of social factors and the potential for prevention, while establishing a platform for future research on the cost effectiveness of social determinant interventions.

5.3. Implications for policy and practice

5.3.1. Mental health policy makers

Primary Health Networks (PHNs) were the principal stakeholders for this project, participating in the core functions of model development and use of completed models and their output. There are three ways that PHNs are able to make use of the economic evidence generated by the SDM-based decision-support tools created by this research, aligning with the three broad stages of joint regional planning for integrated mental health and suicide prevention services expected by the (national) Australian Government: (i) needs assessment; (ii) joint regional planning; and (iii) commissioning of services and programs [14].

The first example is for **needs assessment**, an Australian Government requirement where the PHN uses data from various sources to describe the population characteristics of their region, populations at highest risk, the demand and supply of services, identification of gaps and opportunities for improved service delivery [15-17]. Forecasts of costs across different categories and health metrics from the model could be used to compliment the PHN's reporting on past data, along with anticipated health and economic effects from new or expanded programs that would be relevant to include in the needs assessment.

The second example of the implications of this research for PHNs is for **joint regional planning**. Joint regional planning is the structured, collaborative approach where PHNs, Hospital and Health Services (HHSs), state-level authorities, and potentially the Australian Government, come together to assess mental health needs and design coordinated service responses [18]. The goal is for less fragmentation of the mental health system and greater integration of strategy and service delivery between levels of the healthcare system and levels of government. The findings of CEA & CUA could be used for joint strategic priority setting, identifying new interventions that are most likely to be effective and cost effective at the population level (Modelling Study 1). Action on the social determinants of mental health could be prioritised in joint regional plans, supported by the economic credentials identified in Modelling Study 2. Optimisation analysis could be strategically utilised to identify cost-effective combination of interventions that could be implemented while not exceeding a set budget constraint (Modelling Study 3).

The third example is the use of SDM-based CEA & CUA findings to support **commissioning** of specific services and programs through the preparation of business cases for funding towards implementing a new intervention, upscaling an existing program, avoiding defunding an existing program, or supporting the defunding of an existing program (presumably so that funds saved can be reinvested in a more effective and cost effective intervention, a strategic combination this modelling approach is well-suited to analyse). One real-world example of a business case is the expansion of Metro South Hospital and Health Service's (HHS) Child and Youth Acute Crisis Response Service. This is an application of the model developed for Brisbane South per Modelling Study 3 of this thesis. At least four other business cases for sites not included in this thesis have been supported by other iterations of this modelling framework for the 'Right Care, First Time, Where you Live' project, the broader project within which this PhD research project sits.

Other levels of government are inherently involved in these three stages of planning for local regions. In addition, State/Territory governments or the Australian Government could use the research findings of this thesis for their own decision making, either directly by generalising the findings to their own resource allocation decisions, or in the future by adapting these models for their own, larger population catchments, adding or subtracting interventions and social determinants as relevant for their strategic context.

5.3.2. Health economists

This research project has demonstrated that SDM can be used to conduct economic evaluation for mental health treatment and prevention interventions. Our understanding is this is first time this combination has appeared in the literature. The findings of this research project also have applicability outside of mental health (i.e. greater use of SDM-based economic evaluation in general). This is a complementary approach that can be used alongside more conventional, Markov health state-based approaches or other DSM approaches (i.e. agent-based modelling (ABM) and discrete event simulation (DES)). Chapter 1 details the circumstances in which different modelling techniques may be more applicable than others [1]. Existing literature articulated that SDM-based economic evaluation is better suited to system-wide, strategic decisions and interventions that have the potential to impact a broad population, and where the aggregate representation of the population is appropriate. The three modelling studies created for this research project confirm this advice. Examples of relevant decision problems include the cost effectiveness of Technology-enabled integrated care and the social determinants of mental health. This contrasts with, for example, the use of esketamine for treatment-resistant depression, where conventional economic modelling techniques, or within-trial economic evaluation, are likely to be more applicable due to narrow scope of the disease, treatment options, comparator and population. Microsimulation, ABM or DES may also be candidates for this latter scenario, where individual-level modelling approaches are likely to more accurately represent the course of disease, treatment pathway and side-effects, dependent on individual characteristics.

Beyond the field of mental health, this research provides a template for SDM-based economic evaluation to be more utilised in other areas of healthcare.

5.3.3. Dynamic simulation modellers

Systematic reviews have found that economic evaluation is rarely included in DSM and, when they are, they often use the output from a DSM to conduct a CEA, rather than being fully integrated into the model and development process [19-22]. Here, we have demonstrated the integration of best-practice economic evaluation methods into a SDM. Economic measures can supplement model output on health effects for a more complete picture for decision makers that includes value-for-money. Simulation modellers can adopt similar techniques in the future, in the mental health field or other areas of healthcare, given access to appropriate skills and expertise as part of a multidisciplinary research and model development team.

5.4. Transferability of results to other jurisdictions

Because each of the studies was developed in collaboration with, and for, local decision makers and the region they represent, the question may arise as to how applicable the findings and methods are to other regions, states or countries. Insomuch as the populations are similar in other regions of Australia, the findings on the cost effectiveness of interventions, alone or in combination, could be used to inform resource allocation decision in other areas and PHNs around Australia. They could also be generalised and used to inform similar decisions at the state or national level, or even to other countries, to the degree that the population is similar and the intervention design and associated costs would be similar.

However, there is no substitute for the representativeness and specificity of SDM-based economic evaluation developed and customised for a specific region, using data that represents the characteristics of that population and the service system interventions that reflect the design preferences and costs of the location, and a group model-building process that has leveraged the skills, expertise and lived experience of local stakeholders. We have demonstrated the ability of SDM-based economic evaluation, supported by participatory model building processes to be carried out in other jurisdictions, given sufficient time and resources are dedicated to such exercises. This includes the potential for models being adapted or developed for state and national agencies.

5.5. Research translation

Beyond the journal article output of this research project, there are four modes by which research findings were disseminated to varied audiences.

Firstly, I have presented the research findings related to this thesis in several settings and seminars:

- Oral presentation: 'Cost effectiveness of eight system-level strategies for enhancing youth mental health'. Australian Health Economics Society, Adelaide, September 2023.
- Invited oral presentation: 'Combining system dynamics and local knowledge to generate economic evidence for mental health'. Oxford Mental Health Economics and Policy, Oxford University, online, April 2024.
- Oral presentation: 'Combining system dynamics and local knowledge to generate economic evidence for mental health in ACT'. Right Care, First Time, Where You Live Symposium, Sydney, November 2024.

- Invited oral presentation: ‘Combining system dynamics and local knowledge to generate economic evidence for mental health’. Centre for Disability Research and Policy, University of Sydney and research collaborators seminar, online, February 2025.
- Oral presentation: ‘The economic value of improving the social determinants of mental health’. Sydney Health Economists Discussion group, online, May 2025.
- Invited oral presentation: ‘The economic value of improving the social determinants of mental health’. Queensland Brain Injury Collaborative, University of Queensland, online, August 2025.
- Oral presentation: ‘Exploring the optimal mix of interventions and mental health services capacity with optimisation analysis’. Discovery Seminar, Youth Mental Health and Technology, Brain and Mind Centre, University of Sydney, October 2025.

The second mode of dissemination is an ‘Economic Insights Brief’ that was prepared for each site. Aimed at a non-academic audience, these documents summarise key economic insights uncovered by the model and examples of the kind of economic analysis the models can produce. There is a focus on headline findings for people with non-technical backgrounds. In line with the modelling studies presented in this thesis, this includes the cost effectiveness of interventions, alone or in combination, an explanation of synergistic effects, the value of improving the social determinants of mental health, the combinatorial effects of implementing both new interventions and service capacity growth changes, and opportunities for improving the data ecosystem.

Thirdly, the business cases mentioned above in Section 5.3.1 are a practical form of real-world, applied research dissemination. These are ad-hoc, discrete exercises aimed at using the model for a specific implementation question currently being considered by a PHN or their funding agency. At the date of writing, model output supporting five business cases has been delivered across three sites. Model support for other business cases is currently in progress.

The fourth mode of research dissemination is the models themselves. They are available for use by the sites on ‘isee Exchange’, enabling them to run the model, produce scenarios of various system changes, and use the outcome measures on health benefits and economic findings to inform their decision making. Support from myself and the University of Sydney research team is available at any stage.

New publications and research updates are also posted to LinkedIn.

The translation of economic analyses described above has occurred amongst a broader body of quantitative and qualitative research evaluating the application of SDM to mental health investment planning. In one study a SDM was used to simulate the impact of direct access to specialist mental health care (without referral from a General Practitioner), and of increasing the annual growth rate in specialist mental health care capacity [23]. It found that direct access increased emergency department presentations, self-harm hospitalisations and deaths by suicide due to an increase in consultation waiting times, unless the growth rate of mental health service capacity was increased to respond to this increased demand [23]. Another study used SDM to evaluate the impact of different service capacity growth trajectories and digital technologies on youth mental health outcomes [24]. It found that digital technologies were able to mitigate the slow and uncertain growth in specialised mental health care services but a combined approach that included expanding the specialised mental health workforce as well offered the most effective pathway to improving youth mental health outcomes [24]. SDM was used to show that improving social cohesion was able to offset some of the negative impacts of constrained mental health service capacity but that a combined involving both improvements to social cohesion and mental health services capacity was able to achieve substantial improvements in ED presentations and years lived with symptomatic mental disorder [5]. A qualitative evaluation of the participatory systems modelling for developing an SDM found that the process was able to enhance transparency and accountability but that more support and time was required to facilitate transformational change [25]. Another qualitative evaluation of the participatory systems modelling process found that the adoption of more adaptive and flexible workshop activities, and a move away from more structured systems modelling scripts, is required to engage diverse participants within the youth mental health space [26]. SDM has also been used to conduct cost-utility analysis of nine intersectoral strategies to improve youth mental health in Colombia [27]. These findings demonstrate the feasibility of embedding systems-modelling infrastructure into regional mental health planning, supporting adaptive, data-informed resource allocation.

5.6. Strengths, limitations and opportunities for future research

5.6.1. Strengths

One of the key strengths of this research project is the participatory model-building process, involving iterative workshops, systems mapping exercises and diverse stakeholder engagement throughout [28,29]. Qualitative aspects of this group model-building process have been evaluated as part of the broader project [25,30,31]. Stakeholders brought a variety of expertise to the project, being clinicians, policy makers, service providers and young people with a lived experience of mental health conditions. The combination of different forums for stakeholders to provide advice and feedback included workshops, model development group meetings, and lived experience working groups ensured an open, transparent and thorough process of capturing their skills and experience in the model development process. Stakeholder participation was crucial to the economic development of the model, such as the inclusion of peer worder costs in some interventions, microcosting for interventions costs, and providing alternative sources of costing for core economic input data. Although stakeholder participation is not exclusive to SDM, and would be considered standard practice in at least some shape or form for conventional modelling exercises, the process is more structured, necessary, and intensive for SDM due to the requirement of mapping the relevant system, and identifying the various subcomponents and the relationships between them, for both the existing system and any intended changes in the form of interventions.

Another overall strength of the PhD research project is taking a system-level approach to mental health policy and planning. This research demonstrated an advantage in moving beyond individual interventions to analyse the complex interaction of factors with broader systems, such as mental health services capacity constraints [2], social determinants of mental health [3], and overall budget constraints [4]. Unique attributes of adopting a SDM approach to economic modelling (compared to conventional techniques) revealed by this research included the ability to identify synergistic and antagonistic effects of combinations of system change; uncovering the effects of, and on, existing services capacity, and performing constrained optimisation analysis.

Thirdly, this research integrated best-practice methods of economic modelling within SDM. This allows for a more realistic and nuanced understanding of how mental health interventions need to be considered within the broader ecosystem of mental health services and social risk factors. The combined use of economic evaluation and SDM pushed beyond conventional boundaries by exploring the economic value of improving the social determinants of mental health and conducting constrained optimisation analysis.

Fourthly, it is worth recognising the underlying premise of the exercise to begin with, which is the value of using simulation modelling to inform mental health policy and strategic planning [32]. By simulating the impact of different interventions within complex systems, this research offers valuable insights for decision makers seeking to optimise resource allocation and achieve more effective mental health outcomes for their populations. Simulation modelling provides a framework for explicit, transparent, and accountable decision making that brings together data and evidence from a variety of sources.

Finally, the use of both health care and societal perspectives makes the research findings flexible and relevant to policy makers in different parts of government. The health care perspective aligns with the majority of conventional CUAs produced for the health sector and provides useful information on the opportunity costs for health decision makers working with constrained budgets. The societal perspective takes in a broader range of cost categories, including productivity, and may be more applicable to decision makers in treasury departments [33] (discussed further below).

5.6.2. Limitations

There are several overarching limitations to this research project.

The first limitation is the model's dependence on the quality of time-series data used for calibration and the empirical data used to parameterise intervention effects. Calibration data underpin an SDM's behavioural validity—that is, confidence that the model's structure and feedback mechanisms capture real-world dynamics. The precision and credibility of policy results largely depend on the accuracy of input data describing intervention impacts, costs, and baseline system processes. Although uncertainty analysis goes some way to identifying the impacts of parameter uncertainty on outcome measures, there will be unaccounted-for, unknown biases in the collection or analysis of the data sets used to inform the model, or known gaps and limitations in this data. Several measures were taken to try and enhance the reliability of input data, such as obtaining it from reputable government sources or high-quality peer-reviewed literature. The comprehensive participatory-model building process also plays a part in ensuring we used the best available data, but the degree to which all input data, and therefore the model forecasts, are a true and accurate reflection of the real-world is unknowable.

One potential solution is for known data limitations to be brought to the attention of government data collectors (e.g. Australian Bureau of Statistics) and clearing houses (e.g. Australian Institute for Health and Welfare) for improvement. To that end, the research team specifies the most pressing data gaps in the insights briefs for each site. One way that confidence in the evidence on the effectiveness of interventions could be enhanced, or at least made fully transparent, is adopting more formal methods of systematic review for searching and identifying relevant studies (for example, following the Preferred Reporting Items for Systematic

Reviews and Meta-Analyses (PRISMA) standard [34]) and assessing the strength of this body of evidence (for example, using the Grading of Recommendations Assessment, Development and Evaluation (GRADE) framework, which rates the quality of evidence by assessing risk of bias, inconsistency, indirectness, imprecision and publication bias [35]). These tools are widely used in clinical guideline development and HTA agencies but were not adopted for current project due to time and resource constraints. Rapidly-evolving artificial intelligence (AI) tools (like Elicit, Semantic Scholar and Rayyan for systematic reviewing; and the URSE-automated system [36] for GRADE assessment) present an opportunity to overcome this barrier and achieve better precision and transparency when using scientific evidence to inform model parameters. These AI tools were not available or only at a nascent stage of development at the beginning of this project. The models developed for this research program are living decision-support assets that can be updated as these solutions are implemented and new evidence and improved data become available.

The second overarching limitation is that, as with all models, the decision-support tool developed here is a simplified representation of multiple complex social and health systems. Again, uncertainty analysis and stakeholder engagement play an important role in confirming the validity and transparency of this representation, such as 'sense-checking' model outputs, identifying counter-intuitive results, and revealing the circumstances in which conclusions on cost effectiveness have the potential to change. The simplification of complex systems can be a useful endeavour if it results in better decisions that improve population health. Robust implementation evaluation processes with circular feedback mechanisms to inform model updates would help to assess the validity of past models and contribute to better accuracy of future iterations.

The third limitation is related to uncertainty. Uncertainty analysis is crucial in economic analysis for establishing how confident we can be in results and uncovering scenarios in which conclusions might change. Although one-way and probabilistic sensitivity analysis (PSA) were performed in Modelling Study 1, only limited one-way sensitivity analysis was performed for Modelling Study 2 and no sensitivity analysis was conducted in Modelling Study 3. For Modelling Study 2, I argued that the usefulness of comprehensive sensitivity analysis was limited by the hypothetical nature of improvements to social determinants, in contrast to CEA/CUA of a discrete intervention where sensitivity analysis reveals the degree of confidence about conclusions of cost effectiveness. Therefore, the sensitivity analysis conducted for Cast Study 2 was limited to testing the robustness of ranking social determinants between themselves by varying the degree of improvement, utilities, and some costs. For Modelling Study 3, conducting probabilistic-based optimisation analysis would have taken at least several weeks to perform for a single scenario within the current software, so was considered extraneous considering there were seven scenarios in the analysis. One-way sensitivity analysis was subject to the same barrier, including the challenges of compiling and reporting the results for all seven scenarios. Probabilistic-based optimisation analysis and one-way sensitivity analysis can be explored in future iterations of the model through an alternative software solution (e.g. Stella Simulator, Vensim, AnyLogic), high-performance computing (e.g. RONIN by Amazon Web Services, Nectar Research Cloud by Australian Research Data Commons), and restricting the exercise to a single modelled scenario of constrained parameters.

One-way and probabilistic sensitivity analysis are different ways of examining parameter uncertainty but this is only one type of uncertainty that could affect confidence in the estimates. There are at least two other types of uncertainty that could have a material impact on conclusions, both of which were outside the scope of this research project. *Heterogeneity* refers to the variability between patients that can be attributed to observed characteristics of those patients [37]. This is not possible within the aggregate-based modelling approach of SDM used for this research project so a different analytical approach, such as microsimulation, ABM, DES or within-trial economic evaluation would be required to account for this type of uncertainty (beyond the broad population characteristics such as age or level of distress included in the present models). *Structural uncertainty* refers to the assumptions inherent in the decision model itself [37]. Analysing this type of uncertainty would require developing a SDM model with different structural approaches and assumptions or a completely different modelling approach with similar input data. There are at least 80 methods of assessing uncertainty in health economic evaluations [38], highlighting the importance of considering the core economic question underlying the decision problem at hand and identifying the most important type of uncertainty methods that respond to that need, and respond to the practical limitations of the given modelling approach.

The fourth overarching limitation is that, although a societal perspective was adopted across all modelling studies, it is actually a partial societal perspective and may not capture all costs and consequences to society that would constitute a fully-comprehensive societal perspective [9]. Examples of excluded categories include travel and transportation costs incurred by the participant, carer quality of life (i.e. health spillover effects), carer productivity costs, and environmental impacts. This highlights the inevitable judgements that must be made during the model development process when prioritising cost categories that constitute important and material inclusions; limitations in researcher and stakeholder time, even for a well-resourced project like this; and the importance of transparency for stakeholders participating in the development process, users of the model, and consumers of the analytical findings, so they can make their own judgements as to the potential impact of any notable exclusions. It is recognised that the societal perspective is subject to ongoing debate in the health economics field and not necessarily superior than the health care perspective just because it includes a broader range of cost and health consequences. This is due to a range of "ethical, practical and methodological challenges" [8], including discrimination (e.g. productivity calculations favouring workers in paid employment) [8], difficulties with evidence on effects, costs and benefits (including opportunity cost) falling outside the health sector [39], and difficulties with defining, measuring and valuing health spillovers and carer productivity impacts [40,41]. In the present context, the (partial) societal perspective was viewed by the research team and stakeholders as relevant and appropriate for the purpose of informing local decision makers about strategic resource allocation to improve youth mental health and broader societal benefits associated with this, contrasted with the HTA context that is the focus of much of the literature on this topic.

The fifth limitation is the complexity of the models. One of the core objectives of systems mapping exercises and SDM is learning about the system itself, the feedback loops, interactions between different parts of the system and the consequences, intentional and unintentional, of current system structure and design. Although stakeholders in the model development group are taken through each individual sector of the model, and the associated input data, I propose that the final model is so large and complex it is difficult for stakeholders to fully comprehend all the moving parts and truly apply systems thinking for non-quantitative learnings about the ways that the system could be improved. This limitation exposes the delicate balancing act that model developers face between building a model that is sufficiently complex to accurately capture all the important and meaningful influences on health and simple enough that it can be understood by users. Two potential solutions were beyond the scope of the current project, both requiring additional time and resources to deliver, at either end of the development process. The first is more comprehensive systems thinking and SDM capacity building training provided to stakeholders prior to and/or during the systems mapping and SDM development process. The second is more comprehensive 'deep-dive' model output training where, for example, a single intervention is investigated from the point it affects one part of the system and how this flows through to other sectors and eventually impacts on health and economic outcomes, including any unintended consequences or synergistic effects. Whether this substantial investment in researcher time and participant time would actually be of value to, and taken up by, stakeholders is unknown.

Another limitation is that the usefulness of economic evidence and simulation modelling is dependent on the priority-setting and decision-making processes in which it they are deployed and utilised. Compared with the well-developed processes, principles and methods underpinning the operation of National Institute of Health and Care Excellence (NICE) [42], Canada's Drug Agency (CDA-AMC) [43], and the Washington State Institute for Public Policy [44], for example, Australian government agencies, including PHNs, have no formal priority-setting processes in place (with the exception of PBAC/MSAC and their narrow remit of new drugs and medical devices for HTA). This results in a lack of knowledge and capacity for using and applying a system of informed decision making, therefore limiting the independent take-up and application of simulation modelling in general and decision-support tools such as the SDM-based models developed through this research program.

A final consideration is that system dynamics models are aggregate representations of complex real-world systems. They are not intended to predict individual trajectories or fully represent all intersecting population attributes at a granular level. Rather, their purpose is to support decision-making in contexts where outcomes are shaped by feedback loops, delays, accumulations, resource constraints, and interactions across highly interconnected social, health, economic, and service systems. In such settings, decision-makers need to understand how alternative solutions are likely to play out over time, including where benefits, costs, pressures, or unintended consequences may emerge across different parts of the system, and identifying leverage points for whole-of-system change. Variation around projected aggregate trends is therefore expected, particularly for individuals or subgroups whose experiences are shaped by characteristics not explicitly represented in the model.

Despite these limitations, we propose that the systematic, explicit consideration of the trade-off between health benefits, implementation costs and downstream cost consequences made possible through simulation modelling is a more prudent process of priority setting and resource allocation than implicit, politically-driven choices, choices that are inevitable in a context of resource scarcity and a constrained budgetary environment.

5.6.3. Opportunities for future research

There are several streams of potential future research identified by this research project.

It is recognised that economic evidence is only one of many factors taken into account in priority setting and resource allocation. Formal processes do exist to consider these other factors, wrapping around the economic analysis, as described in Section 1.5.1 and Section 1.5.2. For example, in the context of HTA, such factors include strength in the evidence of effectiveness, equity and ethical assumptions or consequences, presence of therapeutic alternatives, severity of the medical condition, treatments for the end-of-life, treatments for children, treatments for rare diseases, or public health issues such as the development of antimicrobial resistance [45,46]. In the context of decision making for public health and prevention, such factors can be referred to as 'implementation considerations' or 'second-stage filters' and include strength of evidence, equity considerations, likely acceptability by government, industry and the public, feasibility of implementation based on overall financial burden or practical considerations, and sustainability issues that may affect long-term effectiveness [47-49]. In the context of clinical guideline development, patient preferences, strength of evidence, equity considerations, health inequalities, degree of overall budget impact, and non-health-related outcomes (such as social care) and considerations that guideline committees need to account for in addition to evidence on effectiveness and cost effectiveness [50]. Given these other factors are already accounted for in other health care decision making contexts and we already have a wide variety of stakeholders involved, more structured consideration of these factors could be added as an adjunct to existing model-building processes for more context and detail that wraps around the economic evidence.

A more formal process of accounting for other factors in addition to the economic analysis is Multi-Criteria Decision Analysis (MCDA) [51]. MCDA is "a set of methods and approaches to aid decision making, where decisions are based on more than one criterion, which make explicit the impact on the decision of all the criteria applied and the relative importance attached to them" [52]. The central feature is a recognition that decisions are based on a series of criteria, some of which may be conflicting, rather than one single measure of effectiveness, like an odds ratio or ICER [53]. Not only could MCDA be conducted alongside SDM-based CEA, where costs and/or ICER are some of the criteria included, there is an opportunity to combine both techniques into an integrated system of SDM-powered MCDA. For example, multi-criteria outcome optimisation analysis (single-outcome optimisation was used in Modelling Study 3) could harness the weights identified during the MCDA process to find the combination of interventions (and/or existing mental health services and/or social determinants) that optimises the 'criteria' identified by stakeholders (to the extent that the criteria of importance are included and measured in the SDM model). The current research program is well-positioned to contribute to research in this space considering that few existing MCDA studies contained lived experience input [54].

Such processes could form part of the fully-integrated SDM-based decision-making framework proposed in the introduction to this thesis (Section 1.6) and associated journal article [1]. The circular, iterative process of implementation, evaluation, and updating the model with new data and evidence has not been realised in the present research program and needs to be sufficiently resourced on an ongoing basis for this to occur. Such a function could be included in the establishment of an 'Independent Value Based Pricing Authority' for mental health reform, working in combination with a Mental Health Advisory Committee, as proposed by Cutler et al. [55], based on a similar premise that the PBAC and MSAC advise the government on the adoption of new medicines and technologies.

Another future research opportunity is investigating the cost effectiveness of interventions targeting the social determinants of mental health. Modelling Study 2 established a modelling framework for analysing the economic value of improving social factors, albeit hypothetically. This work could be extended by adapting the existing modelling framework and group model-building processes to include interventions for improving social factors. Investigating the value-for-money of this type of intervention is likely to be more useful and impactful if done at the state or national level in Australia, where those levels of government have more legislative, administrative and policy powers to enact change at the societal and macroeconomic level.

Existing systematic reviews in the area point towards two types of interventions that target social determinants that hold the most promise based on existing evidence of effectiveness. The first is reducing the stress and anxiety associated with poverty and financial strain. This includes cash transfer programs and employment programs in various forms, like a universal basic income, job guarantee or individual placement and support [56,57]. The second type of intervention best supported by existing evidence is improving social connection and cohesion, such as school-based social development programs, structural support for reducing loneliness and improving social ties, and social network interventions [10,13,58]. An important consideration for these types of interventions is the potential for how they are designed and implemented to influence their effectiveness and produce unintended consequences. This may require more detailed attention for how they are included in models, both from the model developer and consultation process with stakeholders. It also highlights the usefulness of robust uncertainty & scenario analysis and an integrated and properly-funded implementation evaluation framework, that then feeds back into future modelling iterations [59].

Other potential opportunities to extend and improve the existing modelling framework developed through this research project include: improving the evidence informing impacts on unpaid work productivity through de novo analysis of longitudinal population surveys to examine the association between mental health distress and disorders and time away from unpaid work tasks; extending the conceptualisation of productivity impacts related to unpaid work to the broader concept of social production [60]; explicitly accounting for differential effects and outcomes between socioeconomic groups by incorporating Distributional Cost-effectiveness Analysis (DCEA) [61,62]; and refining the representation of system resources towards staff and facilities in the mental health system to supplement the current metric of service contacts and episodes of care, useful for more accurate representation of service capacity and constrained optimisation analysis, within the existing SDM ecosystem or creating a new DES-based modelling approach.

A number of enablers would help to bring this potential research into being:

- capacity building for an ongoing, upskilled, multidisciplinary workforce (systems modellers, health economists, workshop facilitators, people with lived experience, evaluators and evidence-based literature researchers) to develop dynamic models and advance the technical aspects of this approach, including the decision-making processes and agencies in which they are imbedded;
- resourcing to build models that are tailored to each region and decision context, because the population, intervention set and input data vary (compared with HTA modelling which generally applies to a whole country) [63];
- resourcing and processes to enable updating of models on a regular basis as interventions are implemented and evaluated and new data becomes available - this ‘living models’ approach has some similarities to ‘living digital guidelines’, where best practice clinical guidelines are updated as new evidence is published in the literature [64];
- related to the ‘living models’ concept is the ability of the modelling exercise to identify and highlight key gaps in the data ecosystem and feedback this information back to agencies responsible for collecting and gathering primary and administrative data (to improve the robustness of models over time and have greater confidence in strategic and operational decision making); and
- willing and enthusiastic decision makers and political representatives who are keen to collaborate with stakeholders and research teams to guide investment decisions in a transparent, evidence-informed way.

5.7. Conclusion

This PhD thesis described a body of research advancing the field of economic evaluation for mental health by using SDM as the structural framework for modelling. The thesis began with a characterisation of the current literature on the economic evidence supporting mental health interventions, the limited inclusion of economic analysis in SDM, and the rationale for conducting research to fill the knowledge gap at the intersection of these fields. Novel applications of the SDM-based approach to economic evaluation were developed across three modelling studies targeted at improving youth mental health: (i) CEA of eight interventions; (ii) health and economic value of improving the social determinants of mental health; and (iii) constrained optimisation to identify the best configuration of existing mental health services and new interventions that maximised INMB. This research demonstrated the usefulness of SDM-based economic evaluation for mental health policy and planning, identifying its unique attributes compared with conventional economic modelling approaches, along with the limitations associated with the current methods. There are several opportunities for future research to build upon the initial methods developed here, including more robust decision-support tools that can be integrated with agencies that have a remit for mental health reform and more efficient resource allocation in Australia.

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Appendix 1: Original journal article in *PharmacoEconomics* adapted for Chapter 1

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LEADING ARTICLE

Incorporating Complexity and System Dynamics into Economic Modelling for Mental Health Policy and Planning

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Abstract
Care as usual has failed to stem the tide of mental health challenges in children and young people. Transformed models of care and prevention are required, including targeting the social determinants of mental health. Robust economic evidence is crucial to guide investment towards prioritised interventions that are effective and cost-effective to optimise health outcomes and ensure value for money. Mental healthcare and prevention exhibit the characteristics of complex dynamic systems, yet dynamic simulation modelling has to date only rarely been used to conduct economic evaluation in this area. This article proposes an integrated decision-making and planning framework for mental health that includes system dynamics modelling, cost-effectiveness analysis, and participatory model-building methods, in a circular process that is constantly reviewed and updated in a 'living model' ecosystem. We describe a case study of this approach for mental health system policy and planning that synergises the unique attributes of a system dynamics approach within the context of economic evaluation. This kind of approach can help decision makers make the most of precious, limited resources in healthcare. The application of modelling to organise and enable better responses to the youth mental health crisis offers positive benefits for individuals and their families, as well as for taxpayers.

1 Introduction

Mental health conditions are among the leading causes of disease burden and are highly prevalent in high income countries [1–3]. Children, adolescents, and young adults have experienced a greater deterioration in mental health than older adults over the past decade [4, 5]. For example, in Australia, the prevalence of depression and anxiety doubled between 2009 and 2021 in people aged 15–34 years and psychological distress almost doubled between 2011 and 2021 in the 15–24 age group (18.4–32.3%) [6]. Consequently, suicide remains the leading cause of death for people aged 15–44 years of age [7]. These increases have occurred despite greater national attention on youth mental health and suicide prevention, and recent additional funding [8, 9]. However, mental health's share of total health spending has not increased [10]. Systems and processes that enable accountability for mental health are also poorly developed [10, 11]. A recent Australian study revealed that despite increased funding and treatment provisions, the persistent prevalence of mental disorders has not decreased [12]. This is due to a concurrent rise in high-to-very-high psychological distress, driven by the economic and social environments in which we live [13]. Experiencing mental health challenges when younger has important

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Key Points for Decision Makers

Despite increased health policy initiatives and funding, the prevalence of mental health conditions continues to rise in children and young people due to poor implementation of contemporary, evidence-based models of care; workforce limitations; barriers to access appropriate services; and the powerful influence of social, economic, cultural, and technological determinants.

Although much systematic-review-level evidence exists on the favourable economic credentials of mental health treatment and prevention interventions, many gaps remain. Current economic evidence is segmented and lacks evidence on the synergies between different interventions within and beyond mental healthcare.

Economic evaluation using dynamic simulation modelling and participatory model-building methods shows promise as a useful evidence-based technique to guide planning and investments in mental health at regional and national levels. The advantages and disadvantages of this approach are discussed, along with a case study based on system dynamics modelling.

implications for future trajectories of mental and physical health and participation in the labour force in adulthood [14]. Considering that around 75% of mental illness manifests before the age of 25, failure to prevent these conditions in younger people and improve the mental healthcare system means the health and economic consequences will be persistent for many years to come [15, 16]. The intractability of the prevalence of mental ill-health necessitates transformed models of care and prevention, and the re-conceptualisation of mental suffering itself [12, 13, 17, 18].

There is also a substantial economic burden due to poor mental health, with one study estimating $5 trillion (United States [US] dollars) of economic value lost globally due to mental disorders [19]. In the US, more health expenditure is spent on mental health than any other disease area [20]. Broader productivity and economic impacts associated with mental health conditions tend to be greater than mental healthcare spending [21, 22]. For example, the Productivity Commission in Australia estimated $39 billion (Australian dollars) in productivity costs associated with poor mental health and suicide in 2018–2019, compared with $16 billion of healthcare expenditure [23]. However, most productivity loss estimates are only concerned with the economic cost related to paid work—absenteeism, presenteeism, and not participating in the labour force [24, 25]—and rarely include the substantial volume of unpaid work, also known as social production, such as volunteering or informal care [26, 27].

Health economics and, more specifically, economic evaluation provide crucial information for decision making, policy planning, and funding allocation processes by illuminating the path towards allocative efficiency and maximising health outcomes given resource constraints. This is critical in an Australian context, where mental health and substance abuse problems account for 15% of the total burden of disease but attract only 7% of the health budget [28, 29]. However, many gaps remain in the economic evidence on mental health treatment and prevention interventions in terms of both the quantity of economic studies in the areas where this is missing and the techniques used [30, 31]. Furthermore, different policy decisions can result, depending on the accuracy and comparability of economic evaluations, which are influenced by the choice of modelling approach, model structure, input parameters, data sources, time horizon, and perspective [32].

The objective of this article is to outline the need for greater use of dynamic simulation modelling (DSM), with a focus on system dynamics modelling (SDM), for generating economic evidence to guide investments in mental health, particularly in the context of interventions and policy planning for children, adolescents, and young adults. The use of DSM does not preclude the continued use of conventional approaches. Rather, it adds to the repertoire of tools available for economic evaluation to help decision makers have a more complete understanding of the potential influence of systems, complexity, and dynamics on the economic credentials of alternative courses of action. Interest in dynamic approaches for conducting economic evaluation is growing, and they suit some decision-making contexts, such as precision medicine, more than others [33]. This article seeks to provide theoretical reasons why SDM is well-placed to help fill the evidence gaps at the intersection of mental health, economic evaluation, and simulation modelling research across four main sections. Firstly, DSM is explained, including its relevance to mental health. Secondly, we provide a summary of contemporary approaches to mental health prevention and treatment. Thirdly, the current state of economic evidence on mental health interventions is explored. Fourthly, these three fields of research are brought together to explain an integrated process of generating economic evidence using SDM. The benefits of DSM discussed in this paper include the ability to account for the following: the characteristics of complex dynamic systems; context-specific implementation parameters, such as reach and service capacity constraints; synergistic or antagonistic effects; unintended consequences that are not accounted for in conventional economic modelling techniques; participatory model-building processes that make cost-effectiveness analyses directly relevant to intersectoral decision makers and young people with a lived experience of mental health conditions; enhancing the likelihood of implementation of cost-effective interventions; and enhancing transparency and accountability of the decision-making process.

2 Box 1 Definition of key terms

2.1 Agent-Based Modelling (ABM)

A simulation modelling method in which individual agents represent the system, with each agent having their own rules of behaviour, objectives, and history, determined to a large extent through its interactions with other agents and its environment.

2.2 Clinical Staging

A core component of a more personalised approach to mental healthcare provision, which uses symptom severity, duration, and functional impairment to inform treatment decisions, tailoring them to the pathophysiological mechanisms and illness subtypes of individuals at each stage of the disorder.

2.3 Complexity

Complexity is a property of the system in which an intervention operates. Complex dynamic systems exhibit feedback loops, interaction, emergent outcomes, adaption, and non-linearities, and may be composed of smaller subsystems and be part of larger systems.

2.4 Discrete Event Simulation (DES)

A simulation modelling method that focuses on the occurrence of events over time, including queuing processes and networks of queues.

2.5 Dynamic Simulation Modelling (DSM)

A group of simulation modelling methods that refers to DES, ABM, SDM, or some combination of these techniques. These modelling approaches attempt to account for various aspects of complex dynamic systems using different underlying structures.

2.6 Markov Cohort Modelling

A simulation modelling method, also called state-transition models, where aggregate health states represent the movement of a group of homogenous people through time, with the movement of individuals between health states determined by transition probabilities. This is the primary technique falling under the banner of conventional modelling approaches.

2.7 Participatory Systems Modelling

A purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalised and shared representations of reality using computer simulation. It involves an iterative process of engaging with a range of participants, including people with a lived experience of mental health issues. Their knowledge of the local systems, pathways, and drivers is combined with the academic literature and data to populate the models and validate their structure. The process centres around three workshops where participants interact and actively engage in group model-building activities to define, refine, and validate the systems models. ‘Participatory model building’ refers to the application of these methods to any simulation modelling approach (i.e. broader than, but still encompassing, SDM) [34].

2.8 Simulation Modelling

For the purposes of this article, simulation modelling broadly refers to any computational modelling technique that seeks to aid decision making, including both dynamic and conventional approaches.

2.9 System Dynamics Modelling (SDM)

Simulation modelling technique that represents system-level behaviour by using aggregate stocks and flows and differential equations, where the state changes are continuous. Stocks are accumulations of any relevant unit (e.g. people experiencing high distress), and flows are rates of change in and out of these stocks. The initial qualitative stage based on causal loop diagrams enhances understanding of the problem, the system in which it occurs, and relationships between parts of the system.

3 Dynamic Simulation Modelling as a Planning Tool in Health

Simulation modelling in healthcare is increasingly being used for healthcare operations and system design, medical decision making, infectious disease modelling, and other uses like mass casualty event planning [35]. Difficult choices must be made about which interventions to fund in mental health, and simulation modelling is useful because it provides an explicit framework to account for the various influences on the decision, establishing value for money and enhancing accountability and transparency [36]. Modelling combines data from a variety of sources, including expert advice, experimental evidence from literature, observational data, resources, and costs. Mathematical representation of the relationships among system variables allows for forecasting and testing of scenarios in the virtual world before interventions, new policies, or changes to the system are implemented in the real world. Simulation modelling helps us to learn effectively in a world of dynamic complexity by performing 'what if' analysis, forecasting a system's behaviour in the future or under significantly different circumstances, comparing alternative strategies to find an optimal solution, and experimenting with scenarios that are infeasible in the real world [37, 38].

3.1 Types of Dynamic Simulation Modelling

DSM takes a different approach to conventional economic modelling techniques such as Markov modelling. DSM approaches are used to account for the characteristics of the complex, dynamic systems in which we live. These include non-linear relationships, feedback loops that either amplify or diminish desirable or undesirable outcomes, and interactions among different components of the system. Additionally, DSM incorporates mechanisms that enable system adaption, as well as emergent outcomes that may be overlooked by more linear modelling approaches [39]. DSM can be used across a wide variety of contexts and purposes [40, 41].

Examples of DSM include discrete event simulation (DES), agent-based modelling (ABM), and SDM (Table 1) [42, 43]. DES focuses on the occurrence of events over time and the impact those events have on individuals [36]. A typical DES in healthcare will have individual patients moving through time, occupying and releasing system resources like beds, medical practitioners, or equipment, and this movement through the system can be determined by individual characteristics and previous interactions with the system [38]. Examples of software solutions for DES are SIMUL8, Arena, and AnyLogic. ABM focuses on individual behaviour that makes up a system, with each 'agent' having their own definitions or rules, objectives, and history [44]. An agent can make independent decisions based on pre-defined rules, which can impact other agents. Outcomes of the model are determined by the collective states of all the agents and the environment [38]. Examples of software used to conduct ABM are AnyLogic and NetLogo. SDM represents the aggregate behaviour of systems using stocks (for example, the number of people experiencing a high level of distress, emergency department presentations, or cumulative hospitalisation costs) and flows (for example, the rate at which people progress to higher levels of distress, the rate at which people present to an emergency department, or the additional cost incurred due to hospitalisation each time period). Examples of software solutions for SDM are STELLA, AnyLogic, and Vensim.

Various frameworks and decision tools have been published to aid the choice of technique based on the decision context for mental health [32, 36, 44] and healthcare in general [38, 39, 42, 43, 45–49]. For example, Jin et al. survey the literature on tools that can be used to determine the most appropriate economic modelling technique and recommend an optimal model selection process [46]. Marshall et al. and Breeze et al. provide more specific guidance on how to decide whether DSM is appropriate for the decision problem, which technique is most relevant, and other practical considerations when developing DSMs in the context of health economic evaluation [39, 43]. Larrain and Groene define simulation types and provide guidance for selecting the most appropriate technique, with a focus on the technical capabilities of each within the context of complexity and integrated healthcare systems [47]. Table 1 provides a synthesis of this literature by summarising the distinguishing features of each approach in terms of their strengths, weaknesses, and relevance to mental health.

Conceptualising the model structure in terms of stocks and flows using SDM is different to a conventional state-transition Markov model in at least two respects. Firstly, SDMs uniquely incorporate feedback loops and nonlinear relationships, allowing for a more dynamic and realistic representation of complex systems. Secondly, it extends beyond the health states of persons to incorporate any entity or system component of relevance, such as healthcare services or socioeconomic determinants of mental health. These features enable SDM to capture the interdependencies and cyclical behaviours within the system, providing deeper insights for policy analysis and decision making.

3.2 When and How to Use System Dynamics Modelling

SDM is effective in capturing the broader policy landscape, as it integrates feedback loops, interactions, delays, and accumulations. These elements are critical for understanding the long-term effects of policy actions, particularly in the context of strengthening complex health systems and addressing the social determinants of mental health (Table 1). SDM is especially suited for strategic policy advice because it requires less granular data compared to ABM, making it more feasible when detailed individual-level data are scarce or unavailable. Furthermore, the time horizon for SDM can be extended to decades, providing a

Table 1 Key characteristics of modelling techniques

Modelling technique	When to use	Strengths	Weaknesses	Key aspects of complexity accounted for in technique	Relevance to the mental health context
Agent-based modelling (ABM)	• Well-suited to individual-level problems and the interactions that generate emergent behaviour • Instances where capturing heterogeneity is critical, such as equity challenges • Infectious diseases, epidemics	• Individual-level simulation means this method excels at capturing patient heterogeneity, individual characteristics, changes in individual behaviour, and interactions with other agents	• Resource and time intensive to develop, program, and run	• Interaction between individuals, other parts of the system, and the environment • Dynamics • Non-linearity	• Transmission effects of mental health challenges among social networks • Ability to account for service capacity constraints • Ability to track individual patient medical history, behaviour, and treatment response over time
Discrete event simulation (DES)	• Operational research, tactical problems, and process-centred situations when events, the timing of events, and the influence of queuing process are of primary interest • Well-suited to logistical and service planning contexts due to analysis of queuing processes, such as emergency departments and intensive care units based on patient flow • Shorter time horizons more appropriate, like medical decisions	• Individual-level simulation means this method can capture heterogeneity in individual patient characteristics and these are traceable over time • Prior events can affect subsequent event rates • Disease progression can be represented as a continuous process • Great degree of flexibility in the functions and logic governing the flow of entities • Can be very detailed and handle great complexity • Designed to capture queuing processes and networks of queues	• Data intensive • Time and resource intensive to develop • Validation can be difficult	• Dynamic changes in the probability of events over time • Non-linearity • Feedback can be accounted for • Interaction with service providers	• Effectiveness and side-effects of psychiatric medicines, including past treatment history and progression • Service planning where waiting lists are particularly relevant • Ability to account for service capacity constraints
Markov cohort modelling	• Ideally suited for the analysis of health technologies (new medicines) for well-defined conditions and relatively homogenous populations	• Well-established best practices and history of wide adoption in health technology assessment due to relative simplicity due to the cohort approach and ubiquity of relevant software	• Memorylessness of the Markovian assumption (the transition to future states depends only on the present state, not preceding states), which ignores patient history and individual characteristics • Difficult to account for many aspects of complexity • Does not usually account for various constraints faced by healthcare delivery systems	• Limited dynamics, individual characteristics, patient history, and non-linearities can be accounted for by using 'workarounds' (as opposed to being an inherent part of the approach)	• Comparison of medicines or psychotherapies for diagnosed disorders, particularly in the context of health technology assessment

Table 1 (continued)

Modelling technique	When to use	Strengths	Weaknesses	Key aspects of complexity accounted for in technique	Relevance to the mental health context
System dynamics modelling (SDM)	• Well-suited to strategic-level, top-down, and conceptual decisions where a systemwide perspective is required and learning about long-term system behaviour would be advantageous • Also useful for operational research and other contexts where service capacity constraints are important • Less useful for detailed resource allocation problems • Epidemics, disease prevention, developing a new service, and forecasting the demand for services are examples where SDM would be useful • Useful for formalising a mental model of a problem and defining the relations between a system's structure and its behaviour	• Modelling structure of stocks and flows clearly captures feedback loops, interactions between different parts of the system, and dynamic changes over time • The development of causal loop diagrams, also known as influence diagrams, are useful exercises in and of themselves to aid understanding of the problem, the system in which it occurs, and relationships between parts of the system • Participatory systems modelling exercises can be learning experiences about the system in and of themselves, including the influence of the system on health outcomes • Allows optimisation analysis • Generally faster to run than ABM or DES models • Able to model large, complex systems • Range of qualitative and quantitative output can be produced	• Judgement required to draw boundary around parts of the system that will be included • Large amount of data required to populate model • Larger models can be too complex for stakeholders to fully understand • Higher level of aggregation than other dynamic approaches, thereby failing to account for individual characteristics • More homogenous populations compared with other dynamic methods • Resource intensive to develop, both for the participatory systems modelling and technical programming components • Easier to validate	• Incorporates most characteristics such as feedback loops, non-linearity, interaction, dynamics, emergent behaviour as a fundamental model structure • Optimisation analysis extends the ability of SDM to allow the identification of a set of parameter settings and/or combination of interventions that maximises health outcomes, cost reductions, or net monetary benefit	• Ability to quickly test multiple scenarios of interventions alone or in combination, with or without service capacity changes • Interaction between demand and supply for mental health services, and the influence of service capacity constraints on intervention cost-effectiveness • Ability to assist with high-level decision making and strategic resource allocation for mental health interventions

Clear lines are drawn here between modelling techniques to aid conceptualisation and to explore differences. In practice, these lines may be blurred, with simulation models drawing on multiple techniques, and methods that can be used to overcome limitations of a technique. For example, individual microsimulation can be conducted within a Markov model and memorylessness assumption can be overcome by using 'trackers' that account for patient history over time

We also recognise that many other modelling techniques and their variations exist and, here, restrict our analysis to four options for tractability long-term perspective that is essential for evaluating the sustainability and impacts of policy interventions over time, aligning with best practices in conventional economic modelling. Our focus on SDM is based on its promise for the future of health economics, where the need for a system-level understanding of policy implications is paramount. SDM's robust framework for incorporating economic evaluations alongside behavioural dynamics offers a comprehensive tool for decision makers to navigate the complexities of health systems. Although SDM has been applied to simulate mental health and suicide prevention strategies, these instances lack integration with economic evaluations [13, 44, 50–53].

SDM is less suitable in situations where individual characteristics and behaviour are central, as ABM allows for more granular definition of agents within the system. Similarly, SDM is also not ideal for operations research and logistics problems, where DES provides a framework better suited to time-based events and queuing algorithms. For many health technology assessments (HTAs), Markov cohort modelling is often more appropriate, particularly when comparing a narrow class of medicines or medical devices for a specific disease and well-defined population. Another practical consideration is that accurately representing the system through participatory systems modelling is a key aspect of the SDM approach. Thus, gathering the varied perspectives and experiences of individuals with different levels of involvement in the system requires sufficient time and resources.

In practice, the lines between different methods are blurred, with blended models or hybrid simulation [54] incorporating several techniques possible in most simulation modelling software. For example, queuing functionality is available in Stella Architect, DES functionality is available in TreeAge, and all dynamic methods can be carried out concurrently within AnyLogic. Composite models of different approaches can also be produced by linking software programs [55]. Modern software solutions also blur the distinction made in prior literature between discrete and continuous processes, as well as deterministic and stochastic processes. Probabilistic simulations using Monte Carlo methods can now be conducted to varying degrees across different modelling approaches.

3.3 Existing Studies of Simulation Modelling for Mental Health

There have been calls for systems approaches to the evaluation of public health interventions to take into account complexity, spillover effects, and multisectoral consequences [56, 57]. Contemporary approaches to mental health treatment and prevention exhibit many of these characteristics of complex dynamic systems, discussed in more detail in Section 4. Several research groups have developed simulation models for suicide prevention, with a review identifying 53 interventions or hypothetical scenarios that are supported by this type of analysis [44]. However, due to the absence of cost-effectiveness analysis in all of these models, it is unknown whether these interventions represent an efficient allocation of resources, or are even feasible within the current budget constraints of the relevant authority [44]. A systematic review of studies using SDM to assess the economic efficiency of innovations in the public sector found that, in some cases, cost calculations were based on the output of SDM models rather than being embedded and integrated into the models themselves [58]. The review did not specify how many studies adopted this approach [58]. Another systematic review of simulation modelling in general for mental health found that Markov models were the most commonly used method, appearing in 87 out of 166 papers. SDM accounted for only 6.3% of studies [59].

There is limited evidence directly comparing alternative modelling techniques for the same decision-making problem and context. One study compared a conventional epidemiological approach, based on population preventive fractions, with an SDM to evaluate the effectiveness of a psychosocial therapy intervention for suicide prevention. The SDM predicted a significantly lower proportion of suicides would be prevented (0.5%) compared with the conventional approach (5.4%) over the 10-year timeframe of the model, due to factors such as changes in the effect size over time, barriers to uptake, and limitations of service availability. These factors are likely to hinder implementation in real-world situations. However, economic considerations were not included in this analysis [60]. Another study found that interventions designed to reduce self-harm hospitalisations and suicide deaths were less effective when evaluated using an SDM compared with the outcomes expected in existing literature based on static, linear approaches. This discrepancy was largely attributed to the inclusion of real-world factors in the SDM, such as inertia, delay, feedback loops (both vicious and virtuous cycles), implementation challenges in resource-constrained environments, and supply–demand dynamics. However, the economic evaluation was not part of this analysis [61].

In summary, there is a gap in the literature on SDM for mental health that includes economic evaluations despite the usefulness of this technique for high-level strategic decisions at the population-wide level where a long-term time horizon is more relevant to the decision-making context [38].

4 Contemporary Mental Health Prevention and Treatment Paradigms

Contemporary approaches to preventing and treating mental health conditions have introduced greater complexity to healthcare decision making and allocation of public resources. This is due to an increased recognition of the influence of social determinants and life circumstances on mental health [4, 62, 63], as well as the shift towards personalised, integrated, and multidisciplinary models of care for individuals requiring mental health services [17, 64, 65]. These developments contrast with the more traditional, binary, biomedical-based treatment approaches.

There is a wealth of evidence that social determinants, including the cultural, economic, and political systems in which people live, have a great influence on mental health [66, 67]. Social determinants include childhood adversity experienced during critical developmental stages, economic disadvantage, inequality, and poverty, as well as social isolation and feelings of loneliness. They also involve access to safe, stable housing, sufficient food, and clean water, along with the opportunity for meaningful employment. Discrimination and the impacts of climate change further contribute to these determinants [2, 66]. For instance, a study found reductions in the prevalence of sadness, worry, and unhappiness have been linked to greater improvements in income, education, and life expectancy than antidepressant prescribing [68]. Building economic systems and communities that are well-supported and equipped to thrive in the modern world requires accounting for the intersectoral complexity and dynamics involved in decision making. This entails considering bidirectional causality and multidirectional pathways between the social determinants and mental health outcomes.

More personalised approaches have been proposed for people that have mental health challenges requiring treatment provided by mental health professionals [17]. This replaces the stepped-care strategy, where the initial treatment offered is the cheapest, least intensive, and carries the most favourable risk profile with minimal side effects, before progressing to more intensive treatments [69]. This strategy is commonly referred to as the ‘fail first’ approach [70]. More contemporary approaches are ‘stage-appropriate, transdiagnostic, effective, highly personalised and measurement-based’ [70] with stratified treatment options matched to the individual needs of patients and the various dimensions of their lives [69, 71]. Clinical staging uses a classification system similar to general medicine where ‘more advanced stages are associated with a poorer prognosis and a need for more intensive interventions with a higher risk-to-benefit ratio’ [72]. This approach uses symptom severity, duration, and functional impairment to guide treatment decisions, tailoring interventions to the pathophysiological mechanisms and specific illness subtypes of individuals at each stage of the disorder [2, 72–75]. The multidimensional outcomes targeted in personalised treatment include social and occupational functioning, self-harm and suicidal thoughts or behaviours, alcohol and other substance misuse, physical health (including circadian rhythm disturbances), and illness trajectory [71, 76]. Essentially, this means that most young people with emerging mental illness should receive dynamic, multidisciplinary, measurement-based care [64, 77]. This more integrated approach is optimally supported by digital technologies that enhance communication between patients and multidisciplinary teams while tracking health outcomes [2, 78–80]. It includes the use of online e-learning and psychotherapy platforms, which are cost-efficient due to the economies of scale, to treat people with mild and moderate symptoms, thereby freeing up limited face-to-face resources for those with more serious distress or more complex disorders [81, 82]. The model of care referred to and referenced here has been developed over the past decade and has emerged from a body of youth mental health research, which identified that traditional classification approaches and models of care are inappropriate for young people [17]. They fail to capture the complexity of early syndromes that could be used to guide assessment and treatment decisions, and so they rely on ‘fail first’ approaches that wait for treatment non-response before allocating more specific treatments. The more contemporary model referred to here uses a clinical staging model and a highly personalised measurement-based approach to determine the type and intensity of treatment required [17]. While this model has not been directly compared to stepped care, the evidence for its validity for the stratification approach is strong and supported by many clinical and neurobiological studies [71–75].

In summary, contemporary approaches to the treatment and prevention of mental health conditions are more complex and dynamic because they move beyond binary approaches to diagnosis and biomedical treatments based on a single drug or psychotherapy. Conventional economic modelling techniques (discussed further below) are well-suited to analysing single therapies but not necessarily more personalised approaches, impacts on service capacity, and the influence of social determinants. Economic analyses that are being used to guide funding decisions need to be equipped to handle this complexity.

5 Economic Evaluation for Resource Allocation and Priority Setting in Mental Health

Several systematic reviews have been published on the economic credentials of mental health interventions in the last 5 years, with most economic evaluations finding them to be cost-effective or cost-saving, but there are some limitations to this evidence. Ha et al. conducted a systematic review including 49 studies of model-based economic evaluations for mental health prevention, with a focus on the methods used in these studies [83]. Most existing studies, covering a broad range of mental health conditions, were for indicated strategies for high-risk populations (31 out of 49), followed by universal (15 out of 49) and selective preventions (ten out of 49) [83]. Markov cohort modelling was the most common approach (26 out of 49), with no DSM approaches identified [83]. The authors noted that ‘a large number of papers reported little or no details of the model structures and rationale for choosing the models’ [83]. Another review, by Kularatna et al., also focused on the methodological approaches of model-based cost-effectiveness analyses for paediatric mental health interventions. It includes a thorough assessment of the use of utility instruments for children and the limitations of current evidence on the measurement of paediatric mental health-related quality of life [84].

Mental health-related public health interventions and promotions have also received substantial attention in the literature. Feldman et al. conducted a systematic review of public health interventions for improving mental health and reducing suicide [85]. They found that 14 out of 22 interventions were cost-effective. There was a good mix of indicated (13 out of 22 interventions) and universal interventions (nine out of 22 interventions); 14 out of 19 studies were trial-based evaluations (the remaining five studies were model-based evaluations) and were focused on psychological interventions at school (seven out of 19 studies), in the workplace (one out of 19 studies), within elderly care (two out of 19 studies), in the community (two out of 19 studies), in homes (one out of 19 studies), or in primary care (six out of 19 studies) [85]. Another systematic review that focuses on interventions for mental health prevention and promotion excluded those that were directly related to treatment. The authors found that many interventions were cost-effective or cost-saving [86]. Targeted prevention was likely to be cost-effective compared to universal prevention [86]. The authors noted that ‘standard economic evaluation methods commonly applied to health technology assessment may not be transferable to health promotion evaluation’ and ‘economic evaluations with improved methods and capturing intersectoral cost and outcomes of such interventions are needed’, citing services capacity constraints as one of the limitations to generalising trial-based economic evaluations to inform real-world policy implementation [86].

A systematic review of economic evaluations of treatments for depression in low- and middle-income countries, which included 17 studies on adults and five on children and/or adolescents, found inconsistent evidence on the cost-effectiveness of antidepressants [87]. There was stronger economic evidence supporting the use of aripiprazole and task sharing with lay health workers [87].

Lastly, a systematic review of universal mental health interventions for children and adolescents identified nine studies, all but one of which were school-based programmes [88]. Results on cost-effectiveness were mixed, with a parenting programme, a school-based social and emotional wellbeing programme, and anti-bullying interventions showing more positive results than cognitive behavioural therapy-based interventions aimed at the prevention of depression or anxiety [88]. The review confirms that these interventions have high costs and are sensitive to intervention effectiveness, delivery mode and duration, baseline prevalence, and perspective [88]. None of the systematic reviews described here identified economic evaluations for mental health that used an SDM approach.

We argue that greater use of DSM is part of the solution to improving economic evidence for mental health. Many modelling methods exist that are relevant to mental health systems, and the choice of model depends on context and purpose [36, 45, 46]. Currently, most of the evidence is based on conventional (i.e. non-dynamic) modelling techniques developed in the context of HTA where single drugs or medical devices are being compared for very specific conditions and well-defined populations, using evidence from well-controlled, clinical trial settings [89, 90]. For example, most European HTA guideline manuals only mention decision trees and Markov models [91]. Exceptions are submission guidelines issued by the Canadian Agency for Drugs and Technologies in Health (CADTH) and the Pharmaceutical Benefits Advisory Committee (PBAC), which explicitly recognise the existence of SDM, DES, and ABM as options, although they expect a thorough rationale as to why these more complex approaches are required [92, 93]. The technique of optimisation analysis further extends the relevance of SDM for economic evaluation, allowing the identification of a set of parameter settings that maximise a key objective of the decision maker [94]. This is particularly relevant for priority setting in mental health, where a key objective is maximising health outcomes within budgetary constraints. Table 1 provides a summary of modelling approaches in the context of economic evaluation for mental health.

In summary, economic evaluation is critical in the healthcare sector to achieve allocative efficiency in the absence of market mechanisms, and much evidence already exists on the cost-effectiveness of interventions that could be implemented or upscaled now to achieve improvements in population mental health. However, conventional economic modelling approaches may inadequately capture the complexity of contemporary treatment paradigms (described in the previous section), particularly those that require intersectoral collaboration or prevention interventions that seek to move upstream to affect the social determinants of health or economic systems.

6 System Dynamics Modelling-Powered Cost-Effectiveness Analysis as an Enhanced Decision-Making Tool for Mental Health

We propose a fully integrated decision-making and planning framework for mental health that includes SDM, cost-effectiveness analysis, and participatory systems modelling methods, including young people with a lived experience of mental health conditions, with models that are reviewed and updated over time in a circular process as new data become available. This framework would achieve the objectives of implementing effective and cost-effective interventions, maximising both allocative efficiency and technical efficiency, while ensuring rigour, transparency, and accountability. The intersection of economic evaluation within an SDM approach provides an opportunity to inform systems-based investments that improve the lives of young people with mental ill-health while taking into account the complex nature of contemporary models of care and mental healthcare systems. This approach also aligns with the growing interest in learning health systems (LHS). LHS aim to develop an integrated, circular infrastructure for data collection, evidence generation, personalisation, and monitoring to learn from each patient and continually improve the health system [95]. SDM could be a crucial element of an LHS whereby real-time data from the health system is used to update forecasts of simulation modelling to guide planning and learning.

The purpose of participatory model building is to develop simulation models that are useful (in the sense that they are robust, valid, and credible) and used, meaning that end users of the model understand and trust the process and methods that went into developing the model and know how to extract and interpret results to inform decision making. Freebairn et al. describe seven benefits of the participatory systems modelling process as (1) contributing expertise, including lived experience, of participants to model development, (2) social learning between participants, (3) joint problem framing to ensure that the model is focused on priority policy questions, (4) production of regionally customised and socially robust solutions, (5) identification and prioritisation of evidence gaps, (6) opportunities to insert the model into policy and program decision-making dialogues, and (7) development of strategies to address communication challenges [34].

Until recently, there were no economic evaluations of mental health interventions that adopted an SDM approach. A systematic review that included 29 studies conducting economic efficiency analysis of innovations in the public sector did not identify any that related to mental health [58]. The authors concluded that 'SD modelling is not currently used to its full potential to evaluate the technical or allocative efficiency of public sector innovations, particularly in health' [58]. A systematic review of model-based economic evaluations of paediatric mental health intervention identified 12 studies, and all of them used conventional modelling techniques [84]. A scoping review of simulation models for suicide prevention identified 53 interventions that were supported based on health outcomes, but cost-effectiveness analyses were absent from all included models [44].

One example of using a system dynamics approach for conducting economic evaluation of mental health interventions, published after these systematic reviews, was an exercise comparing eight interventions in the Australian context as part of the 'Right care, first time, where you live' project [96–99]. The model incorporates a variety of intervention types that leverage changes in different parts of the system: technology-enabled integrated care, emergency department-based suicide prevention, an acute crisis response service, a family education programme, an online parenting programme, school-based suicide prevention, trauma services for young people, and multi-cultural informed care. Four distinguishing features became apparent by adopting an SDM approach compared with conventional modelling techniques. Firstly, there was the ability to identify synergistic or antagonistic effects for combinations of interventions. Synergistic effects were observed when all four cost-effective interventions were operating concurrently. The total benefits, either measured by quality-adjusted life years (QALYs) or by incremental net monetary benefit (INMB), were higher than a summation of the effects of individual interventions alone. It is only through modelling the dynamic relationships and interactions between different parts of the system that such an outcome can be identified. Secondly, there was the ability to identify and explain unintended consequences and unanticipated outcomes. One of the key unintended consequences identified was the impact that some interventions had on the demand for specialist mental health services, overwhelming the supply of services and increasing the length of time that people experienced higher levels of distress while waiting for care. It is only by including service capacity constraints within the modelled system that such effects can be tested and identified; however, these constraints are not usually included in conventional economic modelling. Thirdly, the effects of changes in service capacity increases or decreases over time can be modelled, independently or in combination with interventions. This function is usually not included in conventional economic modelling, which simply assumes that any adoption of a new technology or intervention is absorbed by the healthcare system without quantifying the opportunity costs incurred by unknown others elsewhere in the system. Finally, a crucial part of the SDM approach is the integration of participatory systems modelling methods that actively involve stakeholders in model development. Linked to this is the creation of a model interface for enabling stakeholders to use the model and produce results themselves to enhance the transparency and accountability of decision making. In addition to these characteristics that are particular to the SDM approach, this modelling exercise maximised the flexibility and usability of the model by producing a range of economic summary measures, including intermediate measures (cost-effectiveness analysis) and final composite outcomes (cost-utility analysis), some of which are more relevant to some decision makers than others. We have also demonstrated that this style of SDM-based cost-effectiveness analysis, including participatory systems modelling processes, can be carried out in low- and middle-income settings, with several strategies being compared in Bogotá, Colombia [100]. SDM has also been used to investigate the cost-effectiveness of increasing buprenorphine treatment initiation, duration, and capacity among individuals who use opioids, with similar features of the SDM approach becoming apparent as stated here [101].

Table 1 provides a summary of the strengths, weaknesses, and potential application to mental health of DSM approaches. One limitation of SDM is the level of complexity of the model structure and how this affects interpretability and transparency for decision makers and other stakeholders. As the CADTH guideline states, the choice of modelling technique 'should be no more complex than is necessary to address the decision problem' [93]. Another limitation of the SDM approach to economic evaluation is the level of resources required to develop the models, conduct stakeholder workshops, and process input data, and this is ideally carried out for each region where local planning needs to occur. Another challenge is the level of data—both the variety of sources and amount of data required to populate the models and also the variety and quantity of results that are produced. Stakeholders need to be prepared for a greater degree of training and sense making than they otherwise might be accustomed to in conventional modelling exercises.

7 Future Research Directions

Leveraging the unique strength of SDM, where system elements such as social determinants of health and system capacity are incorporated and influence the effectiveness of individual (mental health-specific) interventions, we identify some fertile ground for future research.

First, one can investigate the economic value of policy interventions targeting the social determinants of health using the ability of dynamic models to include factors outside the health sector. For example, improved social connection and reduced loneliness are effective at reducing levels of distress and subsequent reduced demand for acute healthcare and in improving employment [102].

There is also the potential to move even further upstream to consider the economic value of reforming the causes of the causes—the social determinants of mental health (the social, political, cultural and economic systems in which we live). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3863696/ Proposals have already been made to develop measures that move beyond gross domestic product as the principal indicator of national prosperity to include wellbeing, Mental Wealth, and social production (unpaid work) [26, 27]. There are calls for a shift towards a wellbeing-orientated economy and for mental health researchers and advocates to, first, recognise these links between economic policies and mental health and then engage with the discourse about how economic structures and policies can reshape the social environment to improve the mental health and Mental Wealth of nations [103]. Governments have already started down this road, implementing 'wellbeing frameworks' to guide policy, funding, and reporting (https://www.act.gov.au/wellbeing/wellbeing-framework and https://treasury.gov.au/policy-topics/measuring-what-matters). SDM is well-placed to aid decision making towards achieving these broader objectives of public wellbeing.

A number of enablers would help to bring this vision to reality:

- Capacity building for an upskilled multidisciplinary workforce (systems modellers, health economists, workshop facilitators, people with lived experience, evaluators, and evidence-based literature researchers) to develop dynamic models and advance the technical aspects of this approach.
- Resourcing to build models that are tailored to each region and decision context, because the population, intervention set, and input data vary (compared with HTA modelling, which generally applies to a whole country) [104].
- Resourcing and processes to enable updating of models on a regular basis as interventions are implemented and evaluated and new data become available. This 'living models' approach has some similarities to 'living guidelines', where best practice clinical guidelines are updated as new evidence is published in the literature. https://www.sciencedirect.com/science/article/pii/S1865921722001362

- Related to the 'living models' concept is the ability of the modelling exercise to identify and highlight key gaps in the data ecosystem and feedback this information back to agencies responsible for collecting and gathering primary and administrative data (to improve the robustness of models over time and have greater confidence in strategic and operational decision making).
- Willing and enthusiastic decision makers and political representatives who are keen to collaborate with stakeholders and research teams to guide investment decisions in a transparent, evidence-informed way.

8 Conclusion

This article has argued for an elevated role of dynamic simulation modelling (DSM) in economic evaluation of mental health treatment and prevention. We contend that the mental healthcare system exhibits the characteristics of a complex dynamic system, and that more accurate and relevant cost-effectiveness analyses can be achieved by adopting a DSM approach. This, in combination with participatory model-building processes that actively and meaningfully involve stakeholders in model development, can offer additional insights and evidence for decision making. As governments and local health authorities consider increasing investments in mental health to address the crisis of children and youth mental health, these sophisticated decision-support tools can help to optimise resource allocation, maximise population health, and alleviate suffering.

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Conflict of Interest Jo-An Occhipinti is both Head of Systems Modelling, Simulation & Data Science at the University of Sydney's Brain and Mind Centre and Managing Director of Computer Simulation & Advanced Research Technologies (CSART). Professor Ian Hickie is the Co-Director at Health and Policy at the Brain and Mind Centre (BMC) University of Sydney. The BMC operates early-intervention youth services at Camperdown under contract to headspace. He is the Chief Scientific Advisor to, and a 3.2% equity shareholder in, InnoWell Pty Ltd, which aims to transform mental health services through the use of innovative technologies. All other authors have no conflicts to declare.

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Ethics Approval Not applicable.

Consent to Participate Not applicable.

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Author Contributions PC conceptualised the article, undertook research of relevant literature, and wrote the original draft. All other authors contributed to reviewing and editing of the manuscript. IBH, YJCS, and JO led the overarching project conceptualisation and funding acquisition. All authors read and approved the final version.

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Appendix 2: Supplementary material for Chapter 2 (Modelling Study 1 as published in *The Lancet Psychiatry*)

Supplementary material

Cost-effectiveness of eight system-level strategies for enhancing the mental health of young people using system dynamics modelling and simulation

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Contents

Supplementary results tables

Table S1: Cost-utility analysis results per quality-adjusted life year, deterministic

	HEALTH CARE PERSPECTIVE					SOCIETAL PERSPECTIVE				
Intervention	**Incremental costs ($)**	**Incremental QALYs (n)**	**ICER vs. BAU ($/QALY)**	**INMB vs. BAU ($M)**	**Rank NMB**	**Incremental costs ($)**	**Incremental QALYs (n)**	**ICER vs. BAU ($/QALY)**	**INMB vs. BAU ($M)**	**Rank NMB**
Business as usual	-	-	-	-	7	-	-	-	-	7
Tech-enabled integrated care	7,518,049	4,116	1,826	322	3	-76,975,729	4,116	Dominant	406	3
ED-based suicide prevention	4,081,379	47	87,443	0	8	3,945,588	47	84,534	0	8
Crisis response service	8,374,602	-11	Dominated	-9	10	7,800,468	-11	Dominated	-9	10
Family education program	-3,829,436	323	Dominant	30	5	-12,386,587	323	Dominant	38	5
Online parenting program	-29,115	753	Dominant	60	4	-3,772,448	753	Dominant	64	4
School-based suicide prevention	73,417,766	-178	Dominated	-88	11	89,778,646	-178	Dominated	-104	11
Trauma services for youth	8,388,093	9	939,059	-8	9	8,297,431	9	928,909	-8	9
Multi-cultural informed care	-35,610	186	Dominant	15	6	-4,325,250	186	Dominant	19	6
TechInt+FamEd+OnlPar+MultCult	3,629,113	5,431	668	430	1	-98,860,276	5,431	Dominant	533	1

All figures are cumulative over 10 years between 2023 and 2032 for the entire ACT population and discounted at 5%.
All costs are in 2019-20 Australian dollars.
It has been assumed that interventions are not mutually exclusive so all incremental amounts are compared with business as usual. Although the combination intervention in the last row is mutually exclusive with the corresponding individual interventions, the comparison with business as usual is retained rather than undertaking separate incremental analysis for the sake of tractability of results.
A willingness to pay of $79,930 per QALY was used to calculated net monetary benefit.
ICER: incremental cost-effectiveness ratio; NMB: net monetary benefit; QALY: quality-adjusted life year; INMB: incremental net monetary benefit; BAU: business as usual; $M: million dollars

Table S2: Cost-effectiveness analysis results per suicide death avoided, deterministic

		HEALTH CARE PERSPECTIVE		SOCIETAL PERSPECTIVE	
Intervention	**Incremental suicide deaths avoided (n)**	**Incremental costs ($)**	**ICER vs. BAU ($/suicide death avoided)**	**Incremental costs ($)**	**ICER vs. BAU ($/suicide death avoided)**
Business as usual	-	-	-	-	-
Tech-enabled integrated care	5.10	7,518,049	1,474,659	-76,975,729	Dominant
ED-based suicide prevention	42.32	4,081,379	96,434	3,945,588	93,226
Crisis response service	-0.03	8,374,602	Dominated	7,800,468	Dominated
Family education program	0.34	-3,829,436	Dominant	-12,386,587	Dominant
Online parenting program	0.18	-29,115	Dominant	-3,772,448	Dominant
School-based suicide prevention	3.63	73,417,766	20,247,799	89,778,646	24,759,946
Trauma services for youth	0.01	8,388,093	1,169,775,408	8,297,431	1,157,131,937
Multi-cultural informed care	0.21	-35,610	Dominant	-4,325,250	Dominant
TechInt+FamEd+OnlPar+MultCult	5.89	3,629,113	615,842	-98,860,276	Dominant

All figures are cumulative over 10 years between 2023 and 2032 for the entire ACT population. Costs are discounted at 5%. Suicide deaths are not discounted.
All costs are in 2019-20 Australian dollars.
It has been assumed that interventions are not mutually exclusive so all incremental amounts are compared with business as usual.
ICER: incremental cost-effectiveness ratio; BAU: business as usual

Table S3: Cost-effectiveness analysis results per self-harm hospitalisation avoided, deterministic

		HEALTH CARE PERSPECTIVE		SOCIETAL PERSPECTIVE	
Intervention	**Incremental self-harm hospitalisations avoided (n)**	**Incremental costs ($)**	**ICER vs. BAU ($/hospitalisation avoided)**	**Incremental costs ($)**	**ICER vs. BAU ($/hospitalisation avoided)**
Business as usual	-	-	**-**	-	**-**
Tech-enabled integrated care	141	7,518,049	**53,150**	-76,975,729	**Dominant**
ED-based suicide prevention	1,150	4,081,379	**3,548**	3,945,588	**3,430**
Crisis response service	-1	8,374,602	**Dominated**	7,800,468	**Dominated**
Family education program	11	-3,829,436	**Dominant**	-12,386,587	**Dominant**
Online parenting program	6	-29,115	**Dominant**	-3,772,448	**Dominant**
School-based suicide prevention	266	73,417,766	**275,568**	89,778,646	**336,978**
Trauma services for youth	0	8,388,093	**26,239,695**	8,297,431	**25,956,085**
Multi-cultural informed care	6	-35,610	**Dominant**	-4,325,250	**Dominant**
TechInt+FamEd+OnlPar+MultCult	166	3,629,113	**21,911**	-98,860,276	**Dominant**

All figures are cumulative over 10 years between 2023 and 2032 for the entire ACT population. Costs are discounted at 5%. Hospitalisations are not discounted.
All costs are in 2019-20 Australian dollars.
It has been assumed that interventions are not mutually exclusive so all incremental amounts are compared with business as usual.
ICER: incremental cost-effectiveness ratio; BAU: business as usual

Table S4: Cost-effectiveness analysis results per ED presentation avoided, deterministic

		HEALTH CARE PERSPECTIVE		SOCIETAL PERSPECTIVE	
Intervention	**Incremental ED presentations avoided (n)**	**Incremental costs ($)**	**ICER vs. BAU ($/ED presentation avoided)**	**Incremental costs ($)**	**ICER vs. BAU ($/ED presentation avoided)**
Business as usual	-	-	**-**	-	**-**
Tech-enabled integrated care	2,599	7,518,049	**2,893**	-76,975,729	**Dominant**
ED-based suicide prevention	3,483	4,081,379	**1,172**	3,945,588	**1,133**
Crisis response service	5,238	8,374,602	**1,599**	7,800,468	**1,489**
Family education program	2,631	-3,829,436	**Dominant**	-12,386,587	**Dominant**
Online parenting program	268	-29,115	**Dominant**	-3,772,448	**Dominant**
School-based suicide prevention	-676	73,417,766	**Dominated**	89,778,646	**Dominated**
Trauma services for youth	8	8,388,093	**1,099,549**	8,297,431	**1,087,665**
Multi-cultural informed care	122	-35,610	**Dominant**	-4,325,250	**Dominant**
TechInt+FamEd+OnlPar+MultCult	5,474	3,629,113	**663**	-98,860,276	**Dominant**

All figures are cumulative over 10 years between 2023 and 2032 for the entire ACT population. Costs are discounted at 5%. Hospitalisations are not discounted.
All costs are in 2019-20 Australian dollars.
It has been assumed that interventions are not mutually exclusive so all incremental amounts are compared with business as usual.
ICER: incremental cost-effectiveness ratio; BAU: business as usual

Table S5: Disaggregated costs per category, deterministic, societal perspective

	SOCIETAL PERSPECTIVE							
	INCREMENTAL COSTS vs BAU						SUMMARY MEASURES	
Intervention	**Incremental intervention costs ($)**	**Incremental health services costs ($)**	**Incremental domestic violence & homelessness costs (excl. health & productivity, $)**	**Incremental carer costs ($)**	**Incremental productivity costs ($)**	**Incremental total costs ($)**	**ICER vs. BAU ($/QALY)**	**Rank NMB**
Business as usual	-	-	-	-	-	-	**-**	**7**
Tech-enabled integrated care	13,869,123	-6,380,096	-1,562,835	-21,221,123	-61,680,797	-76,975,729	**Dominant**	**3**
ED-based suicide prevention	8,217,056	-4,135,677	19,533	234,468	-389,793	3,945,588	**84,534**	**8**
Crisis response service	14,581,931	-6,207,329	9,928	165,826	-749,887	7,800,468	**Dominated**	**10**
Family education program	57,530	-3,886,966	-105,433	-1,412,872	-7,038,846	-12,386,587	**Dominant**	**5**
Online parenting program	884,188	-913,303	-55,479	-786,005	-2,901,849	-3,772,448	**Dominant**	**4**
School-based suicide prevention	79,013,504	-5,595,738	-1,547,621	1,342,762	16,565,739	89,778,646	**Dominated**	**11**
Trauma services for youth	8,429,033	-40,939	-19,722	-41,098	-29,842	8,297,431	**928,909**	**9**
Multi-cultural informed care	399,246	-434,856	-60,439	-891,981	-3,337,220	-4,325,250	**Dominant**	**6**
TechInt+FamEd+OnlPar+MultCult	15,202,787	-11,602,695	-1,803,605	-24,552,341	-76,104,421	-98,860,276	**Dominant**	**1**

All figures are cumulative over 10 years between 2023 and 2032 for the entire ACT population. Costs are discounted at 5%.
All costs are in 2019-20 Australian dollars.
ICER: incremental cost-effectiveness ratio; BAU: business as usual; NMB: net monetary benefit
The ICERs and NMB ranking that appear in the final two columns are identical to Table S1.

Table S6: One-way sensitivity analysis, deterministic

Intervention/parameter	Unit of measure	Default	Low	High	ICER vs. BAU ($/QALY) Health Care Perspective* Low	High	ICER vs. BAU ($/QALY) Societal Perspective* Low	High
Technology-enabled integrated care					**1,820**		**Dominant**	
Uptake - % of MH services that involve intervention	%	0.5	0.25	0.75	1,851	1,798	Dominant	Dominant
Setup cost per clinical governance area	AUD$	80000	64000	96000	1,817	1,823	Dominant	Dominant
Annual subscription cost per clinician	AUD$	6000	4800	7200	1,151	2,489	Dominant	Dominant
ED-based suicide prevention					**87,266**		**84,376**	
Effect duration	Weeks	24	12	36	165,877	51,906	164,579	47,346
Referral rate	%	1	0.8	1	112,946	87,266	110,633	84,376
Annual budget for intervention	AUD$	1263894	1011115	1516673	52,120	122,412	49,230	119,521
Crisis response service					**Dominated**		**Dominated**	
Uptake - % of MH responses crisis response team attends	%	1	0.8	1	Dominated	Dominated	Dominated	Dominated
% of ED presentations that are MH related	%	0.237	0.1896	0.2844	Dominated	Dominated	Dominated	Dominated
Family education					**Dominant**		**Dominant**	
Uptake - % of families that consent to service	%	0.5	0.25	0.75	Dominant	Dominant	Dominant	Dominant
Number of participants per session	#	5	3	6	Dominant	Dominant	Dominant	Dominant
Online parenting					**Dominant**		**Dominant**	
Uptake	%	0.5	0.25	0.75	1,109	Dominant	Dominant	Dominant
Program decay rate	%	1	0.8	1	Dominant	Dominant	Dominant	Dominant
Annual budget for ACT population	AUD$	136000	108800	163200	Dominant	193	Dominant	Dominant
School-based suicide prevention					**Dominated**		**Dominated**	
Uptake - % student participation	%	1	0.8	1	Dominated	Dominated	Dominated	Dominated
Effect on distress onset rate	%	1	0.8	1	35,972	Dominated	27,004	Dominated
Trauma services for youth					**937,796**		**927,630**	
Treatment duration	#	12	10	14	1,114,384	811,551	1,105,768	800,274
% FDV victims requiring services	%	0.5	0.25	0.75	923,025	947,226	912,734	937,131
Max number of services per year	#	520	416	624	943,089	933,653	932,958	923,461
Number of sessions per patient	#	24	19.2	28.8	741,466	1,134,125	729,553	1,125,706
Multi-cultural informed care					**Dominant**		**Dominant**	
Effect on disengagement rate	%	1	0.8	1	Dominant	Dominant	Dominant	Dominant
Uptake - % CALD patients receiving multi-cult informed ca	%	0.5	0.25	0.75	1,948	Dominant	Dominant	Dominant

* Base case ICER appears in intervention header row between low and high columns.

Blue shading indicates an ICER that changes quadrant on the cost-effectiveness plane due to the new high/low parameter value compared with the base case default value (for example, Dominant to positive ICER) but does not switch sides of the willingness-to-pay threshold of $79,930.

Orange shading indicates an ICER that has switched sides of the willingness-to-pay threshold (for example, is now considered to be cost effective due to the new high/low parameter value when it was not cost effective for the base case default value).

Table S7: One-way sensitivity analysis for alternative timeframes and discount rates, deterministic

10 years (base case)	Health care perspective ICER vs. BAU ($/QALY)			Societal perspective ICER vs. BAU ($/QALY)		
Intervention	**0%**	**5% (base case)**	**7%**	**0%**	**5% (base case)**	**7%**
Business as usual	-	-	-	-	-	-
Tech-enabled integrated care	1,514	1,826	1,962	Dominant	Dominant	Dominant
ED-based suicide prevention	76,066	87,443	92,554	73,919	84,534	89,324
Crisis response service	Dominated	Dominated	Dominated	Dominated	Dominated	Dominated
Family education program	Dominant	Dominant	Dominant	Dominant	Dominant	Dominant
Online parenting program	Dominant	Dominant	36	Dominant	Dominant	Dominant
School-based suicide prevention	Dominated	Dominated	Dominated	Dominated	Dominated	Dominated
Trauma services for youth	874,215	939,059	967,164	863,360	928,909	957,318
Multi-cultural informed care	Dominant	Dominant	Dominant	Dominant	Dominant	Dominant
TechInt+FamEd+OnlPar+MultCult	431	668	771	Dominant	Dominant	Dominant

30 years	Health care perspective ICER vs. BAU ($/QALY)			Societal perspective ICER vs. BAU ($/QALY)		
Intervention	**0%**	**5% (base case)**	**7%**	**0%**	**5% (base case)**	**7%**
Business as usual	-	-	-	-	-	-
Tech-enabled integrated care	Dominant	Dominant	Dominant	Dominant	Dominant	Dominant
ED-based suicide prevention	24,438	36,526	42,189	45,510	49,703	52,877
Crisis response service	Dominated	Dominated	Dominated	Dominated	Dominated	Dominated
Family education program	Dominant	Dominant	Dominant	Dominant	Dominant	Dominant
Online parenting program	Dominant	Dominant	Dominant	Dominant	Dominant	Dominant
School-based suicide prevention	168,567	549,712	1,585,487	181,409	636,388	1,868,992
Trauma services for youth	726,348	728,427	738,906	714,096	716,167	726,741
Multi-cultural informed care	Dominant	Dominant	Dominant	Dominant	Dominant	Dominant
TechInt+FamEd+OnlPar+MultCult	Dominant	Dominant	Dominant	Dominant	Dominant	Dominant

Blue shading indicates and ICER that changes quadrant of the cost-effectiveness plane (for example, Dominant to positive ICER) but does not switch sides of the willingness-to-pay threshold.
Orange shading indicates an ICER that switches sides of the willingness-to-pay threshold.

Detailed methods

Interventions

The interventions that were included in the model were identified through the participatory modelling process. Interventions were suggested by stakeholders in the workshops. This list was then shortlisted through consensus by the model development group. The set of final interventions was further narrowed based on (a) the availability of high quality evidence identified in the literature through non-systematic literature searching, usually in the form of published systematic reviews with meta-analyses or controlled trials, and (b) the ability of the model development group to define the intervention in sufficient detail as to allow identification of resources required and costs that would be required to implement the intervention.

Technology-enabled integrated care (TechInt)

The modelled platform has the following combined features:

1. Triage function – this function includes an initial assessment to determine who are suitable for different levels of care upon initial presentation (i.e., low intensity versus high intensity) and identifies appropriate service pathways which differ according to care type and urgency. Subgroups with differential service needs can be triaged or stratified based on suicidality, risk of illness progression, and functional impairment.
2. Provision of online materials / information / contact to prevent disengagement while awaiting care. This facilitates early engagement in online evidence-based treatment sooner, which is likely to provide a more positive experience of care and keeps people engaged with mental health care.
3. Care coordination function – The use of the platform to assess and identify the care needs of an individual and share information across providers to improve multidisciplinary team-based care approaches. These approaches embrace collaborative care models, which recognize that effective care coordination between service providers, including intensive assessment, personalized treatment plans, targeted referrals, clinical information systems use, and outcome monitoring can improve treatment engagement, satisfaction with care, and mental health outcomes.

Starting year
The year in which technology-enabled integrated care is introduced (the default is 2023, or January 2023).

Years to reach full effect
The time required for technology-enabled integrated care to be fully implemented (the default is 2 years).

Program duration
The duration of investment in technology-enabled integrated care (the default is set to 999 years, ensuring that investment continues until the end of the simulation).

Program uptake
The maximum proportion of mental health services provided that involve technology-enabled integrated care. This proportion will depend on the number of medical and allied health

professionals adopting online care coordination technologies, as well as the number of patients consenting to the use of these technologies in the management of their care (i.e., take-up among service providers and patients). The default value (0.5) assumes that technology-enabled integrated care will be provided in 50% of mental health services completed when fully implemented, based on expert advice.

Effect on recovery rate
The multiplicative effect of technology-enabled integrated care on the per-service recovery rate (i.e., the probability that a patient's level of psychological distress will decrease after receiving treatment). The default estimate (1.177) is derived from a study by Woltmann et al.[1] and implies that technology-enabled coordinated care increases the per-service probability of a reduction in psychological distress by 17.7%.

Effect on referral rate
The multiplicative effect of technology-enabled integrated care on general practitioners' rates of referral to specialised mental health services (psychiatrists and allied mental health services). The default value (1.266) implies that technology-enabled integrated care increases the per-consultation probability that a general practitioner will refer a patient with moderate to very high psychological distress to specialised psychiatric care by 26.6%, and is derived from a study by Badamgarav et al.[2]

Effect on disengagement
The multiplicative effect of technology-enabled integrated care on per capita rates of disengagement from mental health services. The default estimate (0.72) is derived from a study by Campbell et al.[3] and implies that technology-enabled integrated care reduces rates of disengagement by 28%.

Emergency department-based suicide prevention (EDSP)

This intervention is based on 'ED-Safe' which provides universal suicide risk screening and an intervention which include a secondary suicide risk screening by a clinician, discharge resources and follow-up phone calls post-discharge from ED focused on reducing suicide risk.[4]

Starting year
The year in which EDSP is introduced (the default is 2023, or January 2023).

Program duration
The duration of investment in EDSP (the default is set to 999 years, ensuring that investment continues until the end of the simulation).

Years to reach full effect
The time required for EDSP to be fully implemented and reach the maximum services rate (the default is 2 years).

Maximum self-referral rate
The maximum proportion of people presenting to emergency departments for suicidal ideation or behaviour who would be referred to EDSP. The default value (1) assumes that 100% of people in suicidal crisis who would normally present to an emergency department would be intervened with EDSP.

Effect of on self-harm rate
The proportion of potential re-presentations for suicidal ideation or behaviour expected. The default value (0.72) implies that 72.0% of re-presentations that would have occurred if a person in crisis was treated in an emergency department actually occur when care is provided via EDSP i.e., ED-Safe is assumed to prevent 28.0% of potential re-presentations for suicidal ideation or behaviour. The default value is derived from a study of ED-Safe by Miller et al.[4]

Effect duration
The average time in weeks that care provided in a safe space service has an effect on the probability of repeat episodes of suicidal ideation or behaviour (the default value is 24 weeks) based on the ED-Safe study by Miller et al.[4]

Self-harm re-presentation rate per year
The expected number of re-presentations for suicidal ideation or behaviour in the year after an initial suicide-related emergency department attendance. The default value (3.84) is derived from a study by Perera et al.[5] and implies that in the year after presenting to an emergency department for suicidal ideation or behaviour, patients will re-present 3.8 times (on average).

Crisis response service (CRS)

Mental health clinicians travel with police officers and paramedics, and work together to manage individuals in crisis requiring a specialist mental health response. Some situations are de-escalated and require no further response. Individuals requiring immediate treatment are transported to the Emergency Department as usual; patients with less severe symptoms are referred to community mental health services.

Starting year
The year in which CRS is introduced (the default is 2023, or January 2023).

Program duration
The duration of investment in crisis response service (the default is set to 999 years, ensuring that investment continues until the end of the simulation).

Years to reach full effect
The time required for crisis response service to be fully implemented (the default is 2 years).

Response service de-escalation rate
The proportion of situations that can be de-escalated by the crisis team and require no further response. The default value (0.105) indicates that 10.5% of situations can be de-escalated. This was sourced from an evaluation of a CRS in Victoria, Australia.[6]

Response service ED referral rate
If the situation cannot be de-escalated, proportion of situations where the individual is transported to the Emergency Department. The default (0.52) means that if the situation cannot be de-escalated, 52% of individuals will be transported to the Emergency Department.[6]

Proportion of MH ED presentations

Proportion of mental health-related Emergency Department presentations involving police and paramedics. The default (0.237) means that 23.7% of mental health-related Emergency Department presentations involve police and paramedics. Source: AIHW Mental health services provided in emergency departments 2020-21 Table ED2.

Response service implementation rate
Varies between 0 (no crisis response team) and 1 (full implementation so that all Police and ambulance calls requiring a specialist mental health response can be answered with the crisis response team). The default (1) means the program is fully implemented.

Family education (FamEd)

Provision of psychosocial education and support to families and carers of patients engaged with mental health services, with the aim of supporting family or carer involvement in the management of psychotic mental disorders. This family psychoeducation program can improve the rates of recovery from service and decrease the rates of presentation to emergency departments. The default parameters correspond to family psychoeducation for patients with schizophrenia.

Starting year
The year in which family psychoeducation and support programs are introduced (the default is 2023, or January 2023).

Program duration
The duration of investment in family psychoeducation and support programs (the default is set to 999 years, ensuring that investment continues until the end of the simulation).

Years to reach full effect
The time required for scaling up family psychoeducation and support programs (the default is 2 years).

Program uptake
The maximum proportion of patients who would consent to having their family involved in the management of their care. The default value (0.5) implies that family psychoeducation and support would be provided to a maximum of 50.0% of patients.

Effect on recovery rate
The multiplicative effect of family psychoeducation and support on the recovery rate among psychotic patients treated by a GP, psychiatrist, or allied mental health professional. The default value (2) is derived from a study by Rodolico et al.[7] and implies that family psychoeducation and support programs will increase the per-service probability of recovery by a factor of 2.

Effect on MH ED presentations
The multiplicative effect of family psychoeducation and support on the rate of presentations to emergency departments for patients diagnosed with psychosis. The default value (0.18) is derived from the same study by Rodolico et al.[7] and implies that family psychoeducation and support programs will decrease by 82% the rate of presentation to emergency departments for patients diagnosed with psychosis.

Proportion of patients with psychosis.
Proportion of patients diagnosed with psychosis. The default value (0.022) corresponds to the proportion of patients with schizophrenia (2.2%).

Proportion of MH ED presentations with psychosis.
Proportion of mental health-related emergency department presentations that correspond to patients diagnosed with psychosis. The default value (0.155) means that 15.5% of mental-health related emergency department presentations correspond to diagnosed patients with schizophrenia. Source: AIHW Mental health services provided in emergency departments 2020-21 Table ED13.

Online parenting program (OnlPar)

This intervention is based on the Triple P program (Positive Parenting Program). Through this program, participants will develop new skills to help raise their children and strategies to prevent problems from developing. This will increase the emotional well-being of children, resulting in more self-sufficient and resilient young people and families. The effects of this program will be applied to children aged 0-11 years of age.

Starting year
The year in OnlPar is introduced (the default is 2023, or January 2023).

Program duration
The duration of investment in OnlPar (the default is set to 999 years, ensuring that investment continues until the end of the simulation).

Years to reach full effect
The time required for scaling up OnlPar (the default is 2 years).

Program uptake
The maximum proportion of the population who are parents who would enrol in OnlPar. The default (0.5) assumes that 50% of eligible parents would enrol based on expert advice.

Effect on behavioural difficulties onset
The multiplicative effect of the Triple P program has on the rates of transition to higher levels of strengths and difficulties. The default value (0.631) is derived from a study by Li et al.[8] and assumes that this program will decrease these transition rates by 36.9%.

Program decay rate
The fractional rate per year at which the effects of OnlPar decline to a value of 1 (i.e., no effect) after these programs conclude. The default value (1) implies that the effects of reduced behavioural difficulties onset would decrease to a value of 1 in one year given the initial rate of decline.

School-based suicide prevention program (SSP)

School based mental health education & suicide prevention programs delivered to secondary school students aged 12-17 years of age. The modelled program had the combined features of:

1. Universal component: Curriculum based mental health education and awareness of suicide ideation with a focus on young people developing skills to help peers who are experiencing mental health and substance use problems - this should be co-designed with young people with lived experience.
2. Indicated intervention component: Brief screening for depression and other risk factors associated with suicidal behaviour – and inclusion of cognitive– behavioural content relating to cognitive restructuring, problem-solving skills, and interpersonal skills (assertion, conflict resolution, and negotiation) for those with high to very high psychological distress.
3. Treatment seeking component: providing assistance with barriers to seeking professional help.

Starting year
The year in which school-based mental health programs are introduced (the default is 2023, or January 2023).

Program duration
The duration of investment in school-based mental health programs (the default is set to 999 years, ensuring that investment continues until the end of the simulation).

Years to reach full effect
The time required for scaling up school-based mental health programs (the default is 2 years).

Effect on engagement
The multiplicative effect of school-based mental health programs on the per capita rates that students perceive a need for care and engage with mental health services. The default value (1.45) is derived from a study by Lubman et al.[9]

Effect on suicidal behaviour
The multiplicative effect of school-based mental health programs on the per capita suicide attempt rate. The default value (0.625), derived from a study by Aseltine et al.[10] implies that school-based mental health programs reduces the rates of suicidal behaviour of students by 37.5%.

Effect on distress onset
The multiplicative effect of school-based mental health programs on the rates of transition to more severe levels of psychological distress in students. The default value (1), based on a study by Sheffield et al.[11] implies that school-based mental health programs have no impact on these transition rates.

Trauma services for youths (TSY)

This intervention models a mental health service providing trauma-informed care for young people under 18 years of age who are victims of family and domestic violence.

Starting year
The year in which trauma services for youths is introduced (the default is 2023, or January 2023).

Program duration
The duration of investment in trauma services for youths (the default is set to 999 years, ensuring that investment continues until the end of the simulation).

Years to reach full effect
The time required for trauma services for youths to be fully implemented and reach the maximum services rate (the default is 2 years).

Maximum number of trauma services per year
The maximum number of trauma informed care services that can be provided per year. The default is 520 services based on expert advice.

Proportion of victims of FDV requiring trauma services
The proportion (default is 0.5, or 50%) of people under 18 years of age who are victims of family and domestic violence who would require access to trauma services for youths based on expert advice.

Treatment duration
The average time in weeks that care provided in trauma service for youths has an effect on the probability of recovery from mental health services (the default value is 12 weeks).

Effect on recovery rate
The multiplicative effect of trauma services for youths has on the per-service recovery rate. The default estimate (2.345) is derived from a study by Zhang et al.[12] and implies that trauma services for youths would increase the per-service recovery rate by a factor of 2.345.

Multi-cultural informed services (MultCult)

This intervention provides mental health professionals with the resources and training to deliver multi-cultural informed care for people from a culturally and linguistically diverse background engaging with mental health care system.

Starting year
The year in which multi-cultural informed care programs are introduced (the default is 2023, or January 2023).

Program duration
The duration of investment in multi-cultural informed care programs (the default is set to 999 years, ensuring that investment continues until the end of the simulation).

Years to reach full effect
The time required for scaling up multi-cultural informed care (the default is 2 years).

Program uptake
The maximum proportion of patients from a culturally and linguistically diverse background who would receive multi-cultural informed care. The default value (0.5) implies that culturally adapted care would be provided to a maximum of 50% of patients from a culturally and linguistically diverse background based on expert advice.

Effect on recovery rate
The multiplicative effect of multi-cultural informed care on recovery rates amongst patients from a culturally and linguistically diverse background. The default value (2.84), derived from a study by Hall

et al.[13] implies that multi-cultural informed care will increase the per-service probability of recovery by a factor of 2.84, which is a more conservative half the effect size reported by Hall et al. based on expert advice.

Effect on disengagement rate
The multiplicative effect of multi-cultural informed care on service disengagement rates amongst patients from a culturally and linguistically diverse background. The default value (1), derived from a study by Pringle et al.[14] implies that multi-cultural informed care has no effect on disengagement rates.

TechInt+FamEd+OnlPar+MultCult (combination intervention)

Here the four cost-effective interventions are implemented concurrently. For the combination intervention, most of the effects driven by the four interventions require no assumption as they are influencing different parts of the system (Table 1 of the main manuscript). The only parameter influenced by three of the four interventions concurrently when combined is the ‘per service recovery rate’. The effects of different interventions that alter the same flow(s) in the model (treatment dependent recovery in this case) are assumed to be multiplicative, i.e., if interventions A and B increase the per service recovery rate by 10% and 20%, respectively, the combined effect of both interventions (when implemented simultaneously) is 1.1 * 1.2 = 1.32, or a 32% increase. This multiplicative approach to specifying combined effects is generally preferred over an additive approach (partly because it prevents nonsensical mathematical results) and is widely used in system dynamics modelling.[15]

Model development process

A participatory modelling approach was used to develop the system dynamics decision-support tool to inform investments and actions to strengthen the mental health system to deliver better outcomes for young people. The purpose of the decision-support tool was to establish which programs, initiatives and health system reforms work best to improve young people’s mental health specific to the region, thereby providing young people with the support they need to get back to work, back to school and thriving in their communities.

Protocols have been published describing the development process and the implementation of cost-effectiveness analysis alongside it.[16,17] Briefly, the participatory model building component of the project includes three face-to-face workshops with attendance from a range of stakeholders including mental health professionals, General Practitioners, allied health service providers, people with a live experience of mental health conditions health agency representatives:

- Workshop 1 identified outcomes of interest, mapped the youth mental health service system in the ACT and identified programs and initiatives of interest for integrating in to the model (31 March 2022).
- Workshop 2 presented the prototype model, based on workshop 1, to participants for their critique. Worked together to better define and model the prioritised programs and initiatives (20 July 2022).
- Workshop 3 presented the interactive model to stakeholders for user testing and exploration of key policy and planning insights (17 October 2022).

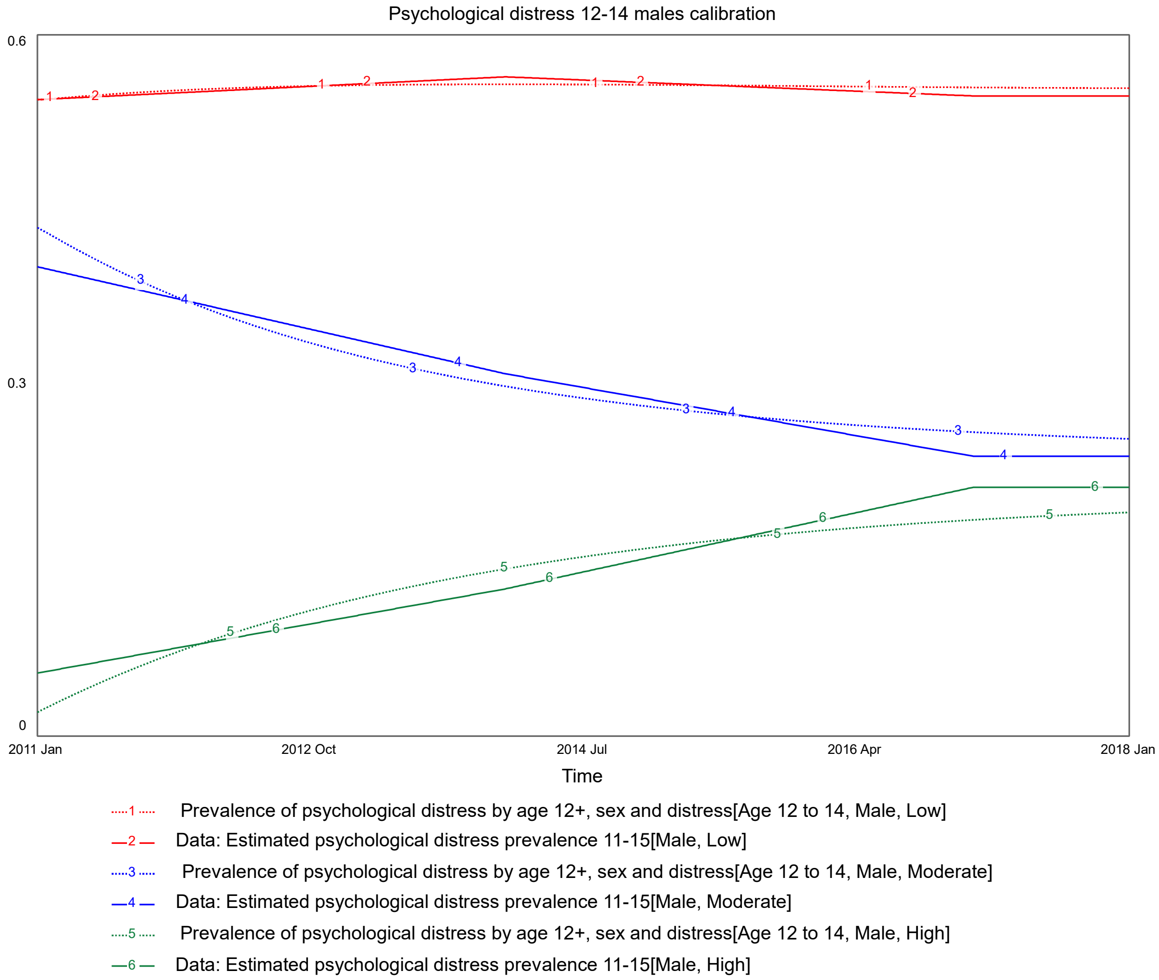
Regular meetings were held with a model development advisory group between the workshops for more detailed components of the model development process. Where model inputs of development decisions were informed by expert advice, this could be informed through any of the workshops, model development group meetings or personal communication with subject matter experts from any of the following roles, noting that these categorisations are somewhat arbitrary and individual participants are likely to span multiple roles and identities:

1. Young people with a lived experience of mental health conditions and their carers.
2. Clinician subject experts, such as psychiatrists, psychologists and General Practitioners.
3. Academic researchers including health economists, systems modellers, data scientists and research support.
4. Policy, health administration and management representatives, including those from the Primary Health Network and state department of health.

Both research evidence and data were used to parameterize the model and data was used to calibrate the model. With regards to searching of the literature, a rapid review approach was used, relying where possible on systematic reviews. Parameter values that couldn't be derived directly from these sources were estimated (or calibrated) via constrained optimisation, using historical time series data for a wide range of sociodemographic and health-related outcomes, including participation and unemployment rates, the prevalence of moderate to very high psychological distress, intentional self-harm hospitalisation and suicide mortality rates, and rates of mental health services usage (numbers of mental health-related emergency department presentations, community-based mental health services consultations, psychiatric hospital admissions, etc. per year). Powell's method (Powell, 2009, The BOBYQA algorithm for bound constrained optimization without derivatives. Technical repot no. DAMTP 2009/NA06. Department of Applied Mathematics and Theoretical Physics, Cambridge University, Cambridge) was used to obtain the set of (optimal) parameter values minimising the mean of the absolute differences between the observed time series values and the corresponding model outputs, where each difference was expressed as a percentage of the observed value (i.e., the mean absolute percent error served as the objective function).

Figure S1 shows an example of model calibration to historical data for males age 12 to 14 with low, moderate and high levels of distress.

Figure S1: Model calibration to historical data for males aged 12 to 14 at various levels of distress



Model structure

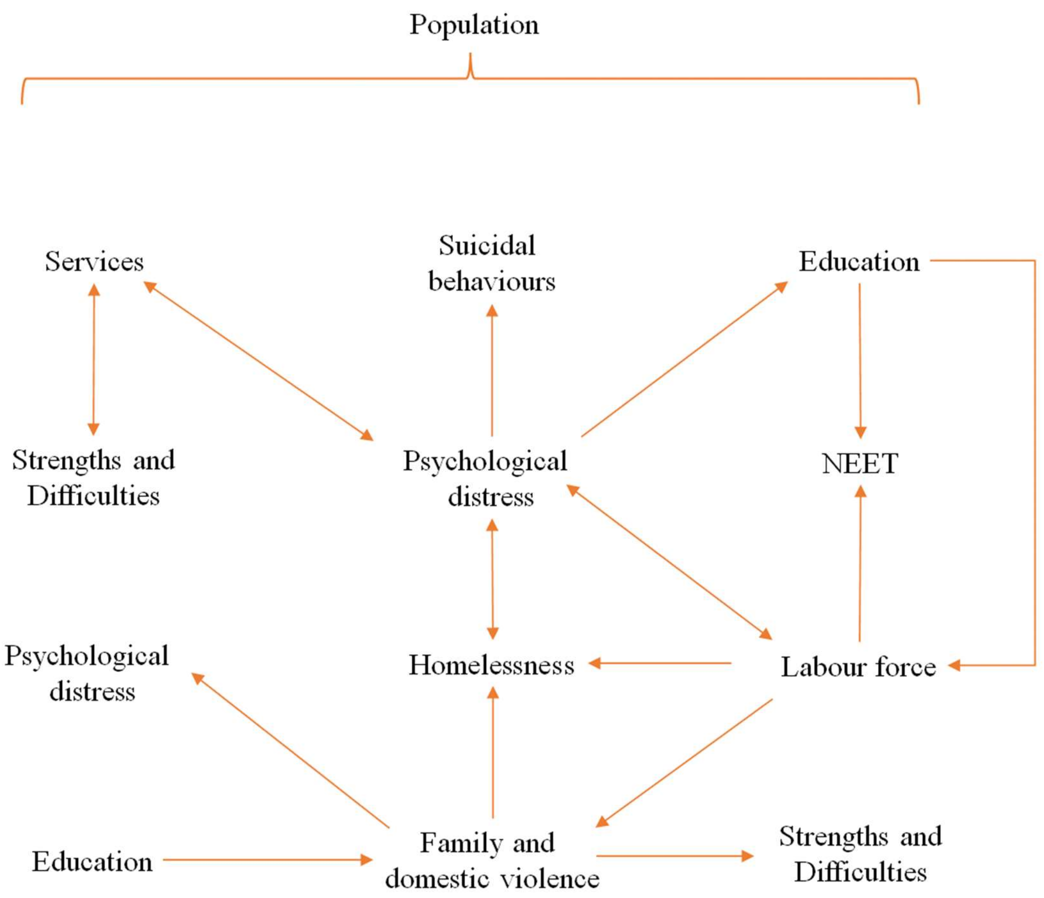
The co-developed digital decision support tool can be used to test possible responses within complex real-world environments. The model is a logically consistent mathematical framework that integrates best available data and evidence sources with expert and local knowledge (including the expert knowledge of those with a lived experience of mental ill-health and carers). The model captures population and demographic dynamics, pathways to youth mental health care, service interactions and workforce capacity, and the potentially non-additive effects of intervention combinations (Figure S2). The model was validated through face validity among stakeholders and by observing its ability to reproduce historic trends across observed data (listed below) in the ACT from 2011 to 2021 giving confidence in its forward projections:

- Population
- Secondary school students
- Post-secondary education students
- Unemployment rate
- Proportion of population aged 15-24 who are not in employment, education or training
- Suicide deaths per year
- Self-harm hospitalisations
- Mental health-related ED presentations

- Prevalence of psychological distress (low, medium, high to very high)

The model has an interactive interface allowing the simulation of a series of intervention scenarios (individually and in combination) to explore their likely impact on a variety of youth mental health-related outcomes over a 10 year period (2023 to 2032). These scenarios were compared to a 'business as usual' reference scenario, in which youth mental health and suicide prevention measures currently in place remain unchanged until the end of the simulation period (2032).

Figure S2: Overview of model sectors

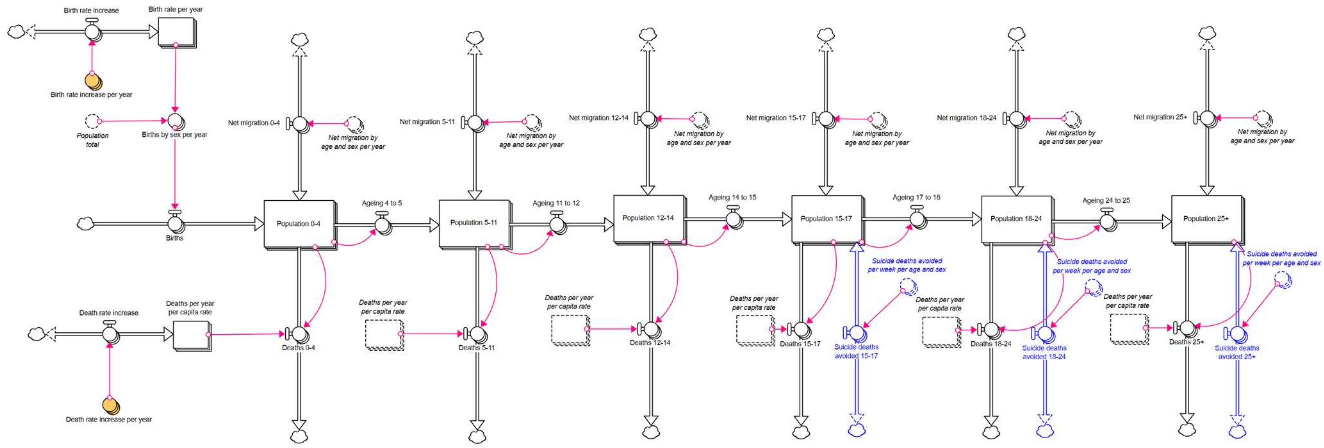


Description of sectors

Population

The population sector divides the total resident population of the ACT into six age groups, represented by six accumulation variables called stocks. Each stock is disaggregated by males and females. The stocks correspond to people aged 0-4 years, 5-11 years, 12-14 years, 15-17 years, 18-24 years, and 25 years and older. These age groups reflect the focus of the model on youth mental health, and also schooling years, labour force statistics and data availability from the Australian Bureau of Statistics (ABS). Each stock has a mortality outflow and a net migration biflow. Births flow into the stock of 0–4-year-olds and people follow an ageing chain flowing from younger to older age groups. This sector is calibrated using estimated resident population, birth, deaths, and migration statistics from the ABS.

Figure S3: Structure of the population sector



Education

The education sector is divided into two sub-sectors.

Education - Students

The students subsector captures people currently studying in the ACT. The stocks correspond to primary education, secondary education and post-secondary education. Each stock is disaggregated by males and females, has a mortality outflow and a net migration biflow. All five-year-olds are assumed to be attending primary school, hence children turning 5 years flow into the primary education stock. Graduates of primary education then transition to secondary education, and graduates of secondary education can either transition to post-secondary education or not (e.g. those commencing full-time employment). Students in secondary or post-secondary education may discontinue studies at rates dependent on sex and levels of psychological distress. People may enter secondary or post-secondary studies without directly transitioning from primary education or secondary education respectively (e.g. re-enrolling after discontinuation). This sector is calibrated using student statistics from the ABS and from the ACT Education Directorate.

Education – Qualifications

The qualifications subsector captures holders of different qualifications in the ACT. The stocks correspond to people aged 15-24 years and 25 years and older, and by their highest level of qualification. More specifically, the stocks correspond to people whose highest level of qualification is Year 12 completion, and to people whose highest level of qualification is post-secondary completion. Each stock is disaggregated by males and females, has a mortality outflow and a net migration biflow. People who complete secondary education then flow into the "Secondary qualification only" stocks. People who then complete their first post-secondary qualification flow into the "Post-secondary qualification" stocks. People also follow the ageing chain from 15-24 years to 25 years and older depending on their highest level of qualification. This sector is calibrated using qualifications, education and work statistics from the ABS.

Labour force

The labour force sector captures the employment statuses of ACT residents. The stocks correspond to people aged 15-24 years and 25 years and older, and by their employment status. More specifically, people can be either employed or unemployed. People who are not in either of these stocks (e.g. full-time students, retirees) are deemed to be not in the labour force (NILF). Each stock is disaggregated by males and females, has a mortality outflow and a net migration biflow. People can transition between being employed and unemployed, between being NILF and unemployed, and flow out from the employed stock into NILF (e.g. retirement). People who are NILF must transition into unemployment prior to transitioning into employment to reflect people actively looking for work prior to being employed. The rates of transition between employed and unemployed, and between NILF and unemployed are dependent on age, sex, levels of psychological distress and highest levels of qualifications. This sector is calibrated using labour force statistics from the ABS.

NEET

The NEET sector captures young people aged 15-24 years who are not in employment, education nor training (NEET). This uses model outputs from the labour force and education sectors to calculate the numbers of young people who are NILF and not currently studying. This sector is calibrated using education and work statistics from the ABS.

Strengths and difficulties

The strengths and difficulties sector represents children aged 0-4 years and 5-11 years at different levels of prosocial behaviour and psychopathology as measured using the strengths and difficulties questionnaire (SDQ). These children are divided into three stocks representing lower to higher risk of clinically significant problems: “Close to average”, “Slightly raised” and “High”. Each stock is disaggregated by males and females, has a mortality outflow and a net migration biflow. People are assumed to be born with close to average levels of SDQ and hence flow into the “Close to average SDQ” stock for 0-4-year-olds. People can flow between close to average and slightly raised levels of SDQ, and between slightly raised to high levels of SDQ with rates dependent on age, sex, rates of family and domestic violence, rates of disengagement with the mental health services systems and rates of treatment. Furthermore, children age from the 0-4 year stocks to the 5-11 year stocks following an ageing chain. This sector is calibrated using SDQ statistics from the Longitudinal Study of Australian Children. The data for 0-4-year-olds were imputed using data for 5-11-year-olds.

Psychological distress

This sector represents people aged 12-14 years, 15-17 years, 18-24 years, and 25 years and older at different levels of psychological distress as measured using the Kessler Psychological Distress Scale (K10). These people are divided into three stocks representing lower to higher levels of psychological distress: “Low”, “Moderate” and “High”, the last capturing people at high or very high levels of psychological distress. Each stock is disaggregated by males and females, has a mortality outflow and a net migration biflow. People can flow between low to moderate levels, and between moderate to high levels of psychological distress. These transition rates are dependent on age, sex, homelessness rates, rates of family and domestic violence, unemployment rates, rates of disengagement with the mental health services systems and rates of treatment. Furthermore, people age following the ageing chain across the same levels of psychological distress. This sector was calibrated using K10 data from the ABS’ National Health Surveys and from the Young Minds Matter Survey. The data for 15-17-year-olds and 12-14-year-olds were imputed using data from the Young Minds Matter Survey and data from ABS' National Health Surveys.

Homelessness

This sector consists of six stocks corresponding to people aged 0-4 years, 5-11 years, 12-14 years, 15-17 years, 18-24 years, and 25 years and older and follows the statistical definition of homelessness developed by the ABS. Each stock is disaggregated by males and females, has a mortality outflow and a net migration biflow. People aged 15 and older enter homelessness at rates which are dependent on age, sex, levels of psychological distress, unemployment rates, and family and domestic violence rates. For people under 15 years of age, rates of entering homelessness are dependent on age, sex, and family and domestic violence rates. People exit homelessness at rates dependent on age and sex. People age into older stocks following the ageing chain. This sector was calibrated using homelessness statistics from the ABS.

Family and domestic violence

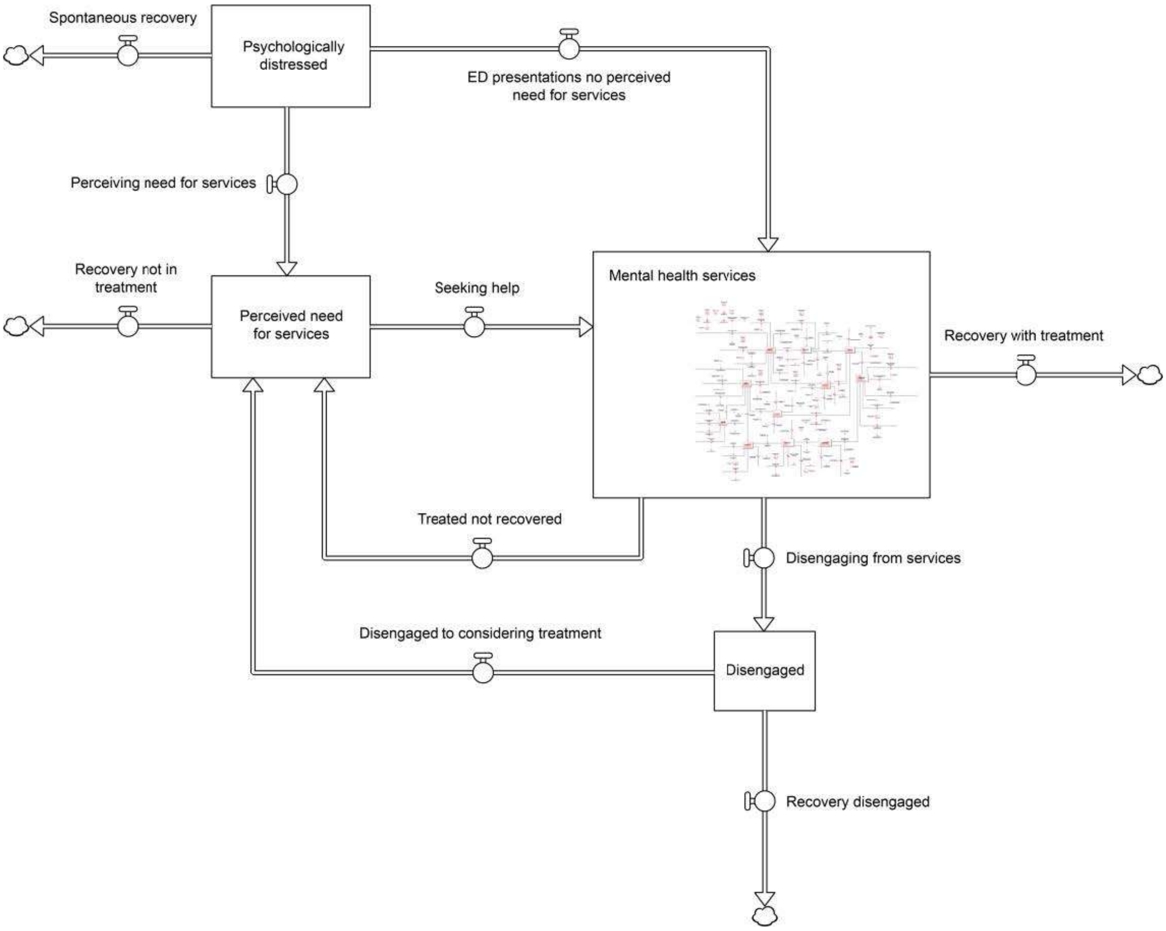
This sector consists of base rates of family and domestic violence modelled as stocks that can change over time. These rates are dependent on age, sex, secondary school completion rates and unemployment rates. This sector was calibrated using victims of family and domestic violence related offences statistics from the ABS.

Suicidal behaviours

This sector captures the rates of intentional self-harm hospitalizations and suicide deaths. Note that we equate suicide attempts with self-harm hospitalizations due to data availability constraints. This sector consists of two stocks. The first stock represents people currently exhibiting suicidal behaviours. People can flow into this stock with an index suicide attempt and people can flow out of this stock depending on whether the attempt was fatal or non-fatal. People who had a recent non-fatal suicide attempt then flow into the second stock and either remain in this stock for 12 months, representing the duration of which people are at higher risk of exhibiting further suicidal behaviours, or people flow back into the suicidal behaviours stock if they have a repeat suicide attempt. The rates of suicide attempts are dependent on age, sex and levels of psychological distress. Suicide deaths are added to the mortality outflows of all sectors. Due to data constraints, this sector captures suicidal behaviours of people aged 15 and above only. This sector was calibrated using deaths statistics from the ABS and intentional self-harm hospitalizations statistics provided by the ACT Government's Office of Mental Health and Wellbeing.

Mental health services

Figure S4: High level view of the mental health services sector



This sector captures the flow of people with moderate or high levels of psychological distress or with slightly raised or high SDQ levels as they engage with the mental health services system. The services stocks represent general practitioners (GP), psychiatrist and allied mental health professionals, online services, community mental health care (CMHC) services, psychiatric hospital care services, non-specialised hospital care services and emergency departments. For GP, CMHC, psychiatrist and allied health services and psychiatric hospital care services, waiting stocks are modelled for each to reflect people waiting for these services due to service capacity constraints prior to commencing treatment. People may perceive a need for service and engage with the mental health system through either presenting directly to an emergency department or seeking help from a GP or online mental health services. After engaging with services, people may either 1) recover through treatment and return to the general population with a lower level of psychological distress, 2) be treated and not recover, 3) disengage with the service reflecting either excessive waiting times or unsatisfactory service, or 4) be referred onto different services.

The rates of flow between stocks of the mental health services sector are dependent on age, sex and levels of psychological distress. This sector was calibrated using services statistics from the Australian Institute of Health and Welfare. We assumed that 95% of services delivered in the ACT were for residents of the ACT.

Outputs and calibration
The primary outputs of the model are mental health-related emergency department presentations, self-harm hospitalisations, suicide deaths and prevalence of mild moderate, and high to very high psychological distress. For model parameters where no public or published data was available, Powell's method was used to perform constrained optimisation.[18] Optimal values were determined by minimising the mean absolute percent error of the model's outputs compared to the historical data.

Health measures

The main health outcome of interest for this cost-utility analysis was quality-adjusted life years (QALYs). QALYs are a composite measure of health that includes both changes in survival and quality of life, reflecting the preference-based utilities of varied health states. Utilities were derived by using a mapping algorithm to convert low, medium and high to very high distress levels based on the K10 disease-specific measure to the EQ-5D multi-attribute utility instrument, applying mapped utility decrements to Australian population norms (Table S8).[19,20] Distress levels based on the K10 was not available for children below the age of 15. In the model, psychological problems for children of 0 to 14 years of age is represented by the Strengths and Difficulties Questionnaire (SDQ). There is no mapping algorithm from the SDQ to the EQ-5D so we assumed that the levels of 'close to average', 'slightly raised' and 'high' in the SDQ were equivalent to low, moderate and high to very high distress in the K10 and mapped to the EQ-5D accordingly using the same algorithm based on this assumption. This is a limitation of the calculation of QALYs in the model for younger age groups.

Cost-effectiveness analyses were also conducted for several intermediate health outcomes: suicide deaths, self-harm related hospitalisations, and mental health-related emergency department presentations.

Table S8: Utilities for health states based on distress levels

Age group	Background	Low distress	Moderate distress	High to very high distress
0-14 years	0.96	0.932	0.903	0.749
15-17 years	0.96	0.932	0.903	0.749
18-24 years	0.95	0.919	0.884	0.711
25+ years	0.89	0.876	0.828	0.608

Costs

Costs were established for each sector of the model including health care costs, homeless costs, costs related to domestic violence and productivity. Each category of cost for the core model (those costs not directly related to an intervention) is listed along with the method of derivation and source materials in Table S10 for productivity measures and Table S9 for all other core model cost categories.
The cost of interventions, methods and sources are presented in Table S11.

Univariate sensitivity analysis

Several parameters related to interventions were varied in sensitivity analysis between plausible high and low values based on expert advice to test whether conclusions on cost effectiveness changed within this range. The list of parameters, the values used in sensitivity analysis and results in terms of ICERs are presented in Table S6.
Sensitivity analysis was also conducted by extending the time horizon out to 30 years (10 years in the base case) as well as alternative discount rates for both time horizons. A lower bound discount rate of 0% (5% in the base case) was selected based on the lower bound of sensitivity analysis specified by the Pharmaceutical Benefits Advisory Committee in their submission guidelines.[21] An upper bound discount rate of 7% was selected based on the discount rate specified by Australian treasury departments for us in cost-benefit analysis.[22] Results of this sensitivity analysis for all combinations of time horizons and discount rates is contained in Table S7.

Assumptions

Assumption	Justification	Implications
Structure, including scope & population		
The model focuses on youth mental health but includes the entire ACT population. Ages below 25 years old are grouped based on advice from the model development group using developmental stages and progression through school. The adult population is represented by a single group of those aged 25 and over.	The whole ACT population was included to capture health and other impacts as young people age, more relevant for longer time horizons, and whole-system representation of mental health service use and other indirect impacts, such as the influence of social determinants.	Economic outcomes are based on all age groups to capture whole-system representation in resource allocation decisions. Stratification of age groups may over or under estimate the impact of interventions in practice that might be targeted at more specific ages. The aggregation of all adults into a single group requires the use of the same average weekly earnings (applied to non-fatal productivity impacts) and the same number of years of productive life lost due to premature mortality for anyone aged 25 and over.
Population is modelled in aggregated stocks rather than individuals	Inherent to system dynamics approach to modelling at the population level and data availability	Individual heterogeneity is not represented at the level of individual trajectories in this system dynamics model
Psychological distress is represented using 3 categories based on the K10	Adopts categories specified by the Australian Bureau of Statistics and simplifies complexity of a greater number of health states	Fails to account for individual complexity and nuance within distress-based health states, potentially oversimplifying clinical reality
Time horizon and discounting		
Default time horizon set to 10 years, 30 years in sensitivity analysis	Balances the need for decision-maker and political relevance, capturing some degree of long term effects, and computational feasibility	10 years is shorter than conventional economic evaluation where lifetime time horizon is common. The cost effectiveness of interventions may change beyond this timeframe.
5% discount rate adopted based on guidance issued by Pharmaceutical Benefits Advisory Committee	Common practice in economic evaluation to take account of time preference for money and opportunity cost of capital	Reduces the value of health and cost consequences that occur in future years
Interventions		
Interventions scale up to achieve full effect over 2 years	Account for realistic time lags in implementation that occur in practice	In reality, implementation of some interventions may reach full effect sooner or later than their default values. They may also waver at levels less than full effect over time.

Intervention duration remained over full time horizon of model	Once an intervention is implemented is likely to remain in place for 10 year period	Assumes ongoing funding for program in its implemented state, potentially overestimating the benefits of interventions. In practice intervention are likely to change form over time.
Strength of evidence is treated the same regardless of source. Most are from peer-reviewed literature, usually systematic reviews with meta-analysis, some from single trial studies. Some are from evaluations published in non-peer-reviewed grey literature.	Ensures parameterisation of effects are based on evidence, but this is subject to evidence available at the time of model development.	Effectiveness of interventions may be over or under estimated. The effectiveness of real-world implementation of interventions may differ from modelled outcomes.
Evidence has been generalised from the literature-based interventions to represent the modelled interventions, and the alignment between the modelled intervention and the evidence upon which it is based varies from intervention to intervention.	Parameterisation of effectiveness is subject to the evidence available at the time of model development. A balance needs to be made between representing the model as closely as what would be implemented in the region in practice, and the intervention design as it appears in the literature.	Effectiveness of interventions may be over or under estimated. The effectiveness of real-world implementation of interventions may differ from modelled outcomes.
Uptake rates are based on expert opinion.	Lack of empirical evidence on uptake rates, particularly in the region for which the model was developed, necessitating expert opinion.	Effectiveness of interventions may be over or under estimated. The effectiveness of real-world implementation of interventions may differ from modelled outcomes.
Where interventions have an identical mechanism of effect and they are implemented in combination with each other, the effects are assumed to be multiplicative.	Avoids invalid effect sizes while accounting for some additional effectiveness in the absence of evidence on the combination of interventions.	May over or under estimate the synergistic effectiveness of intervention combinations in practice.
Interventions are not mutually exclusive	Informed by model development group that all interventions could theoretically be implemented given relevant financial resources	Mainly affects calculation of incremental cost-effectiveness ratios. May not fully reflect resource competition and budget constraints at higher levels of intervention cost.
Behavioural assumptions		
Transition rates between distress states depends on socio-economic factors, such as unemployment and homelessness	Reflects evidence on social determinants of mental health	Relationships may be mis-specified or incomplete
Services were assumed to be operating at 100% based on their current activity levels, and service capacity constraints affect waiting times and outcomes	Key system feedback identified in participatory modelling and assumption checked with model development group	Critical driver of unintended consequences
Calibration		
Where data were unavailable, parameters were estimated via calibration to historical trends using Powell's method of optimisation	Ensures internal consistency with observed data	May over or underestimate actual relationships between system components
Quality-adjusted life years		
For people aged 15 and over, utilities were derived by mapping average K10 scores for distressed health states to the EQ-5D using a published mapping algorithm	Necessary for cost-utility analysis	Uncertainty is introduced, both by the underlying mapping algorithm and the representativeness of the resulting K10-EQ-5D QALY changes to actual quality of life changes in practice as a result of some system change
For children aged under 15 years, SDQ levels were assumed to be	No alternative approach available at the time of model development	May over or under estimate the actual quality of life changes likely to

equivalent to K10 distress categories for the purposes of assigning utilities		occur as a result of some system change
Costs		
Inflation not explicitly accounted for	Costs are indexed to the same financial year, ensuring consistent financial units, but inflation levels in future years is unknown	May under or over estimate actual cash costs that are incurred in any category in future years
Societal perspective includes productivity, selected non-health sector costs	Captures broader economic impact based on judgement of categories most relevant to the decision context	Excludes many cost categories that technically fall within a societal perspective, like environmental impacts. Likely to enhance the cost effectiveness of interventions
Intervention costs informed by stakeholder feedback and model development group, informed by resource use mentioned in literature	Reflects most likely resource use and costs if the intervention were implemented in the region	May over or under estimate actual costs incurred by implementing an intervention
Uncertainty		
Only parameter uncertainty was explored, not structural uncertainty	Resource and time constraints	Alternative model structures may yield different results
Probabilistic analysis limited to parameters with known variability	Reflects availability of distributions from empirical evidence	Likely to underestimate uncertainty compared to having a greater number of variables included in probabilistic analysis
Effects are assumed to be homogenous for all age groups to which they were applied	Simplifies modelling development given data limitations	May obscure differential impacts experienced by subgroups in practice, such as, socioeconomic group, gender, sexual orientation, race or geography

Table S9: Unit costs for core (non-intervention) sectors of the model

Cost group (Level 1)	Cost category (Level 2)	Cost item (Level 3)	Unit of measure	Unit cost (2019-20)	Perspective	Method	Sources	Assumptions
Health care	Specialised mental health services	Specialised psychiatric units or wards in public acute hospitals	per admitted episode	24,133.52	Health Care and Societal	Unit cost given	Unit cost - IHACPA NHCDC Round 24 2019-20 Appendix 23 for ACT https://www.ihacpa.gov.au/resources/national-hospital-cost-data-collection-nhcdc-public-hospitals-round-24-financial-year-2019-20	
Health care	Specialised mental health services	Community mental health care services	per episode	2,444.46	Health Care and Societal	Unit cost given	Unit cost - IHACPA NHCDC Round 24 2019-20 Appendix 23 for Australia (no community mental health events reported for ACT) https://www.ihacpa.gov.au/resources/national-hospital-cost-data-collection-nhcdc-public-hospitals-round-24-financial-year-2019-20	
Health care	Specialised mental health services	Residential mental health services	per residential care day	616.92	Health Care and Societal	Unit cost given	Mental health services in Australia: Expenditure on mental health services, Table EXP.9 https://www.aihw.gov.au/reports/mental-health-services/mental-health-services-in-australia/	
Health care	Medicare-subsidised services	All non-GP psychiatric & psychology services	per service contact	172.21	Health Care and Societal	Total cost of service for ACT divided by number of service contacts for ACT for Commonwealth-funded amount. This is a weighted average for all non-GP specialist mental health consultations. Then out of pocket payments added by calculating the proportion of gap between total fees charged and benefits paid by Medicare for each service type based on national data because this is not provided by state. This approach has the advantage of effectively being a weighted average of all relevant MBS item numbers rather than having to pick a specific item.	Mental health services in Australia: Expenditure on mental health services, Table EXP.18 for total expenditure by service for ACT Mental health services in Australia: Medicare-subsidised mental health-specific services, Table MBS.11 for service counts	
Health care	Medicare-subsidised services	General practitioner	per service contact	90.67	Health Care and Societal	Same as above but for GPs only	Same as above	
Health care	Subsidised Prescriptions	Where the prescriber is a non-GP mental health professional	per patient per year	380.30	Health Care and Societal	Total expenditure on any MH-related medication by all prescribers divided by number of patients with prescription at prescriber region. Additional proportion of out of pocket spend derived from general PBS expenditure on all medicines	Total expenditure on MH-related medicines by all type of prescribers from AIHW Mental Health Expenditure Table EXP.26 Number of patients with prescription from Table PBS.20 Proportion of OOP contribution to PBS medicines derived from AIHW general Health Expenditure Table A3	

Health care	Subsidised Prescriptions	Where the prescriber is a GP	per patient per year	175.36	Health Care and Societal	Same as above	Same as above	
Health care	Emergency care	Ambulance cost weighted average	per attendance	888.09	Health Care and Societal	Weighted average is calculated using proportion from personal communication ACT where 54.6% resulted in transfer to ED.		
Health care	Emergency care	Emergency department presentation	per presentation	957.06	Health Care and Societal	Unit cost given by source	Unit cost - IHACPA NHCDC Round 24 2019-20 Appendix 23 for ACT https://www.ihacpa.gov.au/resources/national-hospital-cost-data-collection-nhcdc-public-hospitals-round-24-financial-year-2019-20	
Health care	Online services	Online cost	per person per year	59.00	Health Care and Societal	Per person accessing paid-for online services	ThisWayUp https://thiswayup.org.au/programs/anxiety-and-depression-program/	All people accessing online services use a paid-for service like ThisWayUp. The cost of services funded by governments that a free to users do not change between interventions and therefore excluded from analysis.
Homelessness	Youth homelessness 15-24yo	Specialised homelessness services	per person per year	14,444.44	Societal only	Total budget allocation for 2021-22 budget divided by number of people currently registered for homelessness services	The Mandarin article https://www.themandarin.com.au/169538-acts-multimillion-dollar-commitment-to-specialised-homeless-support/	Assumes 2021-22 applies to the 2019-20 cost year
Homelessness	Youth homelessness 15-24yo	Additional health care costs	per person per year	9,912.59	Health Care and Societal	Unit cost given Indexed from 2011-12 to 2019-20 using AIHW health price index	CSI report - MacKenzie 2016 - The cost of youth homelessness - Research Briefing https://www.csi.edu.au/media/uploads/CYHA_FINAL_REPORT_18April2016_v0dqGpT.pdf OOP split includes private health insurance and NGO proportions so that splits sum to total unit cost	
Homelessness	Youth homelessness 15-24yo	Criminal justice costs	per person per year	10,725.09	Societal only	Unit cost given Indexed from 2011-12 to 2019-20 using GNE IPD	CSI report - MacKenzie 2016 - The cost of youth homelessness - Research Briefing https://www.csi.edu.au/media/uploads/CYHA_FINAL_REPORT_18April2016_v0dqGpT.pdf Indexation from AIHW Health Expenditure Database 2019-20 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2019-20/data	
Homelessness	Adult homelessness	Specialised homelessness services	per person per year	14,444.44	Societal only	Same as youth homelessness	Same as youth homelessness	Same as youth homelessness
Homelessness	Adult homelessness	Additional health care costs	per person per year	17,208.78	Health Care and Societal	Unit cost given Payer split derived from total funding of general health care expenditure Indexed from 2010-11 to 2019-20 using AIHW health price index	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2019-20 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2019-20/data	

Homelessness	Adult homelessness	Criminal justice costs	per person per year	6,891.48	Societal only	Unit cost given Indexed from 2010-11 to 2019-20 using GNE IPD	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2019-20 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2019-20/data	
Homelessness	Adult homelessness	Welfare and taxation forgone	per person per year	8,271.91	Societal only	Unit cost given Indexed from 2010-11 to 2019-20 using wage price inflator derived from ABS	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from Australian Bureau of Statistics Wage Price Index https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/wage-price-index-australia/latest-release#data-download	
Homelessness	Adult homelessness	Children placed in care	per person per year	2,732.79	Societal only	Unit cost given Indexed from 2010-11 to 2019-20 using GNE IPD	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2019-20 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2019-20/data	
Homelessness	Adult homelessness	Eviction	per person per year	87.51	Societal only	Unit cost given Indexed from 2010-11 to 2019-20 using GNE IPD	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2019-20 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2019-20/data	
Domestic violence	Domestic violence	Additional health care costs	per person per year	1,462.29	Health Care and Societal	Total cost divided by total prevalence	KPMG 2016 - Cost of violence against women and their children in Australia, page 12 Indexation AIHW health price index	Original report relates to costs of violence against women only, but here we assume the same costs apply to violence against men in the absence of data on this.
Domestic violence	Domestic violence	Criminal justice, services and funeral	per person per year	8,877.72	Societal only	As above	As above	
Domestic violence	Domestic violence	Income tax and welfare payments	per person per year	1,642.81	Societal only	As above	As above	

Table S10: Productivity unit costs for core (non-intervention) model sectors

Productivity group	Productivity item	Unit of measure	Amount <25 years	Amount 25+ years	Perspective	Method	Sources	Assumptions
Employed, high and med distress	Absenteeism due to high distress	$ per person per year	1,462.94	3,297.40	Societal only	Days absent for people with MH disorders x weighted average weekly earnings for age group Indexed from FY21 to FY20 using wage price index	Days off work due to psychological distress for people with MH from Productivity Commission Inquiry, Appendix H https://www.pc.gov.au/inquiries/completed/mental-health/report Indexation from Australian Bureau of Statistics Wage Price Index https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/wage-price-index-australia/latest-release#data-download	
Employed, high and med distress	Presenteeism due to high distress	$ per person per year	1,063.95	2,398.11	Societal only	Days working at reduced activity x 50% productivity for those days x weighted average weekly earnings for age group Indexed from FY21 to FY20 using wage price index	Days at reduced capacity and 50% productivity for those days from Productivity Commission Inquiry, Appendix H, link as above. Indexation as per absenteeism.	
Employed, high and med distress	Absenteeism due to suicide attempt and hospitalisation	$ per event	1,875.22	4,226.67	Societal only	Average length of stay for MH-related admission x weighted average weekly earnings for age group indexed from FY21 to FY20 using WPI	ALOS from AIHW suicide data https://www.aihw.gov.au/reports/mental-health-services/mental-health-services-in-australia/report-contents/overnight-admitted-mental-health-related-care Indexation as per absenteeism	
Employed, high and med distress	Productivity lost due to premature mortality, friction cost approach	$ per event	7,979.65	17,985.83	Societal only	3 months of working days lost (240/4) x weighted average weekly earnings for age group indexed from FY21 to fY20 using WPI	Indexation as per absenteeism	3 months productivity impact based on the friction cost approach is an accurate representation of the loss in societal welfare
Employed, high and med distress	Productivity lost due to premature mortality, human capital approach	$ per person per year until age 67	74,248.36	77,938.58	Societal only	Weighted average weekly earnings x 52 weeks	Indexation as per absenteeism average age of death: https://www.abs.gov.au/statistics/health/causes-death/causes-death-australia/latest-release#risk-factors-for-intentional-self-harm-deaths-suicide-in-australia	Person would have otherwise remained alive and employed to normal retirement age
Not employed, high and med distress	Productivity lost due to not being employed due to high distress, friction cost approach	$ per event	7,979.65	17,985.83	Societal only	3 months of working days lost (240/4) x weighted average weekly earnings for age group indexed from FY21 to fY20 using WPI	Indexation as per absenteeism	3 months productivity impact based on the friction cost approach is an accurate representation of the loss in societal welfare
Not employed, high and med distress	Productivity lost due to not being employed due to high distress, human capital approach	$ per person per year	74,248.36	77,938.58	Societal only		Indexation as per absenteeism	
Not employed, high and med distress	Absenteeism due to high distress (unpaid work)	$ per person per year	1,184.98	2,670.90	Societal only	Valued at 81% of the employed value of productivity	Factors used by Productivity Commission MH Inquiry, Appendix H, Table H.7 https://www.pc.gov.au/inquiries/completed/mental-health/report	Assumes days off unpaid work is the same as employed people

Not employed, high and med distress	Presenteeism due to high distress (unpaid work)	$ per person per year	861.80	1,942.47	Societal only	Valued at 81% of the employed value of productivity	Factors used by Productivity Commission MH Inquiry, Appendix H, Table H.7 https://www.pc.gov.au/inquiries/completed/mental-health/report	Assumes working at a reduced capacity for unpaid work occurs for the same length of time and degree as employed people
Not employed, high and med distress	Absenteeism due to suicide attempt and hospitalisation (unpaid work)	$ per event	1,518.93	3,423.60	Societal only	Valued at 81% of the employed value of productivity	Factors used by Productivity Commission MH Inquiry, Appendix H, Table H.7 https://www.pc.gov.au/inquiries/completed/mental-health/report	
Carers	Carers productivity (absenteeism)	$ per person per year	1,606.43	1,606.43	Societal only	44% carers experienced 1 absent in 30 day. Multiply 0.44 *12 for annual absenteeism rate.	Mental health productivity draft report 2019: https://apo.org.au/sites/default/files/resource-files/2019-10/apo-nid265801_5.pdf table page 467 proportion: Shah, A. J., Wadoo, O., & Latoo, J. (2010). Psychological distress in carers of people with mental disorders. British Journal of Medical Practitioners, 3(3).	Assumes only absenteeism (no presenteeism). Assume values carried from 2007
Carers	Carers payment allowance	$ per person per year	8,164.81	8,164.81	Societal only	Dividing total carer expenditure (allowance, payment and supplement) by carer recipient	Mental health producitivity draft report 2019: https://apo.org.au/sites/default/files/resource-files/2019-10/apo-nid265801_5.pdf table 13.2 page 473 proportion: page xiv Diminic S, Hielscher E, Lee YY, Harris M, Schess J, Kealton J & Whiteford H. The economic value of informal mental health caring in Australia: technical report. Brisbane: The University of Queensland; 2016.	Assume values carried from 2017/18

Table S11: Unit costs for interventions

Intervention/cost item	Cost	Perspective	Methods & assumptions	Source
Technology-enabled integrated care				
Setup and customisation cost	$80,000, year 1 only	Health & Societal	Fixed cost as provided	Personal communication, Innowell
Subscription fee per clinician	$6,000 per year	Health & Societal	We assume the number of clinicians using platform is number of clinicians in ACT x 'Maximium technology-enabled care rate per service' uptake from intervention sector.	Personal communication, Innowell
Time cost for 1 hour training session (for attending clinicians, online or face-to-face)	$38.44 per clinician, year 1 only	Health & Societal	Delivered at no cash cost by platform provider $38.44 is one hour x the average minimum hourly rate of health professional employees	Personal communication, Innowell Hourly rate: https://www.fairwork.gov.au/employment-conditions/awards/awards-summary/ma000027-summary
ED-based suicide prevention				
Annual budget of program	$1,263,894 per year	Health & Societal	Budget estimate worked up with health agency based on personnel required, on-costs on top of base salaries, and operational costs	Personal communication, ACT
Crisis response service				
Cost per incident	$2,389 per incident	Health & Societal	Derived from implementation of pilot program, total budget of $3,956,000 for 2020 divided by number of service contacts for that year of 1,656	Personal communication, ACT
Online parenting program				
Annual budget of program	$136,000 per year	Health & Societal	1.6% (ACT population as a proportion of Australian national population) x (($40.6 million (cost of the Triple P online program to the Aus Gov based on media release and confirmed by ACT) - $6.6 million advertising and marketing campaign) divided by 4 years)	Personal communication, ACT
School-based suicide prevention program				
Cost per student	$359 per participating student	Health & Societal	Derived from implementation of pilot program, $500,000 divided by 1,393 students that received the program	Personal communication, ACT
Administration and coordination of program	$200,000 per year	Health & Societal	Fixed cost as provided	Personal communication, ACT
Family education program				
Cost per participant	$1,015.97 per participant	Health & Societal	(3 mental health professionals x $423.32 per psychiatrist/psychologist for 2 hour session x 4 sessions) divided by 5 participants per session	Commcare https://www.comcare.gov.au/service-providers/medical-allied-health/treatment-rates
Time cost for parent attendees	$324.56 per participant	Societal only	$40.57 average hourly salary for employees x 2 hours per session x 4 sessions Assumes parent attending would have otherwise been working	Australian Bureau of Statistics
Multi-cultural informed care				
First time training	$363 per clinician	Health & Societal	First time training cost is for Year 1 and full day training First time and refresher training attendance per year is 50% of clinicians in ACT No time cost has been applied on expert advice that this would form part of clinicians' normal ongoing professional development hours	http://www.cccnt.com.au/
Refresher training	$121.13 per clinician	Health & Societal	Refresher cost is a half-day training course every 2 years after first training	http://www.cccnt.com.au/
Trauma services for youths				
Consultation sessions	$10,159.68 per participant	Health & Societal	Assumes trauma services are in addition to existing mental health care services $423.32 cost of mental health professional for 2 hour session x 2 sessions per week x 12 weeks	Commcare https://www.comcare.gov.au/service-providers/medical-allied-health/treatment-rates
Time cost for patients of attending sessions	$762.35 per participant	Societal only	$15.88 average hourly wage for 17-24 year olds x 2 hours x 24 sessions	Australian Bureau of Statistics

Table S12: Probabilistic sensitivity analysis parameters

Intervention/parameter	Default value	Unit of measure	Distribution type	Mu	Sigma	Alpha	Beta	Source
Technology-enabled integrated care								
Effect on per-service recovery rate	1.177	OR	Lognormal	0.163242	0.240606			Woltmann 2012 meta-analysis, Figure 1, Global Mental Heath
Effect on GP referral rate to specialised services	1.266	OR	Lognormal	0.235794	0.407179			Badamgarav 2003, meta-analysis, Table 2, Referral to specialised care
Effect on per capita rate of disengagement	0.72	HR	Lognormal	-0.3285	0.125062			Campbell 2014, substance use RCT, abstract
ED-based suicide prevention								
Effect on re-presentations	0.72	IRR	Lognormal	-0.3285	0.167604			Miller 2017, RCT, abstract
Crisis response service								
De-escalation rate - % of situations no further response due to intervetion	0.105	%	beta			82	701	Allen Consulting 2012, Vic evaluation, Table 3.2
ED referral rate - % note de-escalated and transferred to ED	0.52	%	beta			147	134	Allen Consulting 2012, Vic evaluation, Figure 4.2
Intervention cost per response	2389	AUD$	gamma			100	9	ACT PACER actual budget & activity for 2020, email
Family education								
Effect on per service recovery rate	2	OR	Lognormal	0.693147	0.196562			Rodolico 2022, schizophrenia meta-analysis, Figure 3 and expert opinion
Effect on rate of ED presentations	0.18	OR	Lognormal	-1.7148	0.20687			Rodolico 2022, schizophrenia meta-analysis, Figure 3, Family psychoeducation
Cost per psychologist per session	423.32	AUD$	gamma			100	8	Comcare treatment rates, website
Online parenting								
Effect on transition to higher levels of strengths and difficulties	0.631	OR	Lognormal	-0.46071	0.206366			Li 021, Triple P meta-analysis, Table 2, emotional problems in child
School-based suicide prevention								
Effect on services engagement (per capita perceived need)	1.45	OR	Lognormal	0.371564	0.213165			Lubman 2020, RCT, Table 3 adjusted with Figure 1
Effect on suicidal behaviour (per capita suicide attempt rate)	0.625	OR	Lognormal	-0.47	0.079231			Aseltine 2007, SOS RCT, Table 3 suicide attempts
Cost per student	359	AUD$	gamma			100	2	ACT annual budget of YAM
Trauma services for youth								
Effect on recovery rate	2.345	OR	Lognormal	0.852486	0.185082			Zhang 2021, meta-analysis, abstract
Cost per session	423.32	AUD$	gamma			100	8	Comcare treatment rates, website
Multi-cultural informed care								
Effect on recovery rate (per service for CALD pop)	2.84		Lognormal	0.850853	0.116327			Hall 2016, meta-analysis, Table 5, average effect size, halved based on expert advice
First time training cost per session	363		gamma			100	2	Cross Cultural Consultants website
Refresher training cost per session	121.13		gamma			100	9	Cross Cultural Consultants website

Additional scenario testing

The combination intervention (TechInt+FamEd+OnlPar+MultCult) was tested with each of the not-cost-effective interventions to see if these were antagonistic as expected. This scenario testing confirmed that the combination of cost-effective interventions (TechInt+FamEd+OnlPar+MultCult) had a higher incremental net monetary benefit than the four alternative scenarios with not-cost-effective interventions added.

Table S13: Additional scenario testing

	HEALTH CARE PERSPECTIVE					SOCIETAL PERSPECTIVE			
Intervention	**Incremental costs ($)**	**Incremental QALYs (n)**	**ICER vs. BAU ($/QALY)**	**INMB vs. BAU (Threshold, $M)**	**Rank NMB**	**Incremental costs ($)**	**ICER vs. BAU ($/QALY)**	**INMB vs. BAU (VSLY, $M)**	**Rank NMB**
Business as usual	-	-	**-**	-	**6**	-	**-**	-	**6**
Combination	3,629,113	5,431	**668**	430	**1**	-98,860,276	**Dominant**	533	**1**
Combination + CRS	11,047,871	5,423	**2,037**	422	**4**	-91,977,989	**Dominant**	525	**4**
Combination + EDSP	8,174,264	5,476	**1,493**	430	**2**	-94,433,657	**Dominant**	532	**2**
Combination + SSP	76,973,859	5,193	**14,824**	338	**5**	-6,629,725	**Dominant**	422	**5**
Combination + TSY	12,009,423	5,441	**2,207**	423	**3**	-90,598,302	**Dominant**	526	**3**

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Appendix 3: Supplementary material for Chapter 3 (Modelling Study 2 as published in *Nature Mental Health*)

Supplementary Material Part A

Modelled estimates of the health outcomes and economic value of improving the social determinants of mental health

Nature Mental Health

March 2025

Model structure

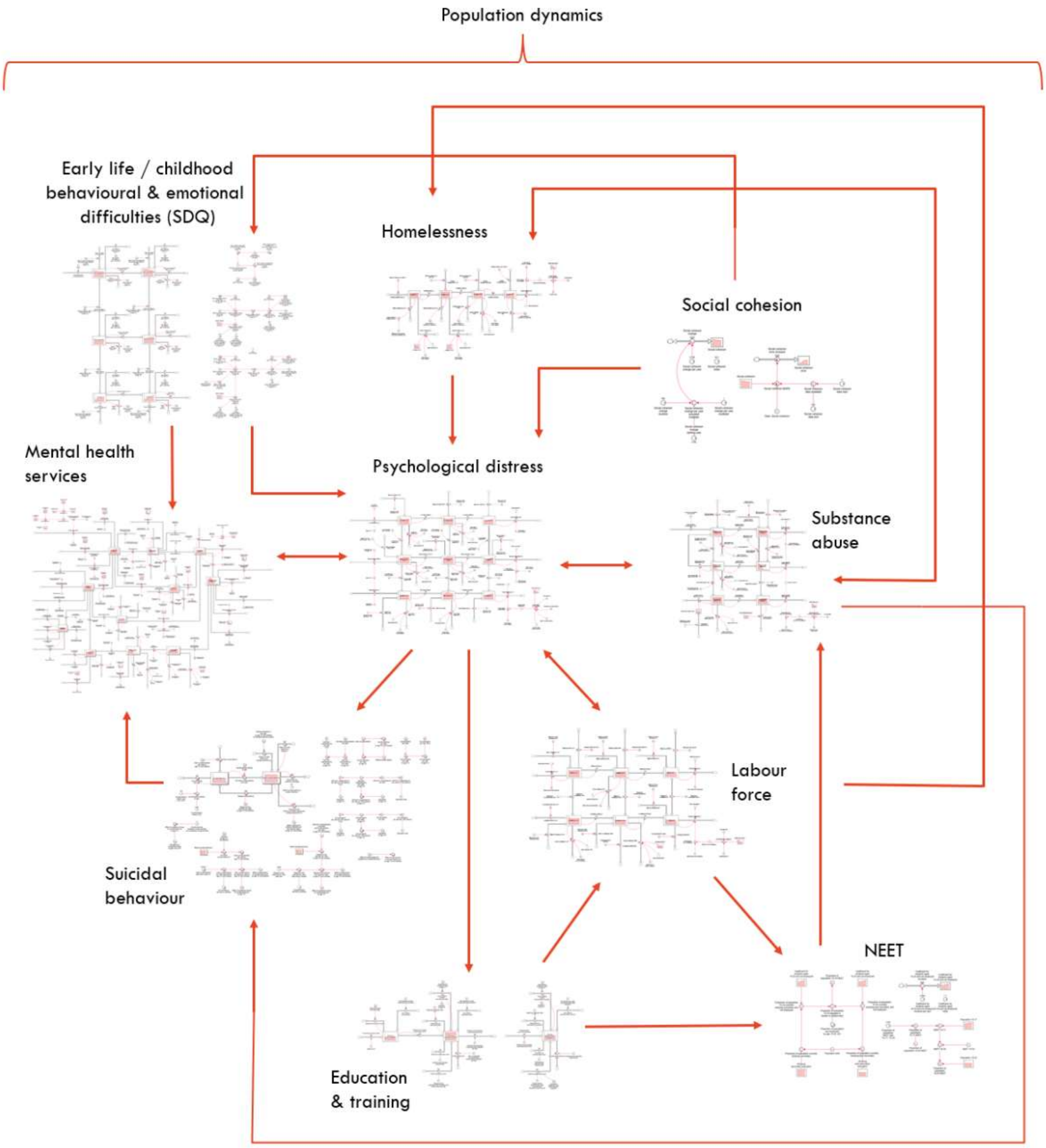
Overview

This system dynamics model was developed for the Brisbane South Primary Health Network (BSPHN) population catchment and consists of multiple sectors that represents different aspects of the population. Supplementary Figure 1 presents an overview of the model structure showing the causal links between different sectors. Supplementary Figures 2 to 22 present the structure of each sector. Please note that for each stock, an inflow representing the suicide deaths prevented through various interventions is included in the model but have been left out of these figures for visual clarity.

The sectors of the model included are:

- **Population** which models the resident population divided into six ages brackets (0-4-year-olds, 5-11, 12-14, 15-17, 18-24, and 25 and older),
- **Education** which models students enrolled in primary, secondary and post-secondary education, and people with different levels of highest qualifications,
- **Labour force** which models unemployment, underemployment and participation rates,
- **Not in education, employment nor training (NEET)** which models the youth population aged 15-24 years not in education, employment nor training,
- **Homelessness** which models the population experiencing homelessness,
- **Substance misuse** which models the prevalence of 12-month substance misuse disorder and substance misuse closed treatment episodes,
- **Psychological distress / disorder** which models the prevalence of low psychological distress and the prevalence of moderate to very high psychological distress based on the Kessler Psychological Distress Scale (K10) (Kessler et al. 2002). The population with moderate to very high psychological distress is further dichotomised by whether nor not they meet the criteria for any 12-month psychological disorder,
- **Strengths and difficulties** which models the prevalence of behavioural and emotional difficulties among children aged 0-4-years and 5-11-years as measured by the Strengths and Difficulties Questionnaire (SDQ),
- **Social cohesion** which models the population level of social cohesion according to the Scanlon-Monash Index of Social Cohesion,
- **Suicidal behaviours** which models the rates of suicide attempts and suicide deaths, and
- **Mental health services** which models the mental health services delivered by health professionals.

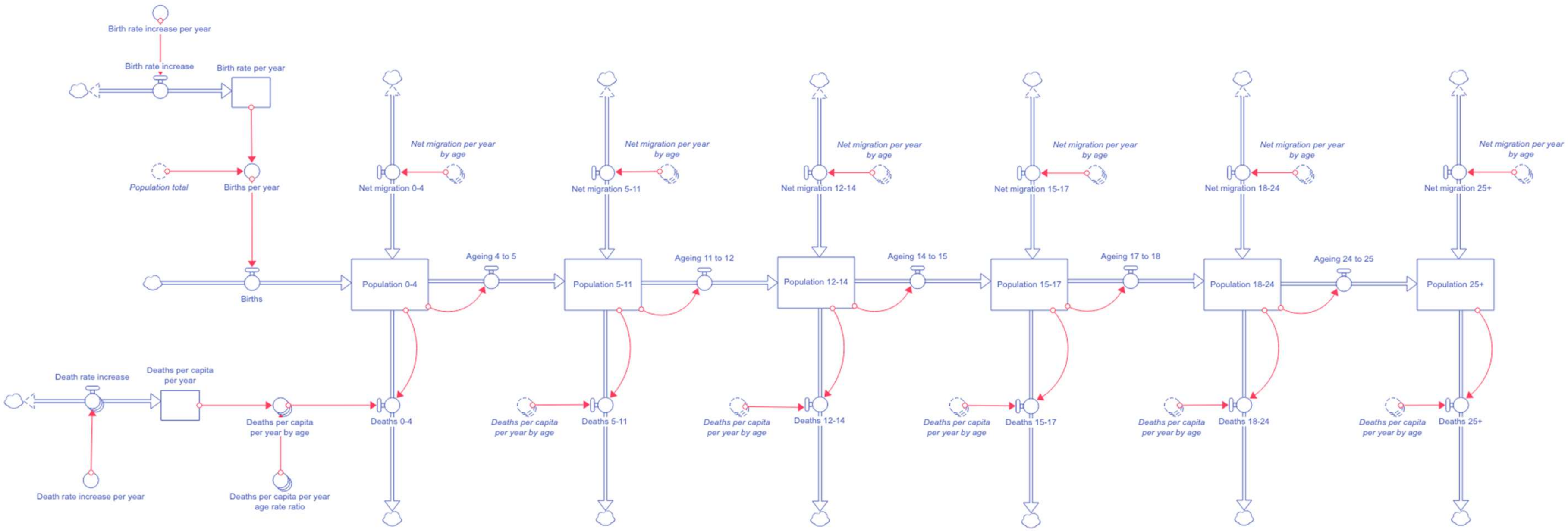
Data used to calibrate each sector are described in figure captions. For any data extracted at the Statistical Area (SA) level of geographic granularity (such as those from the Australian Bureau of Statistics (ABS)), we concorded these data to Primary Health Network (PHN) level estimates through concordance files supplied by the Australian Department of Health and Aged Care (2023).



Supplementary Figure 1. Overview of the causal structure of the system dynamics model
This is a high-level overview of the model structure. The detailed internal structure of each model sector is described in subsequent sections of this document.

Population

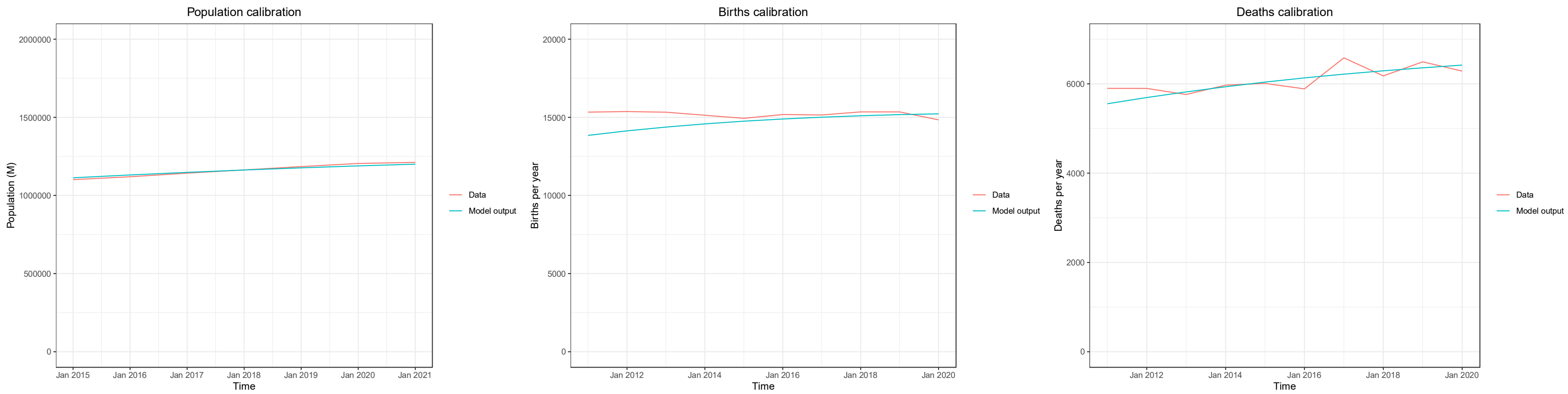
Supplementary Figure 2a. Structure of the population sector



The population sector models the estimated resident population of the BSPHN catchment into six age-specific stocks. The stocks correspond to people aged 0-4 years, 5-11 years, 12-14 years, 15-17 years, 18-24 years, and 25 years and older. Each stock has a mortality outflow and a net migration biflow. Births flow into the stock of 0–4-year-olds and people follow an ageing chain flowing from the younger to older age stocks This sector is calibrated with data based on estimated resident population data from the

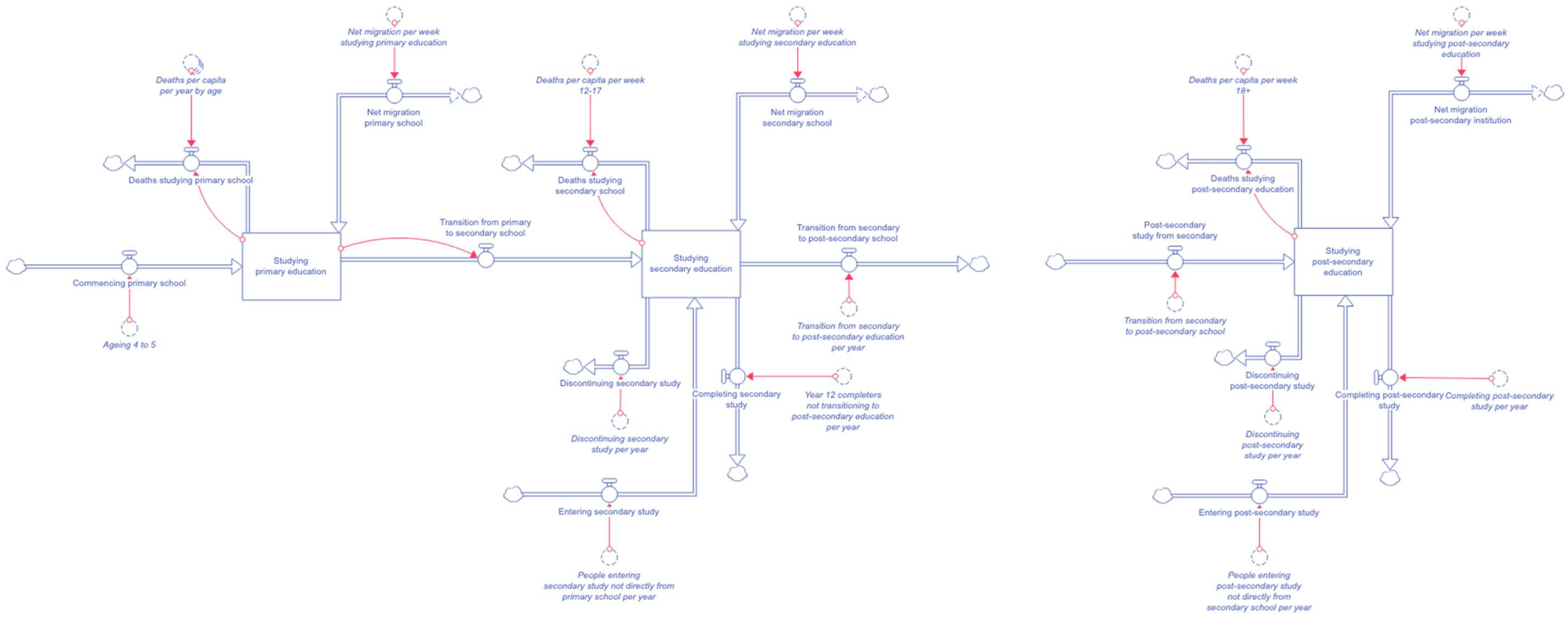
Public Health Information Development Unit (PHIDU) at Torrens University Australia (Public Health Information Development Unit, 2016-2021), and births (Australian Bureau of Statistics, 2021a), deaths (Australian Bureau of Statistics, 2021b), and migration (Australian Bureau of Statistics, 2020) statistics from the ABS.

Supplementary Figure 2b. Calibration plots from the population sector



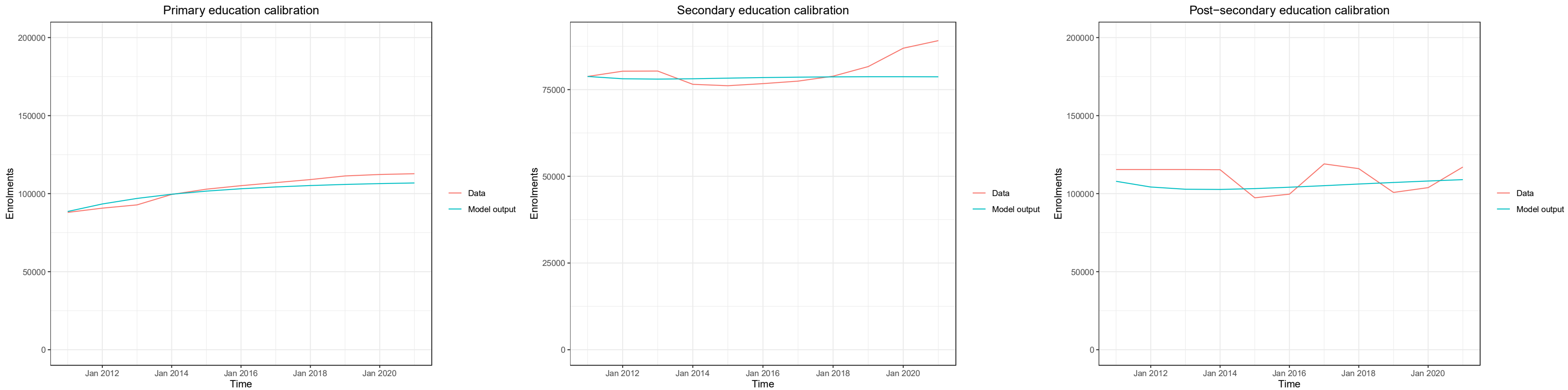
Education (students)

Supplementary Figure 3a. Structure of the education (students) sector



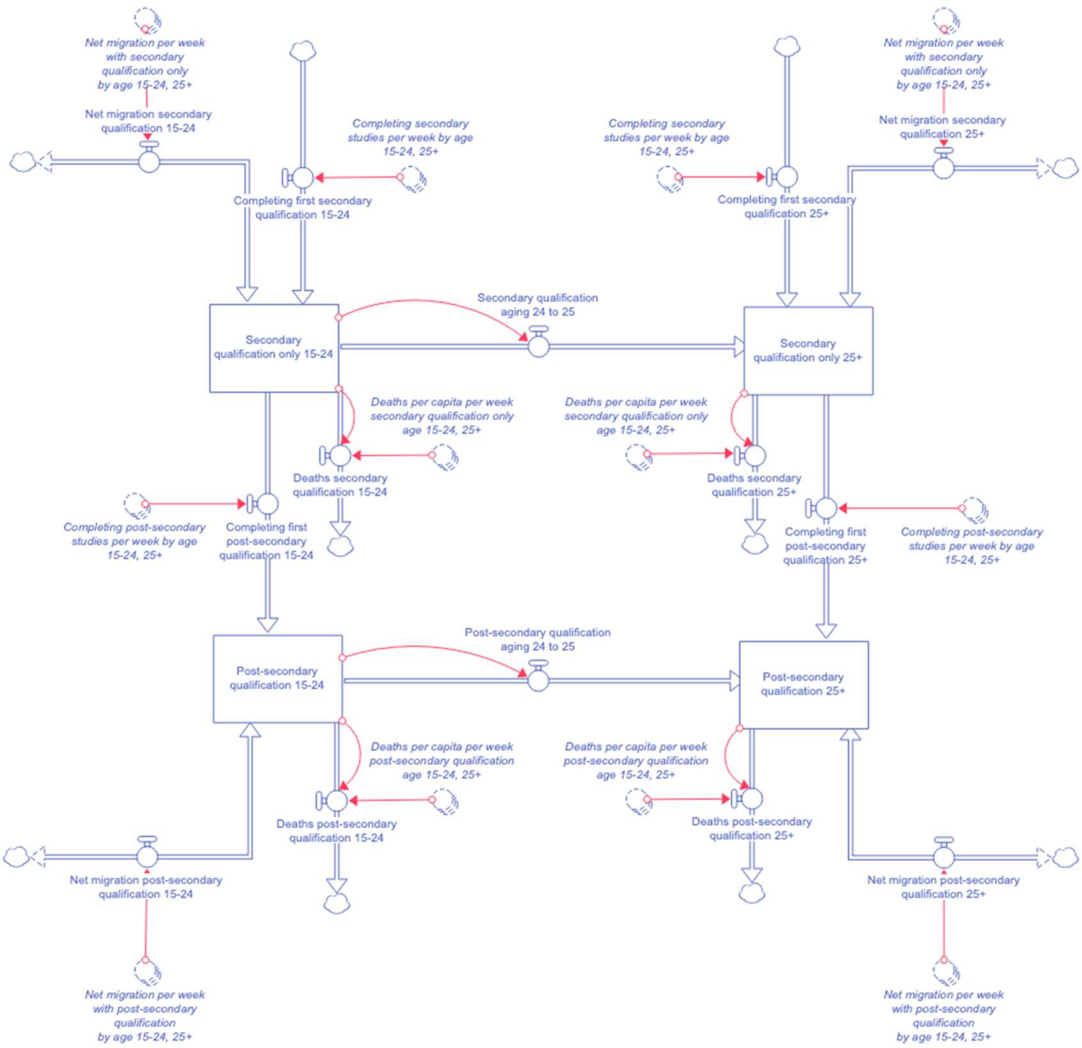
The education (students) sector models students enrolled in education in BSPHN. The stocks correspond to students enrolled in primary education, secondary education and post-secondary education. Each stock has a mortality outflow and a net migration biflow. People flow into the “Studying primary education” stock as they age from 4 to 5 years of age. Graduates of primary education then transition to secondary education, and graduates of secondary education can either transition to post-secondary education or not (e.g. those commencing employment). Students in secondary or post-secondary education may discontinue their studies at rates dependent on the prevalence of psychological distress / disorder (Butterworth & Leach, 2017; Lee et al., 2009). People may enter secondary or post-secondary studies without directly transitioning from primary education or secondary education respectively (e.g. re-enrolling after discontinuation, people enrolled in both secondary and post-secondary studies). This sector is calibrated using student enrolment (Australian Curriculum Assessment and Reporting Authority) and completion (Australian Curriculum Assessment and Reporting Authority) data from the Australian Curriculum Assessment and Reporting Authority (ACARA), post-secondary education destinations data from the Queensland Department of Education (Queensland Department of Education, 2023), and education and work statistics from the ABS (Australian Bureau of Statistics, 2014-2022).

Supplementary Figure 3a. Calibration plots from the education (students) sector



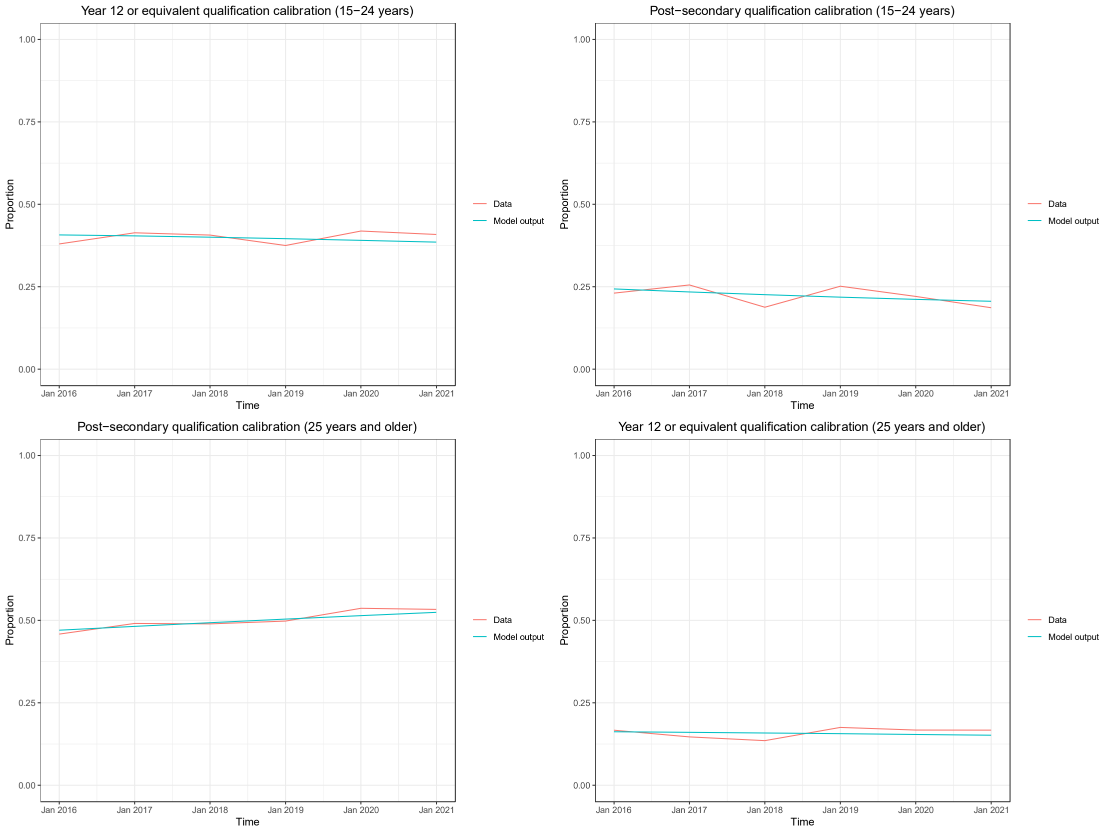
Education (highest level of qualification)

Supplementary Figure 4a. Structure of the education (highest level of qualification) sector



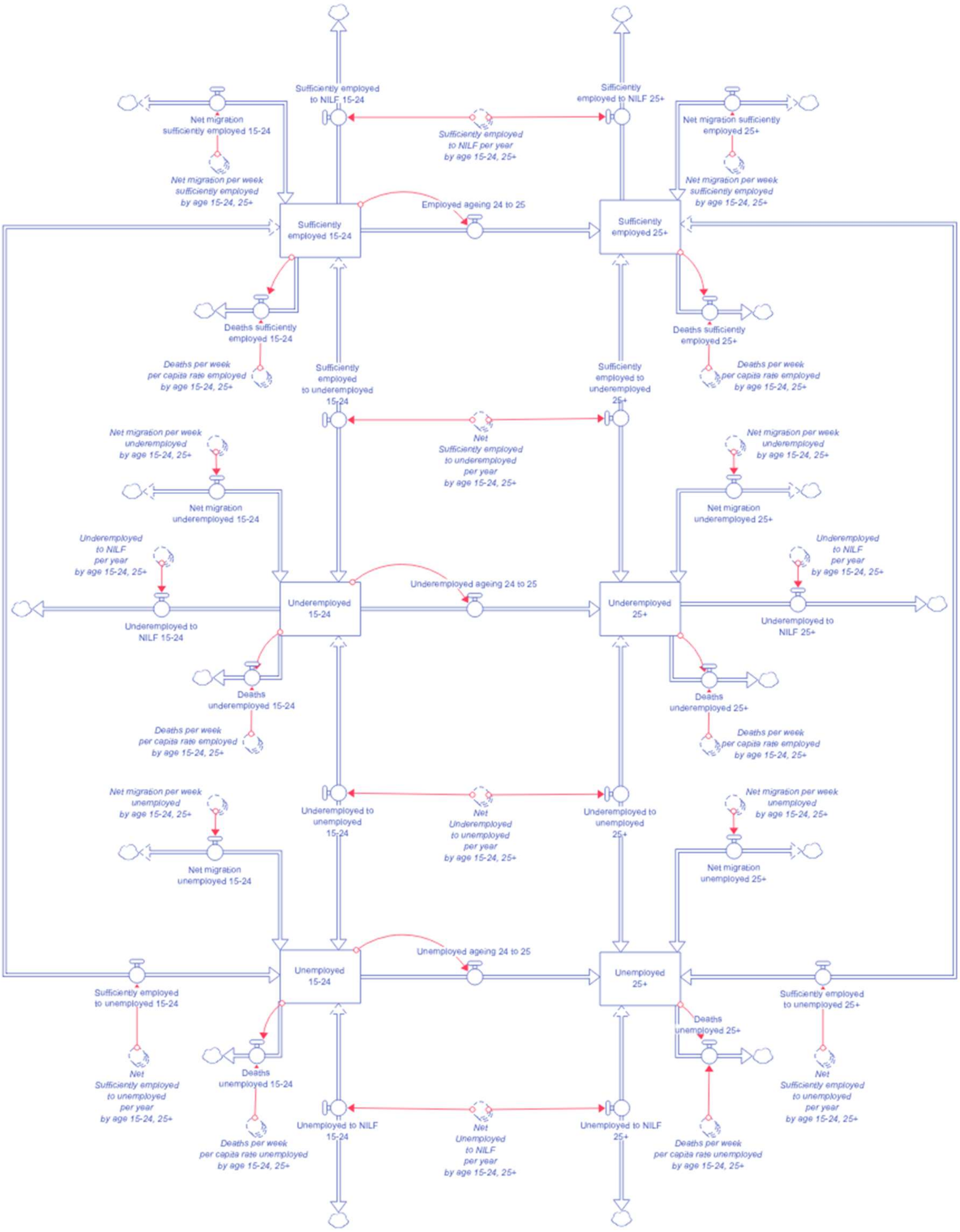
The education (highest level of qualification) sector models holders of different qualifications in BSPHN. The stocks correspond to people aged 15-24 years and 25 years and older, and by their highest level of qualification. More specifically, the stocks correspond to people whose highest level of qualification is Year 12 or equivalent completion, and to people whose highest level of qualification is Certificate III or above. People not in any of these two qualification stocks correspond to people whose highest level of qualification is below Year 12 or equivalent. Each stock has a mortality outflow (Welsh et al., 2021) and a net migration biflow. People who complete secondary education then flow into the "Secondary qualification only" stocks. People who then complete their first post-secondary qualification flow into the "Post-secondary qualification" stocks. People also follow the ageing chain from 15-24 years to 25 years and older. This sector is calibrated using qualifications, education and work statistics from the ABS (Australian Bureau of Statistics, 2014-2022).

Supplementary Figure 4b. Calibration plots from the education (highest level of qualification) sector



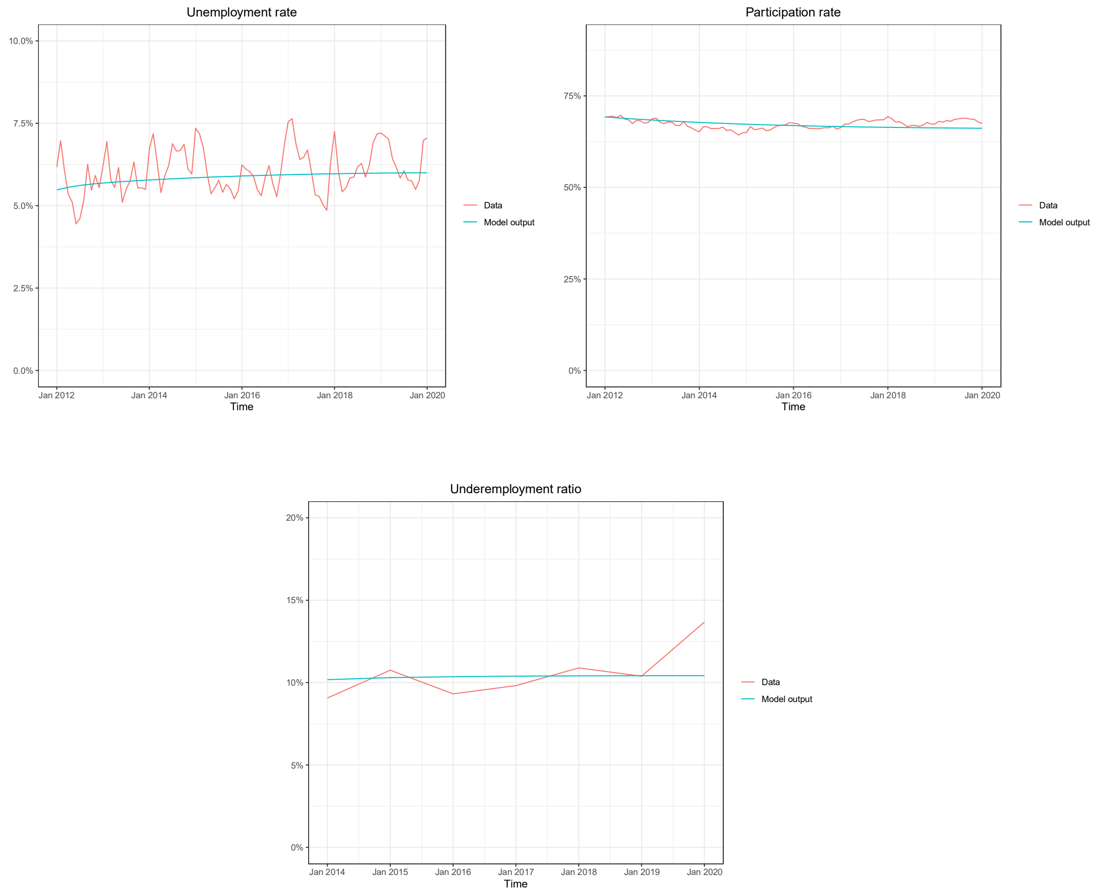
Labour force

Supplementary Figure 5a. Structure of the labour force sector



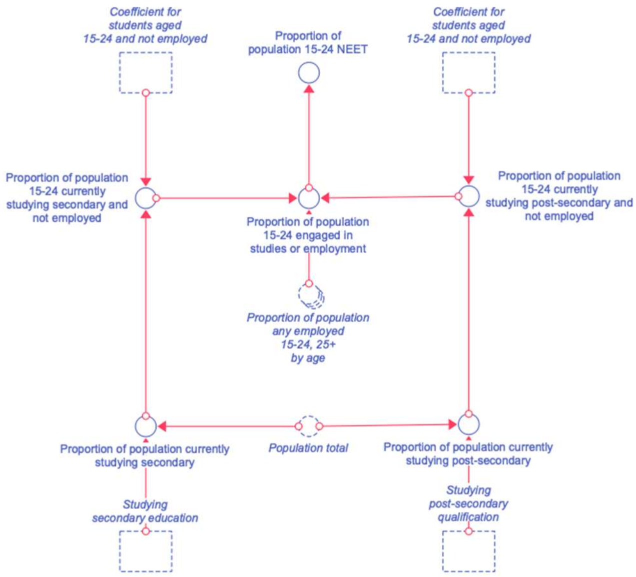
This labour force sector models the employment statuses and flow between these statuses of the BSPHN resident population. The stocks correspond to people aged 15-24 years and 25 years and older, and by their labour force status. More specifically, people can be either sufficiently employed, underemployed or unemployed. People who are not in either of these stocks are deemed to be not in the labour force (NILF) (e.g. retirees). Each stock has a mortality outflow (Sorlie & Rogot, 1990) and a net migration biflow. People can transition between these four labour force statuses with the exception for the NILF population who must transition into unemployment prior to transitioning into employment to reflect people actively looking for work prior to being employed. The rates of transition between employed and unemployed, and between NILF and unemployed are dependent on age and levels of psychological distress / disorder (Australian Bureau of Statistics, 2011-12, 2014-15, 2017-18; Frijters, Johnston, & Shields, 2014) and highest levels of qualifications (Australian Bureau of Statistics, 2014-2022). The rates of transition between sufficiently employed and underemployed are dependent on age and highest level of qualifications (Wilkins, 2004). This sector is calibrated using labour force statistics from the ABS (Australian Bureau of Statistics, 2014-2022, 2023a, 2023b).

Supplementary Figure 5b. Calibration plots from the labour force sector



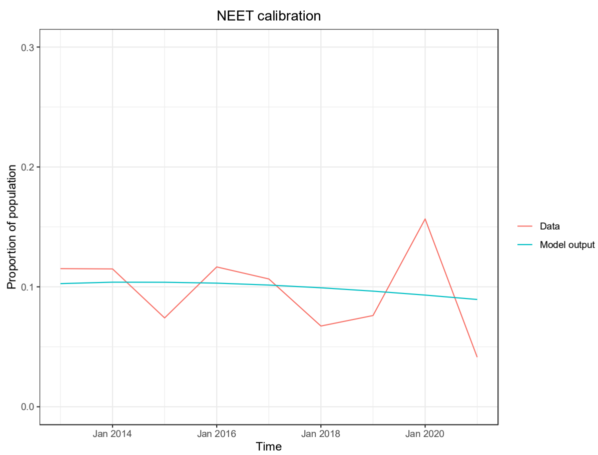
Not in employment nor education (NEET)

Supplementary Figure 6a. Structure of the NEET sector



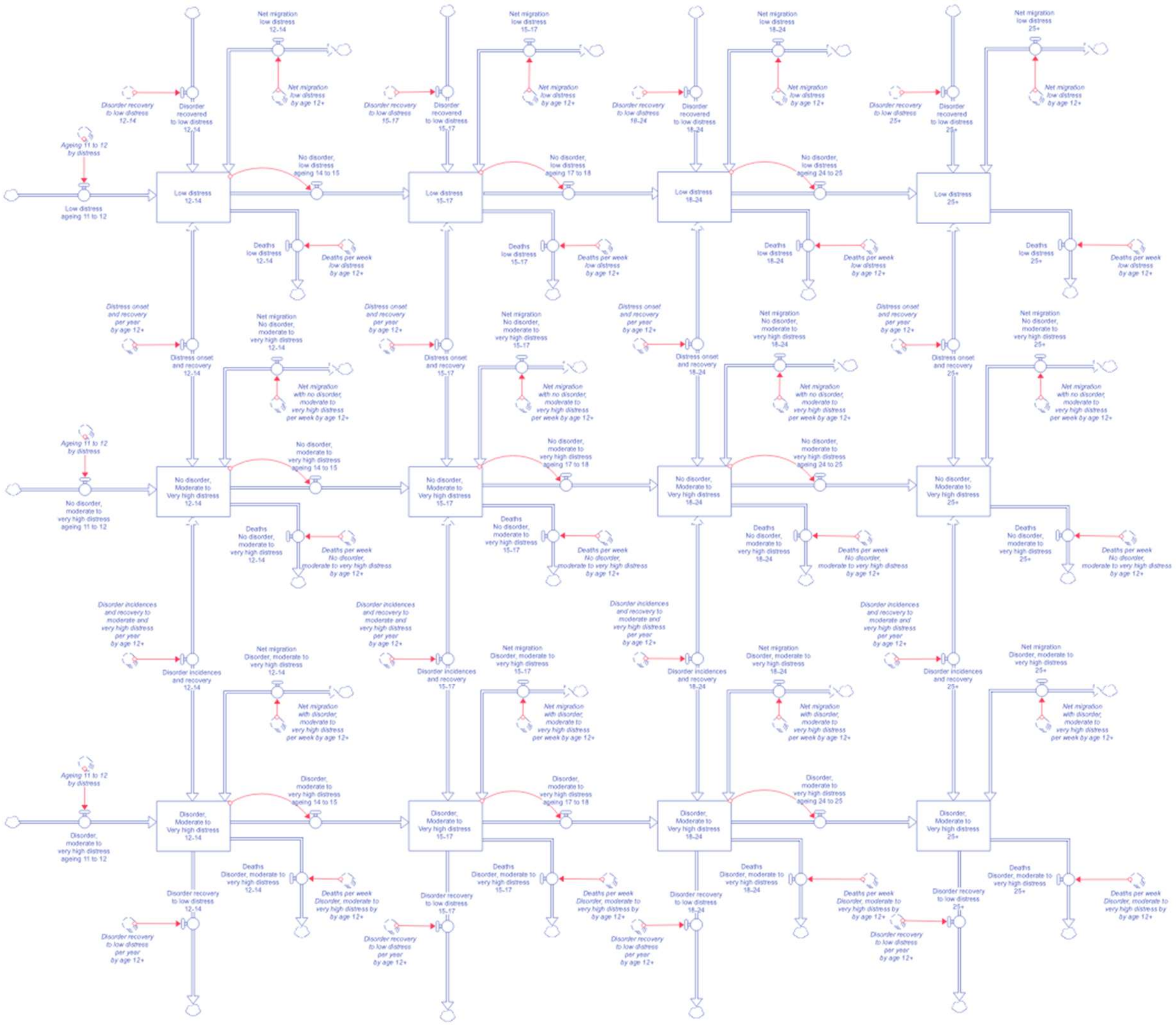
This sector models residents of BSPHN aged 15-24 years who are not in education, employment nor training (NEET). This sector uses model outputs from the labour force and education (students) sectors to calculate the numbers of young people who are NILF and not currently studying. This sector is calibrated using education and work statistics from the ABS (Australian Bureau of Statistics, 2014-2022).

Supplementary Figure 6b. Calibration plot from the NEET sector



Psychological distress / disorder

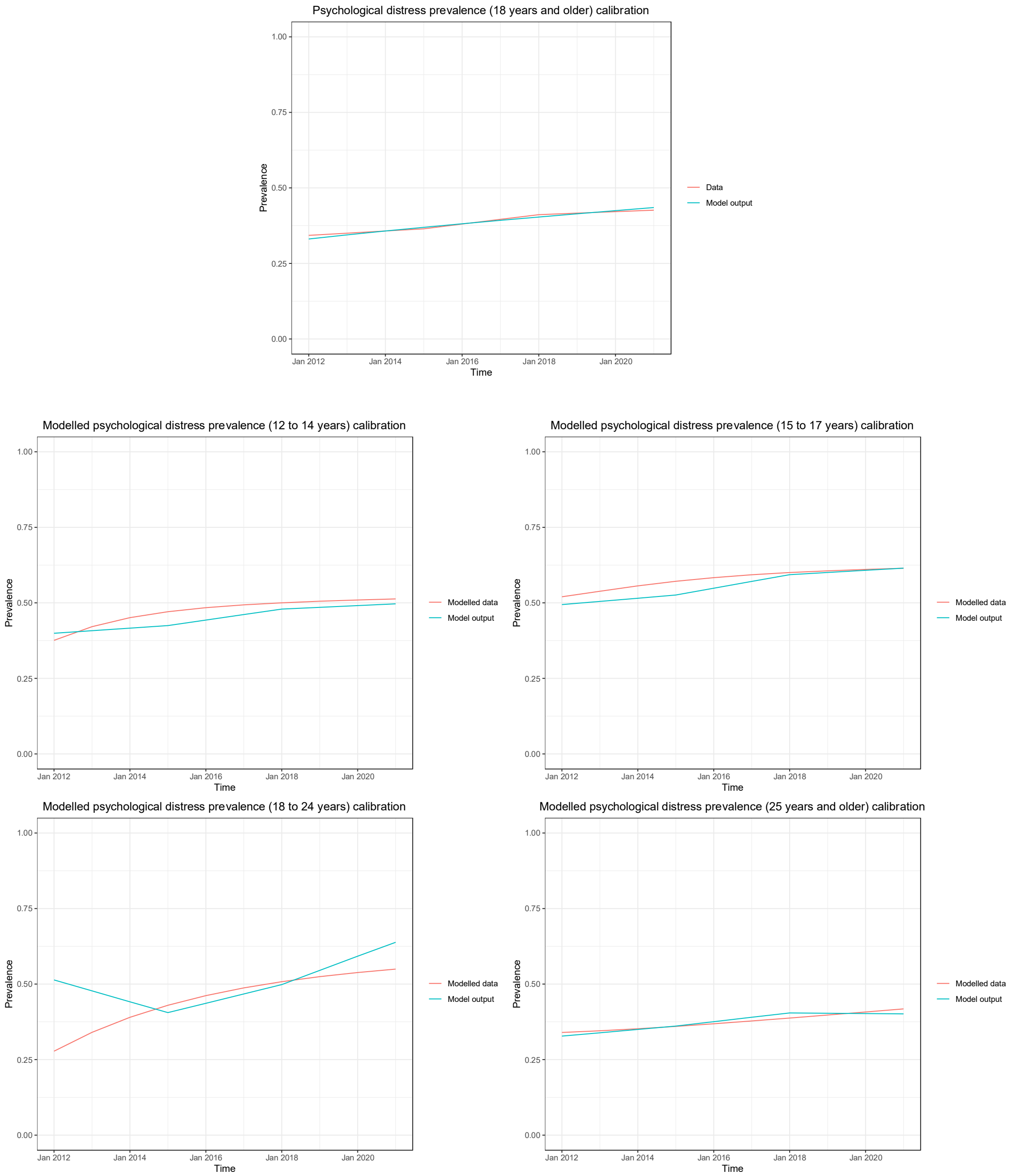
Supplementary Figure 7a. Structure of the psychological distress / disorder sector



This sector models the prevalence of psychological distress and 12-month psychological disorder in people aged 12-14 years, 15-17 years, 18-24 years, and 25 years and older in BSPHN. These stocks model the population with low psychological distress according to the Kessler Psychological Distress Scale (K10) (Kessler et al., 2002), the population with moderate to very high psychological distress who do not meet the criteria for a 12-month psychological disorder, and the population with moderate to very high psychological distress who meet the criteria for a 12-month psychological disorder. Transition rates between these three levels of psychological distress / disorder are dependent on age, rates of homelessness (Australian Bureau of Statistics, 2007a), unemployment (Australian Bureau of Statistics, 2007a), underemployment (Dooley, Prause, & Ham-Rowbottom, 2000; Griffiths et al., 2021), substance misuse (Australian Bureau of Statistics, 2012; Marmorstein, Iacono, & Malone, 2010), engagement and disengagement with the mental health services system and the levels of social cohesion. Each stock has a mortality outflow (Russ et al., 2012) and a net migration biflow, and the population ages following an ageing chain across each level of psychological distress / disorder. This sector is calibrated using psychological distress prevalence data as measured by the K10 from the ABS' National Health

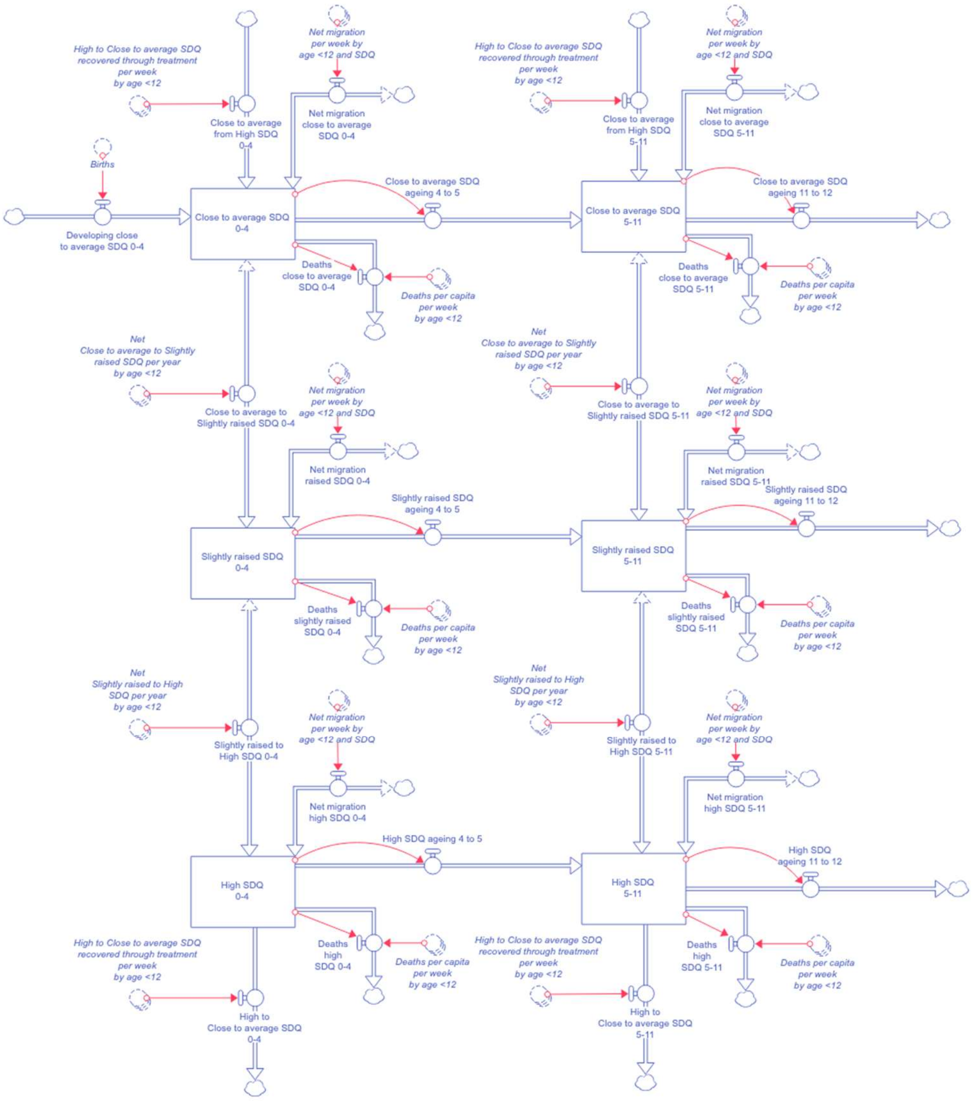
Surveys (Australian Bureau of Statistics, 2011-12, 2013-14, 2017-18, 2011-12, 2014-15, 2017-18, 2020-21) and the Young Minds Matter Survey (Young Minds Matter Survey, 2013-14). The prevalence estimates for 12-month psychological disorder were modelled from data from the ABS' National Study of Mental Health and Wellbeing (Australian Bureau of Statistics, 2007b, 2020-22). Calibration for 12-14-year-olds and 15-17-year-olds used data and modelled estimates inferred using the Young Minds Matter Survey (Young Minds Matter Survey, 2013-14) and the ABS' National Health Surveys (Australian Bureau of Statistics, 2011-12, 2013-14, 2017-18, 2011-12, 2014-15, 2017-18, 2020-21).

Supplementary Figure 7b. Calibration plots from the psychological distress / disorder sector



Strengths and Difficulties

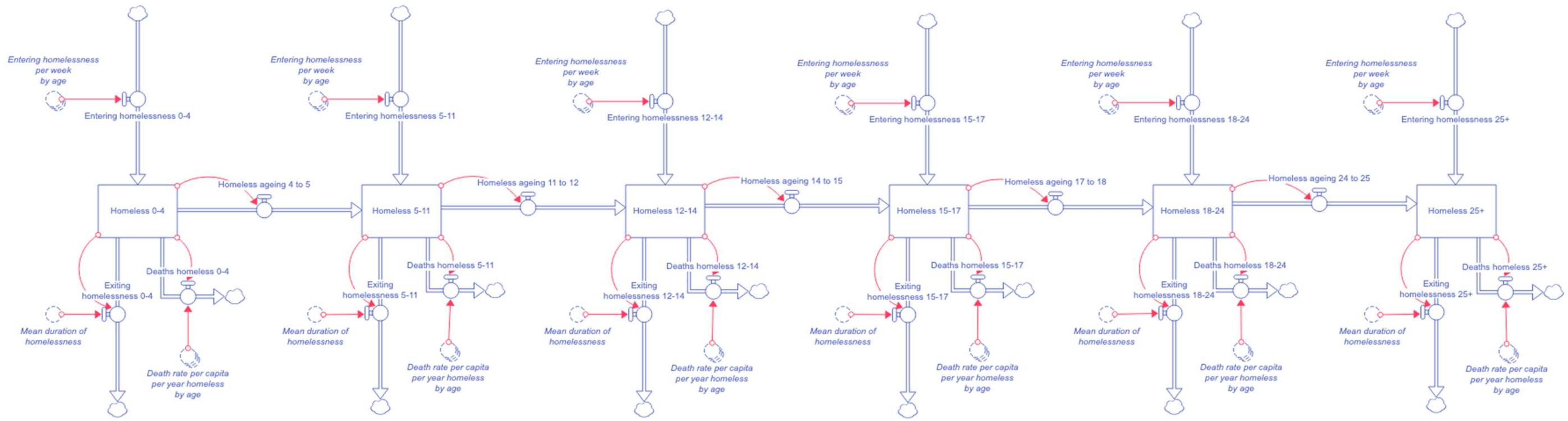
Supplementary Figure 8. Structure of the Strengths and Difficulties sector



This sector models the prevalence of mental health difficulties in children aged 0-4-years and 5-11-years as measured using the Strengths and Difficulties Questionnaire (SDQ). These stocks model the population with "Close to average", "Slightly raised" and "High" SDQ scores. People are assumed to be born with close to average levels of SDQ and hence flow into the "Close to average SDQ" stock for 0-4-year-olds. People can flow between close to average and slightly raised levels of SDQ, and between slightly raised to high levels of SDQ with rates dependent on age and rates of engagement and disengagement with the mental health services systems and the levels of social cohesion. Each stock has a mortality outflow and a net migration biflow, and the population ages following an ageing chain across each level of SDQ stocks. This sector is calibrated using SDQ data from the Longitudinal Study of Australian Children (Australian Institute of Family Studies, 2022). Calibration for 0-4-year-olds used modelled estimates inferred using data for 5-11-year-olds. Please note that, as part of the user agreement between the authors and the Longitudinal Study of Australian Children, SDQ data at the PHN level of geographic granularity cannot be shown. As such, calibration plots for the Strengths and Difficulties sector will not be shown here.

Homelessness

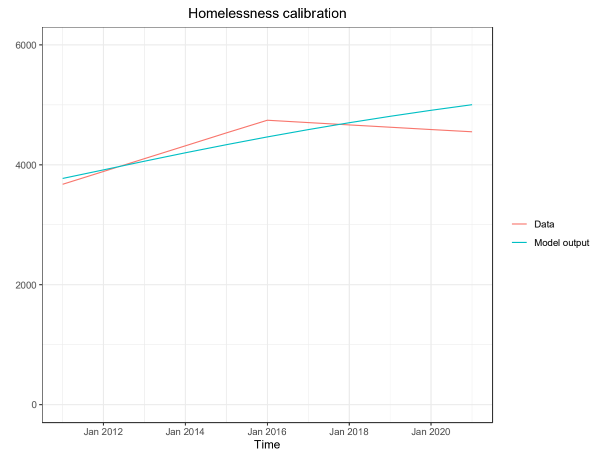
Supplementary Figure 9a. Structure of the homelessness sector



This sector consists of six stocks modelling people experiencing homelessness aged 0-4 years, 5-11 years, 12-14 years, 15-17 years, 18-24 years, and 25 years and older. Each stock has a mortality outflow (Morrison, 2009) and a net migration biflow. People aged 15 and older enter homelessness at rates which are dependent on age, levels of psychological distress / disorder, unemployment rates, and substance misuse rates (Nilsson, Nordentoft, & Hjorthøj, 2019). For people under 15 years of age, rates of entering homelessness are dependent on age. People exit homelessness at rates dependent on the mean duration of homelessness (Ranney, 2023). People age into older stocks following the ageing chain.

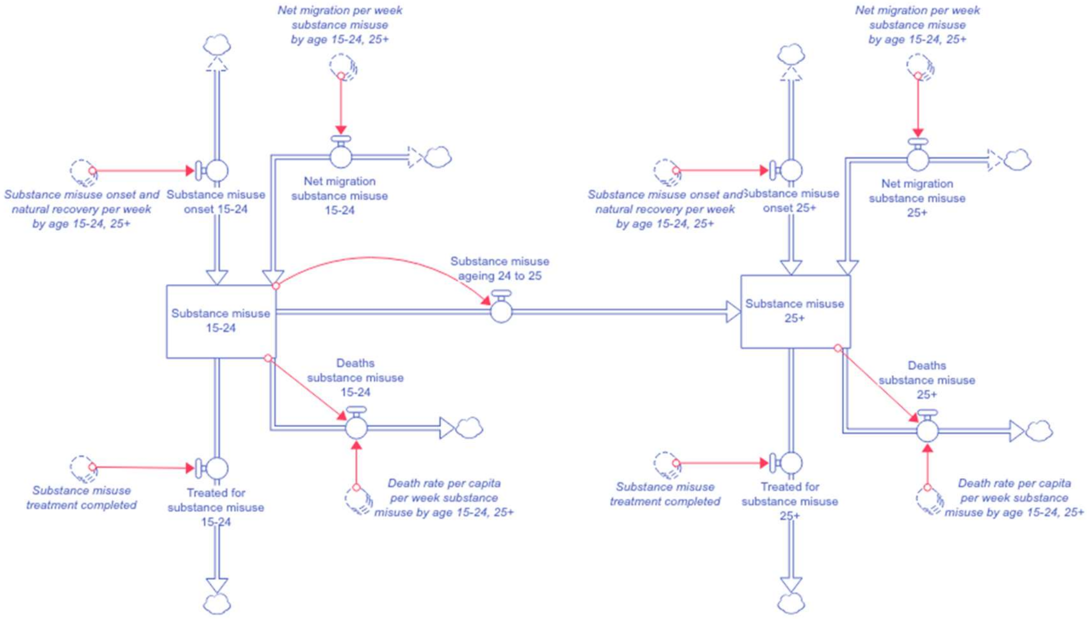
This sector was calibrated using homelessness statistics from the ABS (Australian Bureau of Statistics, 2011, 2016, 2021, 2016, 2021).

Supplementary Figure 9b. Calibration plot from the homelessness sector



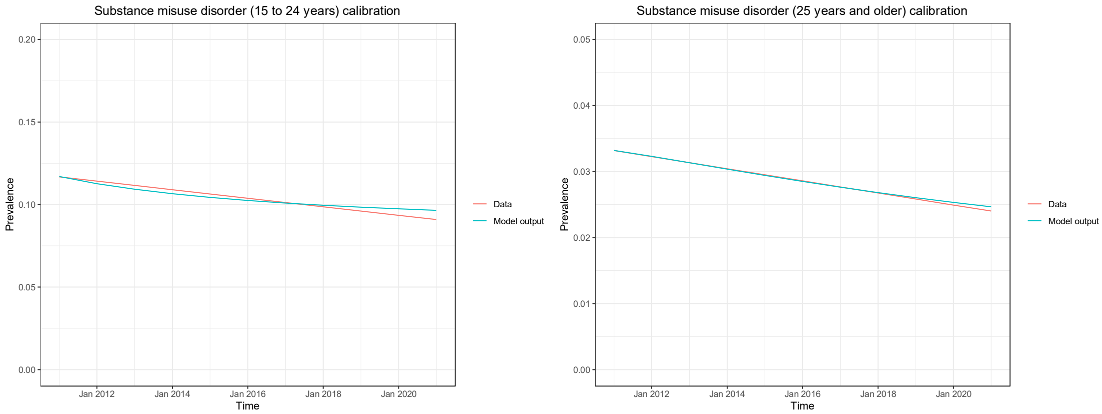
Substance misuse (substance misuse disorder)

Supplementary Figure 10a. Structure of the substance misuse (substance misuse disorder) sector



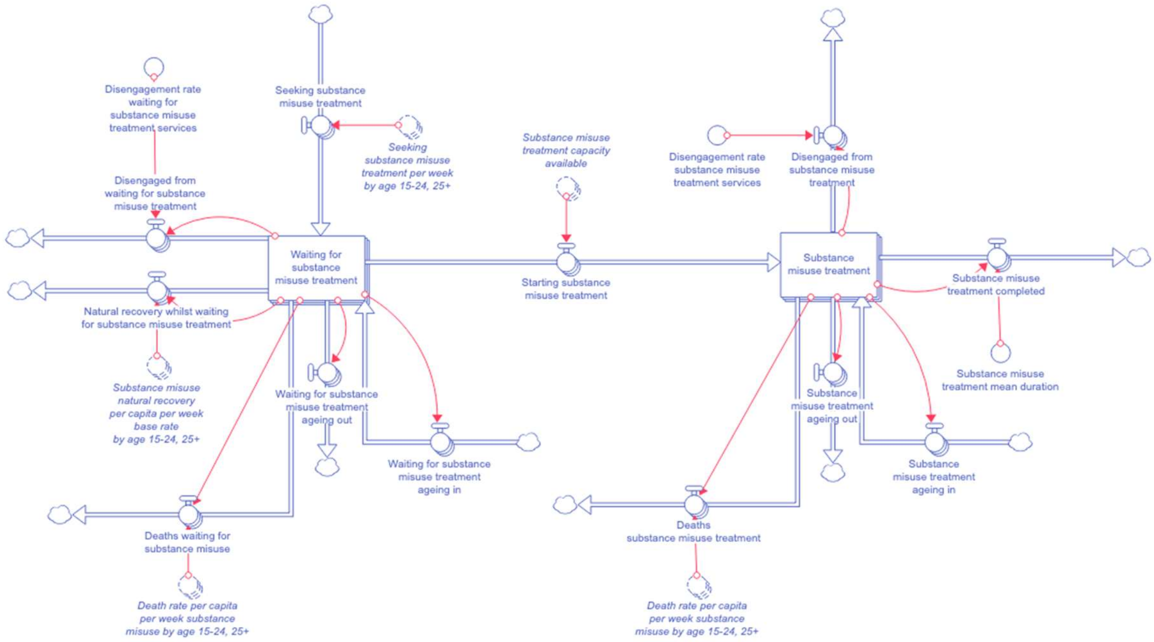
This sector models the prevalence of substance misuse in the BSPHN resident population. The stocks correspond to people aged 15-24 years and 25 years and older who meet the criteria for 12-month substance use disorder. Each stock has a mortality outflow (Roerecke & Rehm, 2013) and a net migration biflow, and the population ages following an ageing chain. Each stock has a disorder onset and recovery biflow which reflect the rates of onset of and the non-treatment based recovery from substance misuse disorder. The onset rates are dependent on age, prevalence of psychological distress / disorder (Australian Institute of Health and Welfare, 2017), homelessness (Johnson, Freels, Parsons, & Vangeest, 1997; Slade et al., 2009) and NEET (Australian Bureau of Statistics, 2020-22; Gariépy, Danna, Hawke, Henderson, & Iyer, 2022). Each stock also has a recovery through treatment outflow representing people who recover from substance misuse disorder through treatment with services. This sector is calibrated using national 12-month substance use disorder data from the ABS' National Study of Mental Health and Wellbeing (Australian Bureau of Statistics, 2007b, 2020-22).

Supplementary Figure 10b. Calibration plots from the substance misuse (substance misuse disorder) sector



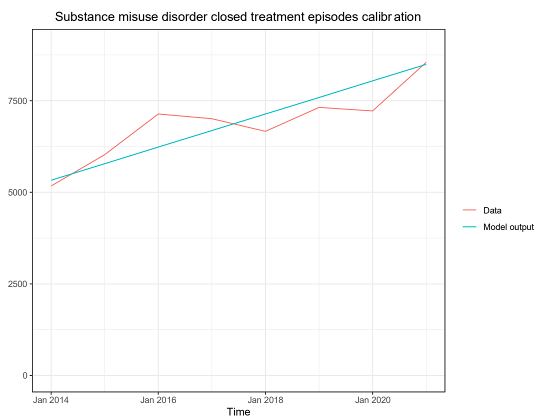
Substance misuse (substance misuse closed treatment episodes)

Supplementary Figure 11a. Structure of the substance misuse (substance misuse closed treatment episodes) sector



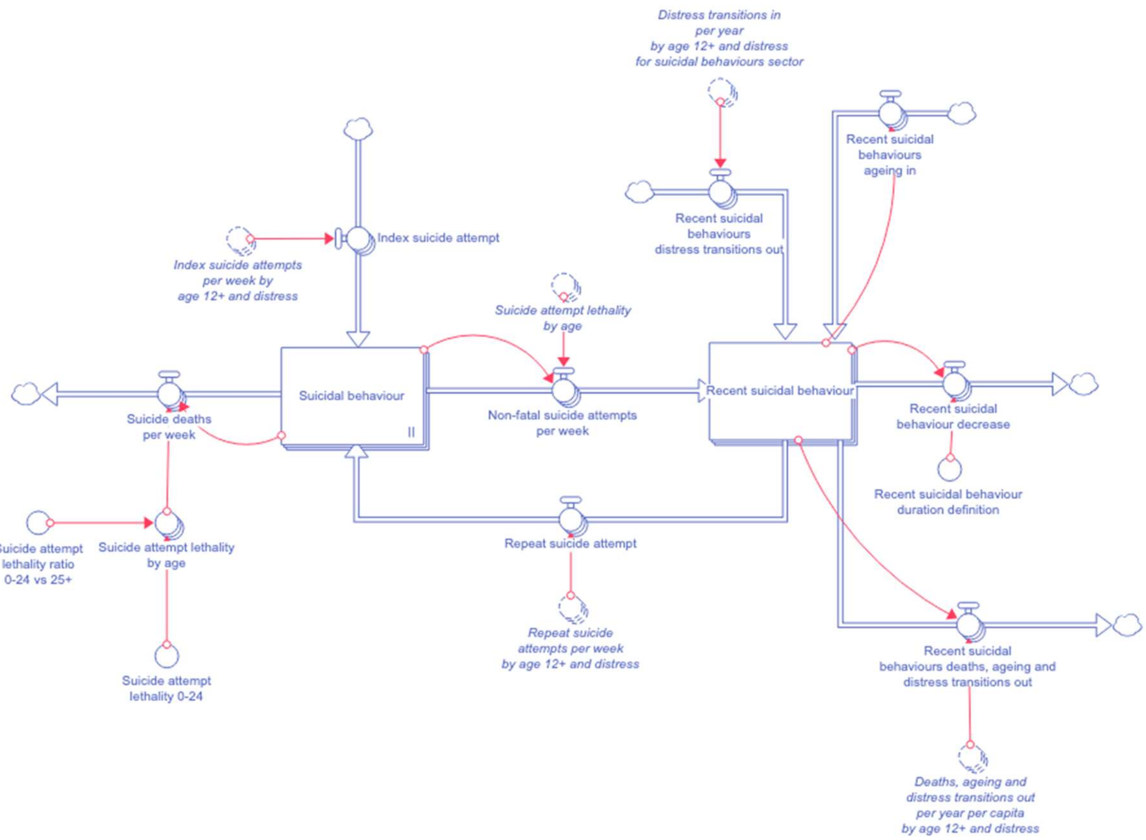
This sector models the flow of people engaging with substance misuse services. People with flow into the substance misuse services waiting stock, representing people on the waitlist for services prior to commencing substance misuse treatment (Brisbane South Primary Health Network, 2016). From the waiting stock, people flow out if they recover without treatment required, if they disengage with services (due to, for example, excessive wait times), through death or, if there are sufficient capacity, through commencing treatment with substance misuse services. From the treatment stock, people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), through death or through the completion of treatment. The remaining flows model ageing, distress / disorder transitions and mortality (Roerecke & Rehm, 2013). This sector was calibrated with substance misuse services data from the AIHW (Australian Institute of Health and Welfare, 2016-21, 2023).

Supplementary Figure 11b. Calibration plots from the substance misuse (substance misuse closed treatment episodes) sector



Suicidal behaviours

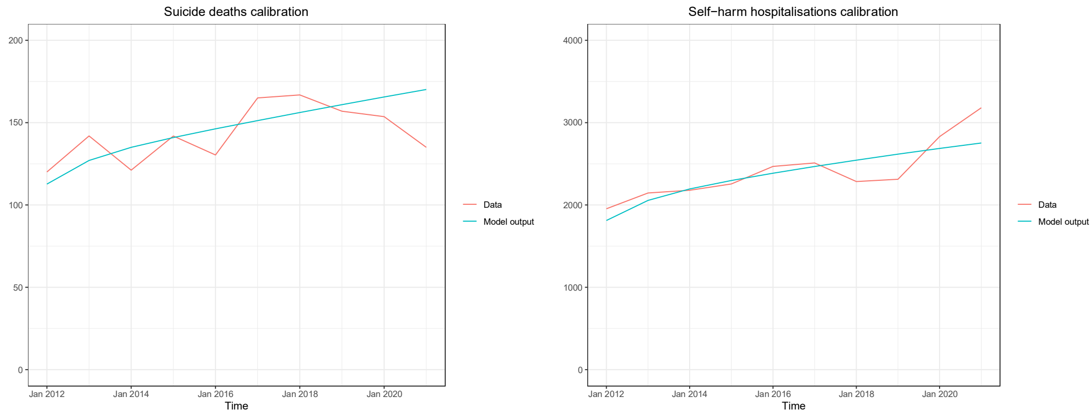
Supplementary Figure 12a. Structure of the suicidal behaviours sector



This sector models suicide deaths and attempts in the BSPHN population. The "Suicidal behaviour" stock represents people currently exhibiting suicidal behaviours. People can flow into this stock with an index suicide attempt and people can flow out of this stock depending on whether the attempt was fatal or non-fatal. People who had a non-fatal suicide attempt then flow into the "Recent suicidal behaviour" stock and either remain in this stock for 12 months, representing the duration of which people are at higher risk of exhibiting further suicidal behaviours, or flow back into the "Suicidal behaviours" stock if they have a repeat suicide attempt. The rates of suicide attempts are dependent on age, prevalence of psychological distress / disorder (Hockey et al., 2022) and prevalence of substance misuse disorder (Too et al., 2019). The remaining flows model ageing, distress / disorder transitions and mortality excluding suicide deaths. This sector was calibrated using suicide deaths statistics from the AIHW (Australian Institute of Health and Welfare, 2021c) and intentional self-harm hospitalisations statistics provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023).

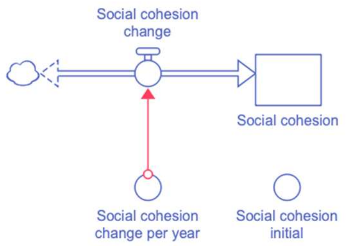
Please note that we calibrated non-fatal suicide attempts with intentional self-harm hospitalisations data. We acknowledge that these data do not fully capture the number of non-fatal suicide attempts (for example, those events not resulting in hospitalisation) and that these data may not accurately record the intention of the event.

Supplementary Figure 12b. Structure of the suicidal behaviours sector



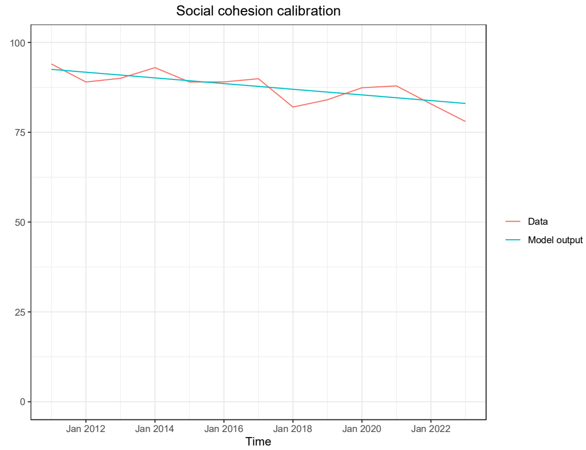
Social cohesion

Supplementary Figure 13a. Structure of the social cohesion sector



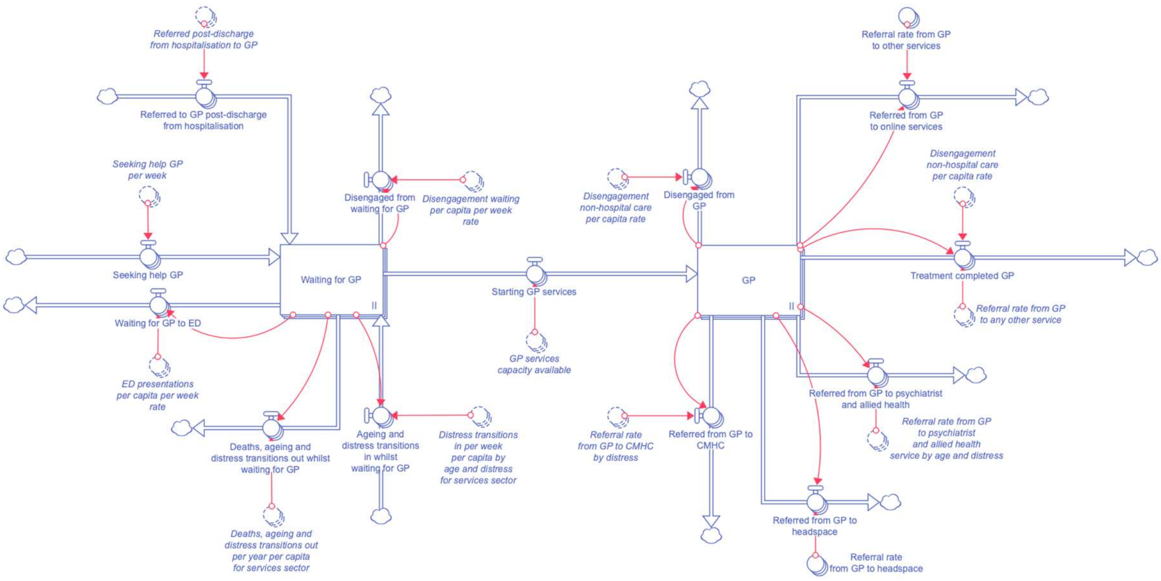
This sector models the level of social cohesion in the population. Social cohesion consists of five domains: belonging, worth, social justice, participation and acceptance and rejection. Social cohesion is a stock and flow structure allowing the level of social cohesion to change at a constant rate per year. This sector was calibrated with the Scanlon-Monash Index of Social Cohesion data from the Scanlon Foundation Research Institute (Scanlon Foundation Research Institute, 2023).

Supplementary Figure 13b. Calibration plot the social cohesion sector



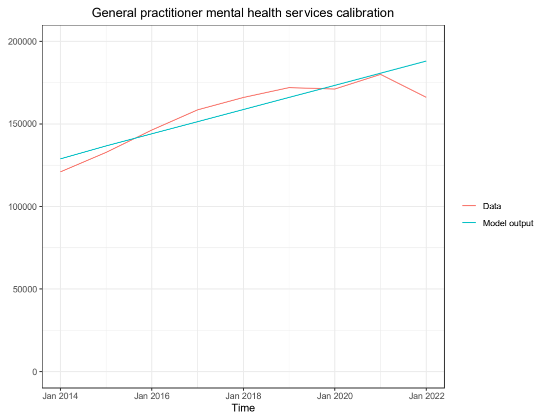
General Practitioner (GP)

Supplementary Figure 14a. Structure of the GP sector



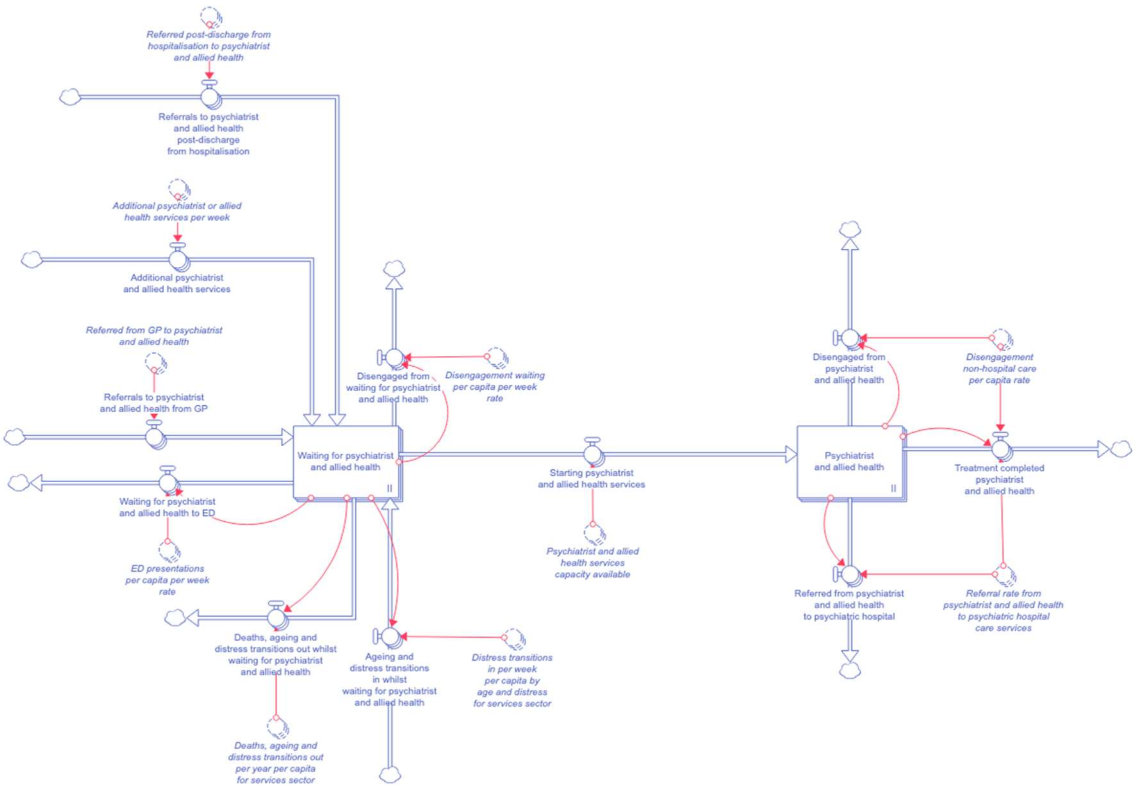
This sector models the flow of people engaging with a GP for their mental health. People flow into waiting stock "Waiting for GP", representing people on the waitlist for GP mental health services. The two inflows into the waiting stock are people in psychological distress who perceive a need for service and commence help-seeking with their GP, and people who have been referred to their GP post-discharge from a mental health related hospitalisation. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their consult with the GP, if services capacity allows. From the service stock "GP", people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), they are referred to other mental health services (e.g. online mental health services) or if their consult is completed without further referrals. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with Medicare-subsidised GP mental health services data from the AIHW (Australian Institute of Health and Welfare, 2022) and from data provided by BSPHN.

Supplementary Figure 14b. Calibration plot from the GP sector



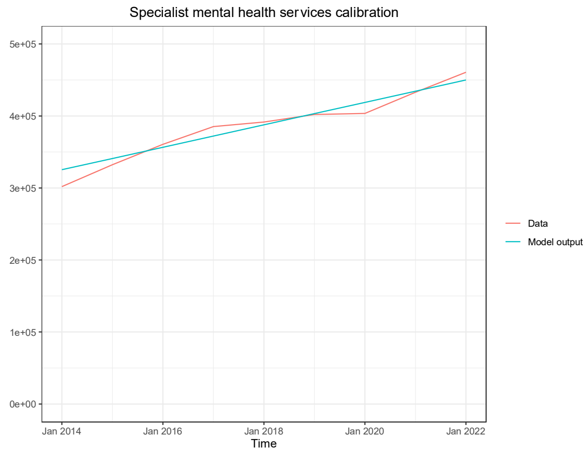
Specialist services

Supplementary Figure 15a. Structure of the specialist services sector



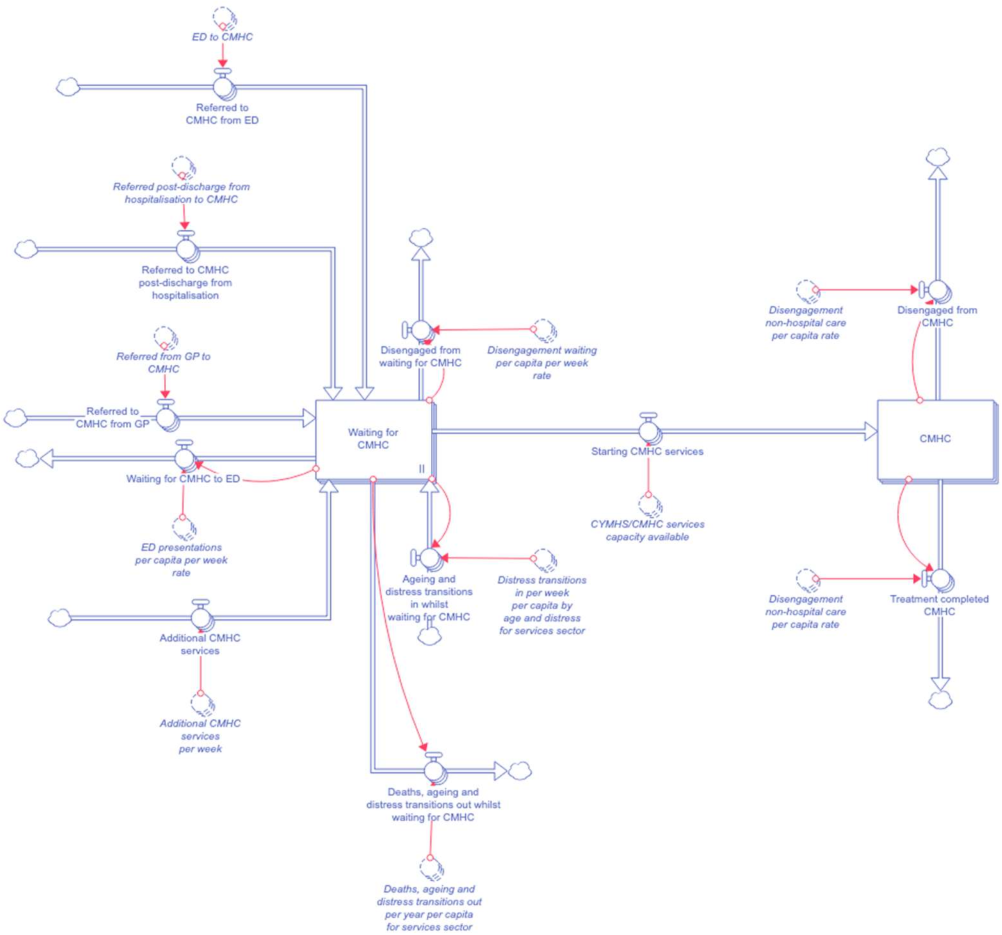
This sector models the flow of people engaging with specialist services (psychiatrists and allied mental health professionals such as psychologists, social worker and occupational therapists). People flow into the waiting stock “Waiting for psychiatrist and allied health”, representing people on the waitlist for services. The inflows into the waiting stock are people referred by their GP, people referred post-discharge from a mental health related hospitalisation and people with follow-up appointments. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their consult with specialised services, if services capacity allows. From the service stock “Psychiatrist and allied health”, people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), they are referred to inpatient psychiatric care or if their consult is completed without further referrals. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with Medicare-subsidised Psychiatrists and Allied Mental Health mental health services data from the AIHW (Australian Institute of Health and Welfare, 2022) and from data provided by BSPHN.

Supplementary Figure 15b. Calibration plot from the specialist services sector



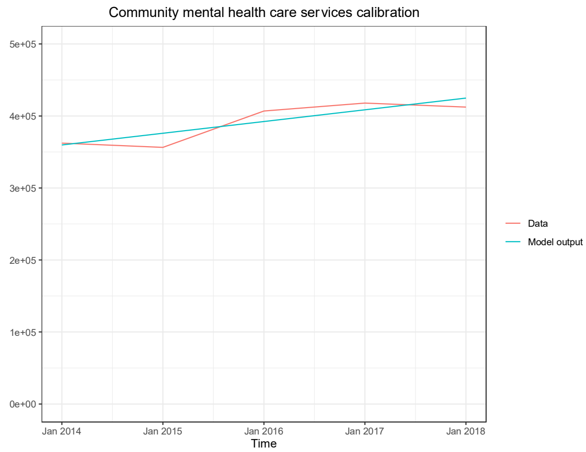
Community mental health care services

Supplementary Figure 16a. Structure of the community mental health care services sector



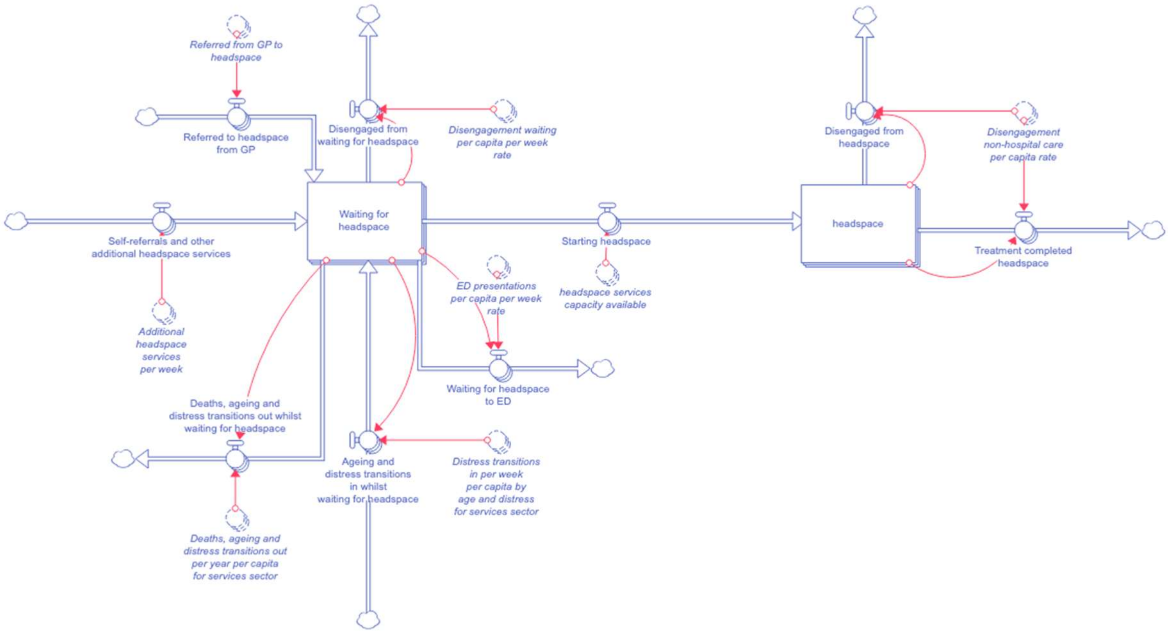
This sub-sector models the flow of people engaging with child and youth mental health services and community mental health care (CMHC). People flow into the waiting stock "Waiting for CMHC", representing people on the waitlist for services. The inflows into the waiting stock are people referred by their GP, people referred post-discharge from a mental health related hospitalisation, people referred post-discharge from a mental health related emergency department presentation and people with follow-up appointments. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their consult with the CYMHS/CMHC, if services capacity allows. From the service stock "CMHC", people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), or if their consult is completed. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with service contacts data from the AIHW (Australian Institute of Health and Welfare, 2017-18).

Supplementary Figure 16b. Calibration plot from the community mental health care services sector



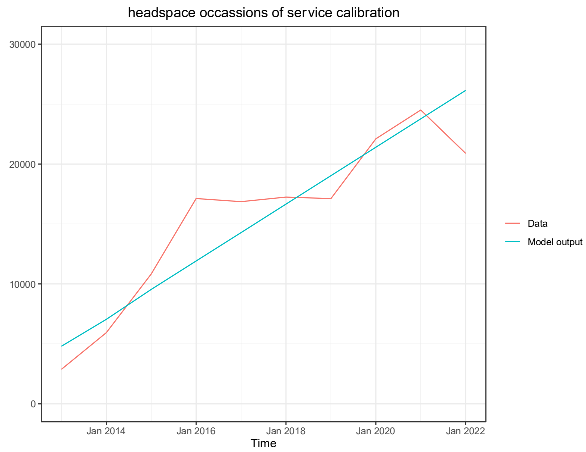
headspace

Supplementary Figure 17a. Structure of the headspace sector



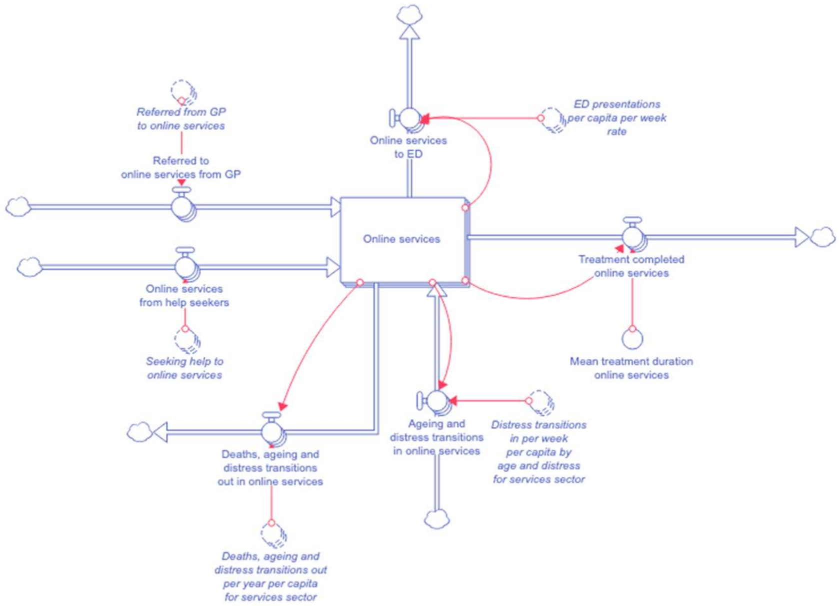
This sector models the flow of young people engaging with youth mental health service provider, headspace. Only people aged 12 and older flow into headspace stocks. People flow into the waiting stock "Waiting for headspace", representing people on the waitlist for services. The two inflows into the waiting stock are people in psychological distress who perceive a need for service and commence help-seeking with headspace, and people who have been referred by their GP. The first inflow reflects people self-referring to headspace, people referred to headspace by family or friends and people with follow-up appointments. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their consult with headspace, if services capacity allows. From the service stock "headspace", people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), or if their consult is completed without further referrals. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with occasions of service data provided by BSPHN.

Supplementary Figure 17b. Calibration plot from the headspace sector



Online mental health services

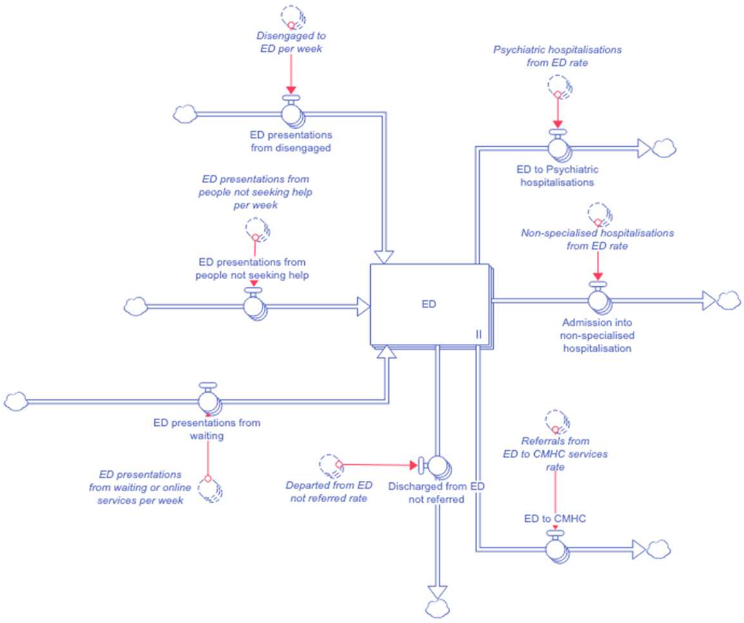
Supplementary Figure 18. Structure of the online mental health services sector



This sector models the flow of people engaging online mental health services. The two inflows into the stock are people in psychological distress who perceive a need for service and commence help-seeking with online services, and people who have been referred by their GP. People flow out when their online course of treatment is completed. The remaining flows model ageing, distress / disorder transitions and mortality.

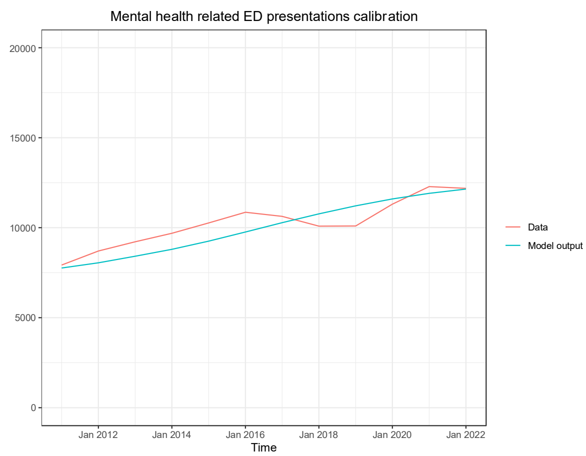
Mental health related emergency department (ED) presentations

Supplementary Figure 19a. Structure of the mental health related ED presentations sector



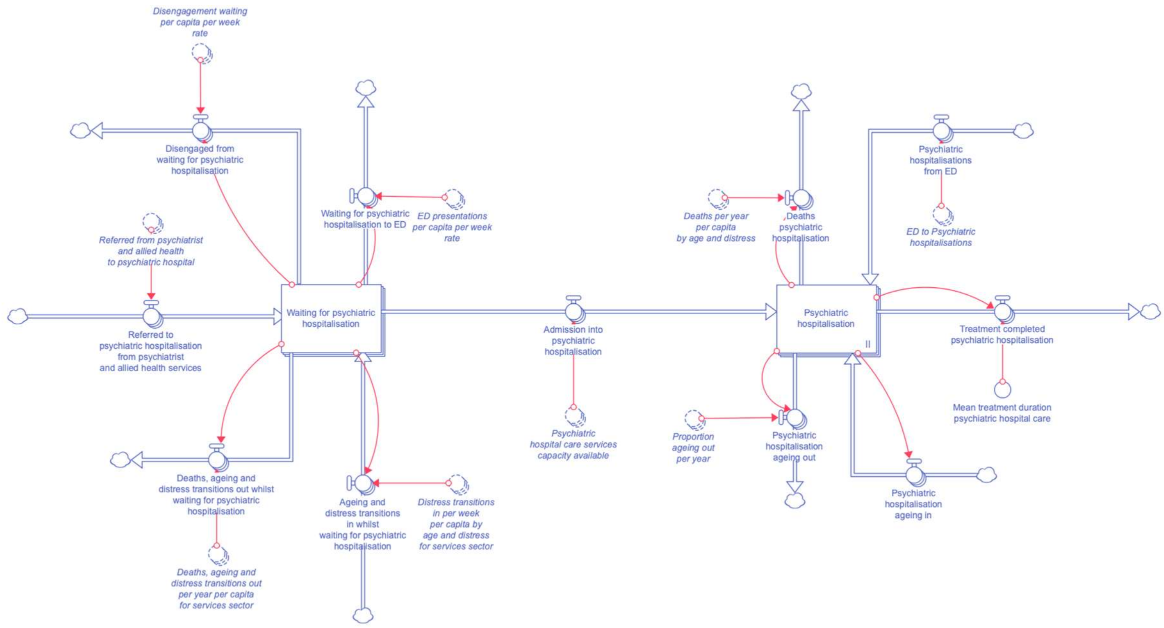
This sector models people presenting to the ED for mental health related presentations. People that flow into the stock are people who are distressed and are currently help-seeking with other services (e.g., whilst waiting for a consult with a psychologist), are not currently help-seeking (e.g., people whose family or friends take them to ED) and people who are disengaged from services. From the stock, people flow out if they are admitted into either psychiatric admitted care or non-specialised admitted care, discharged and referred to CMHC, or discharged without further referrals. This sector was calibrated with mental health related ED presentations data provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023).

Supplementary Figure 19b. Calibration plot from the mental health related ED presentations sector



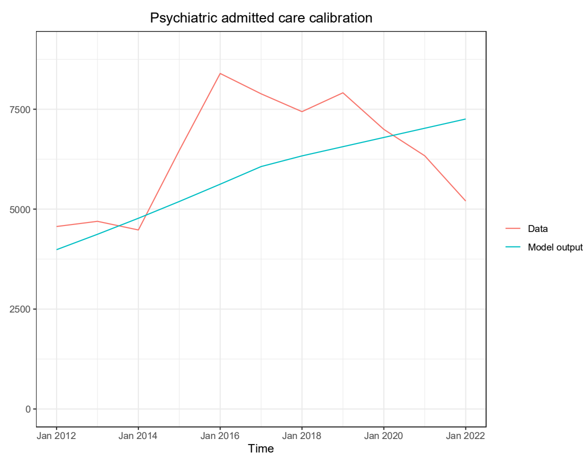
Psychiatric admitted care

Supplementary Figure 20a. Structure of the psychiatric admitted care sector



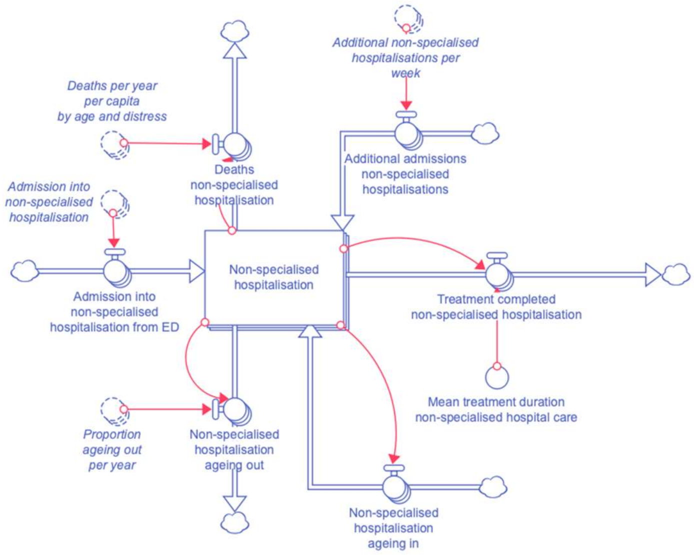
This sector models the flow of people into psychiatric admitted care. People flow into the waiting stock "Waiting for psychiatric hospitalisation", representing people on the waitlist for services. The inflow into the waiting stock are people referred by their specialist. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their psychiatric admitted care, if services capacity allows. People can directly flow into the service stock if the admission is from the ED. From the service stock "Psychiatric hospitalisation", people flow out once they are discharged. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with episodes of admitted care data provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023).

Supplementary Figure 20b. Calibration from the psychiatric admitted care sector



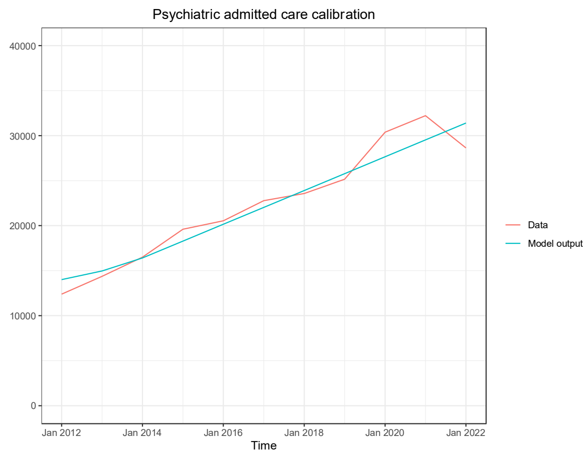
Non-specialised admitted care

Supplementary Figure 21a. Structure of the non-specialised admitted care sector



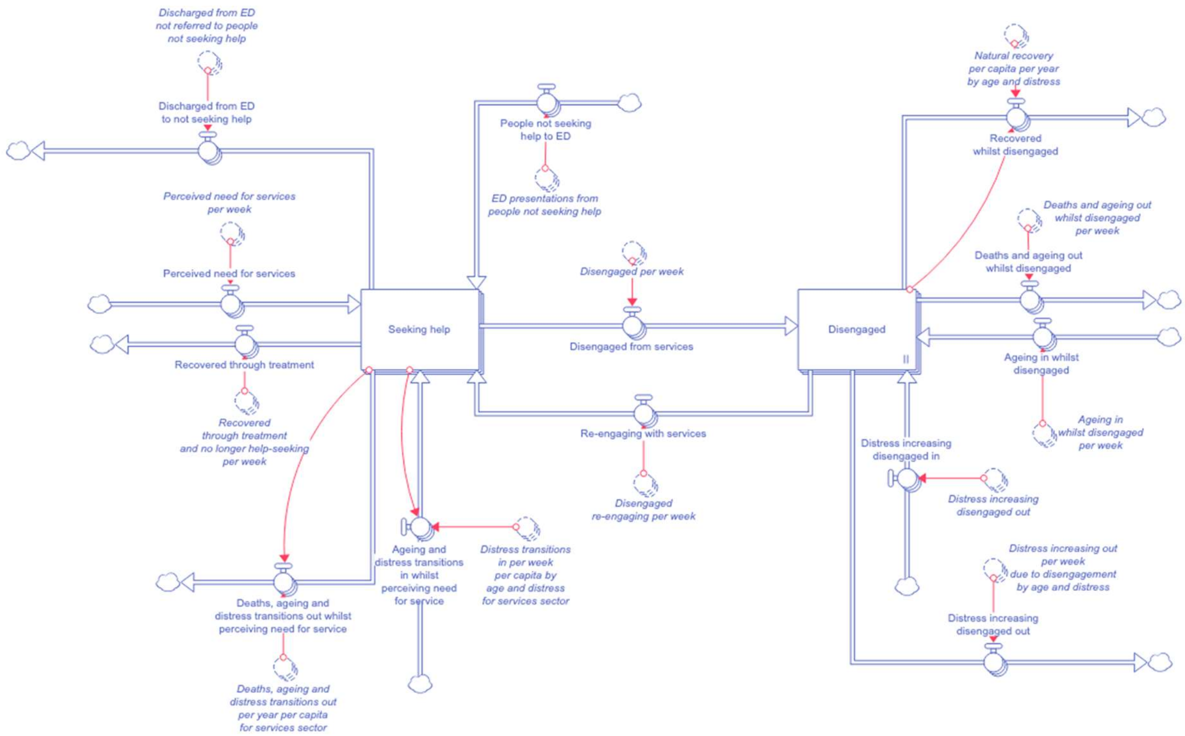
This sector models the flow of people into non-specialised, mental health related admitted care. People that flow into the stock are people who are admitted from ED and any other additional admissions. From the service stock, people flow out once they are discharged. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with episodes of admitted care data provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023).

Supplementary Figure 21b. Calibration plot from the non-specialised admitted care sector



Help-seeking and disengaged

Supplementary Figure 22. Structure of seeking-help and disengaged



This models the flow of people in distress who perceive a need for service and are either seeking help or are disengaged from services. People in distress may develop a perceive need for service and flow into the ”Seeking help” stock. The other inflows are people who present to ED without a perceived need for service (e.g., people whose family or friends take them to ED) and people who were disengaged then re-engaging with services. People who present to ED without a perceived need for service will flow out of the “Seeking help” stock once they are discharged. The flow from “Seeking help” to “Disengaged” models people who disengage from services whilst waiting for services or from their treatment. Whilst disengaged, people develop psychological disorders at a higher rate than the total population’s per-capita rate. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with perceived need for service data from ABS’ National Survey of Mental Health and Wellbeing 2007 (Australian Bureau of Statistics, 2007a) and the AIHW’s Mental health perfomance indicators 2021 (Australian Institute of Health and Welfare, 2021a).

Services capacity growth rate

To reflect a slowing growth rate in services capacity in recent years compared to the longer term historic trend, multipliers have been applied to annual growth rates for forward projections (i.e., from January 2025). These mulipliers can be modified on the user interface.

Service	Growth rate
General practitioner mental health services	Based on Medicare-subsidised services data published by AIHW for the period 2014 to 2022 (Australian Institute of Health and Welfare, 2022), the maximum number of GP mental health services that can be delivered per week has been increasing at an annual rate of 140 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.68) was derived from Medicare-subsidised services data published by AIHW for the period 2017-2020 (pre-pandemic) (Australian Institute of Health and Welfare, 2022) and represents a decrease in the annual growth rate in GP services capacity of 32% from January 2025.
Specialist mental health services	Based on Medicare-subsidised services data published by AIHW for the period 2014 to 2022 (Australian Institute of Health and Welfare, 2022), the maximum number of Psychiatry and allied mental health services that can be delivered per week has been increasing at an annual rate of 298 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.97) was derived from Medicare-subsidised services data published by AIHW for the period 2017-2020 (Australian Institute of Health and Welfare, 2022) and represents a decrease in the annual growth rate from January 2024 onwards.
Child and youth mental health services	Based on Community Mental Health Care Services published by AIHW for the period 2013 to 2018 (Australian Institute of Health and Welfare, 2017-18), the maximum number of child and youth mental health services that can be delivered per week has been increasing at an annual rate of 89 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.41) was derived from Community Mental Health Care Services data published by AIHW (Australian Institute of Health and Welfare, 2017-18) for the period 2016-2018 and represents a decrease in the annual growth rate.

Community mental health care services	Based on Community Mental Health Care Services published by AIHW for the period 2013 to 2018 (Australian Institute of Health and Welfare, 2017-18), the maximum number of community mental health care services that can be delivered per week has been increasing at an annual rate of 222 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.07) was derived from Community Mental Health Care Services data published by AIHW (Australian Institute of Health and Welfare, 2017-18) for the period 2016-2018 and represents a decrease in the annual growth rate.
headspace	Based on headspace occasions of service data provided by BSPHN for the period 2013 to 2022, the maximum number of headspace services that can be delivered per week has been increasing at an annual rate of 45 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.58) was derived from headspace occasions of service data provided by BSPHN for the period 2017-2022 and represents a decrease in the annual growth rate.
Psychiatric admitted care	Based on episodes of admitted patient care provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023) for the period 2011 to 2022, the maximum number of episodes of admitted patient care that can be delivered per week has been increasing at an annual rate of 4 additional episodes per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.08) was derived from episodes of admitted patient care provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023) for the period 2017-2019 and represents a decrease in the annual growth rate.
Substance misuse treatment services	Based on alcohol and other drug closed treatment episodes published by AIHW (Australian Institute of Health and Welfare, 2016-21) for the period 2013-14 to 2020-2021, the maximum number of closed treatment episodes that can be delivered per week has been increasing at an annual rate of 9 additional episodes per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.77) was derived from alcohol and other drug closed treatment episodes published by AIHW

	(Australian Institute of Health and Welfare, 2016-21) for the period 2017-18 to 2019-20 and represents a decrease in the annual growth rate.

Numerical inputs

Variable Name	Stratification / Value		Notes
Population			
Population initial by age	0–4 years	73403.32	Estimated with constrained optimisation
	5–11 years	90745.96	
	12-14 years	35261.66	
	15-17 years	42747.12	
	18-24 years	112203	
	25 years and older	662238.1	
Birth rate per year initial	0.013619180		Estimated with constrained optimisation
Birth rate increase per year	-0.0000904897		Estimated with constrained optimisation
Death rate per year initial	0.005606927		Estimated with constrained optimisation
Death rate increase per year	-0.0000030102		Estimated with constrained optimisation
Deaths per capita per year age rate ratio	0–4 years	0.15787930	Australian Bureau of Statistics (2022a)
	5–11 years	0.01387892	
	12-14 years	0.01618564	
	15-17 years	0.05522237	
	18-24 years	0.07360028	
	25 years and older	1.45942	
Arrivals per year by age initial	0–4 years	21364.22826	Estimated with constrained optimisation
	5–11 years	21421.73749	
	12-14 years	3302.189961	
	15-17 years	7339.889174	
	18-24 years	45644.2283	
	25 years and older	61372.53703	
Arrivals increase per year by age	0–4 years	0	Estimated with constrained optimisation
	5–11 years	31.98119806	
	12-14 years	34.44288621	
	15-17 years	0.66163482	
	18-24 years	0	
	25 years and older	16.90088416	
Per capita departure rate by age initial	0–4 years	0.264754914	Estimated with constrained optimisation
	5–11 years	0.188861708	
	12-14 years	0.076197284	
	15-17 years	0.158536797	
	18-24 years	0.360280937	
	25 years and older	0.079111422	
Per capita departure rate by age increase per year	0–4 years	0.000115989	Estimated with constrained optimisation
	5–11 years	0.000067905	
	12-14 years	0	
	15-17 years	0	
	18-24 years	0.000457962	
	25 years and older	0	
Education - Students			
Studying post-secondary education initial	107910.9861		Estimated with constrained optimisation
Proportion of population not currently studying entering secondary education per year	0.000001319		Estimated with constrained optimisation

Proportion of population not currently studying entering post-secondary education per year	0.04781599		Estimated with constrained optimisation
Discontinuing secondary study base rate	0.0394836834639		Estimated with constrained optimisation
Discontinuing post-secondary study base rate	0.083776167		Estimated with constrained optimisation
Completing secondary study rate	0.144451109414		Estimated with constrained optimisation
Completing post-secondary study rate	0.427533386		Estimated with constrained optimisation
Proportion of secondary study completers transitioning to post-secondary education	0.4796904		Queensland Department of Education (2023)
Proportion of population 5-11 studying primary education ratio: rest of Australia vs QLD	0.969		Australian Bureau of Statistics (2022b)
Proportion of population 12-17 studying secondary education ratio: rest of Australia vs QLD	1.08		Australian Bureau of Statistics (2022b)
Proportion of population 18+ studying post-secondary education ratio: rest of Australia vs QLD	1.013012		Australian Bureau of Statistics (2022b)
Prevalence of moderate to very high psychological distress ratio secondary students vs population	1		Assumes that the prevalence of psychological distress in secondary students is the same as population prevalence for 12-17 year olds.
Effect of moderate to very high distress on discontinuation of secondary education	1.99		Butterworth and Leach (2017)
Prevalence of moderate to very high psychological distress ratio post-secondary students vs population	1.3995		Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
Effect of psychological distress on discontinuation of post-secondary education	1.1		Lee et al. (2009)
Education – Highest qualifications			
Proportion of population with secondary qualification only initial by age 15-24, 25+	15-24 years	0.404604512	Estimated with constrained optimisation
	25 years and older	0.172317986	
Proportion of population with post-secondary qualification initial by age 15-24, 25+	15-24 years	0.29891598	Estimated with constrained optimisation
	25 years and older	0.40157251	
Proportion completing first post-secondary qualification by age 15-24, 25+	15-24 years	0.941009619	Estimated with constrained optimisation
	25 years and older	0.273396566	
Proportion of secondary school graduates who are aged 15-24	0.528945706		Estimated with constrained optimisation
Proportion of post-secondary graduates who are aged 15-24	0.081662928		Estimated with constrained optimisation
Death rate ratio post-secondary qualification vs low education	0.3623188		Welsh et al. (2021)
Death rate ratio secondary qualification only vs low education	0.635		Welsh et al. (2021)
Proportion of population with secondary qualification only ratio Australia vs BSPHN	15-24 years	1.1184972	Australian Bureau of Statistics (2014-2022) Australian Department of Health and Aged Care (2023)
	25 years and older	1.0674508	
Proportion of population with post-secondary qualification ratio Australia vs BSPHN	15-24 years	0.8848893	Australian Bureau of Statistics (2014-2022) Australian Department of Health and Aged Care (2023)
	25 years and older	1.0140127	

Labour force			
Proportion of population 15-24, 25+ sufficiently employed proportion initial	15-24 years	0.645484041	Estimated with constrained optimisation
	25 years and older	0.671011922	
Proportion of population 15-24, 25+ underemployed proportion initial	15-24 years	0.000004229	Estimated with constrained optimisation
	25 years and older	0.000610871	
Proportion of population 15-24, 25+ unemployed proportion initial	15-24 years	0.112349271	Estimated with constrained optimisation
	25 years and older	0.033182918	
Sufficiently employed to unemployed per capita per year base rate by age 15-24, 25+	15-24 years	0.188773316	Estimated with constrained optimisation
	25 years and older	0.041900295	
Unemployed to sufficiently employed per capita per year base rate by age 15-24, 25+	15-24 years	1.966435759	Estimated with constrained optimisation
	25 years and older	0.851576955	
Underemployed to unemployed per capita per year base rate by age 15-24, 25+	15-24 years	0.086418873	Estimated with constrained optimisation
	25 years and older	0.533308196	
Unemployed to underemployed per capita per year base rate by age 15-24, 25+	15-24 years	1.499279338	Estimated with constrained optimisation
	25 years and older	2.25377314	
Sufficiently employed to underemployed per capita per year base rate by age 15-24, 25+	15-24 years	0.062465237	Estimated with constrained optimisation
	25 years and older	0.080178673	
Underemployed to sufficiently employed per capita per year base rate by age 15-24, 25+	15-24 years	0.95585229	Estimated with constrained optimisation
	25 years and older	1.378794293	
Unemployed to NILF per capita per year base rate by age 15-24, 25+	15-24 years	3.031715245	Estimated with constrained optimisation
	25 years and older	2.430982644	
NILF to Unemployed per capita per year base rate by age 15-24, 25+	15-24 years	1.435570397	Estimated with constrained optimisation
	25 years and older	0.268136312	
Sufficiently employed to NILF per capita per year base rate by age 15-24, 25+	15-24 years	0.420654638	Estimated with constrained optimisation
	25 years and older	0.065116267	
Underemployed to NILF per capita per year base rate by age 15-24, 25+	15-24 years	0.049159652	Estimated with constrained optimisation
	25 years and older	0.04791504	
Proportion of population sufficiently employed ratio: rest of Australia vs QLD	0.9999229		Australian Bureau of Statistics (2023a)
Proportion of population underemployed ratio: rest of Australia vs QLD	0.9548649		Australian Bureau of Statistics (2023a)
Proportion of population unemployed ratio: rest of Australia vs BSPHN	0.9051092		Australian Bureau of Statistics (2014-2022)
Death rate ratio: unemployed vs employed	1.22		Sorlie and Rogot (1990)
Effect of post-secondary qualification on underemployment to sufficiently employed rate	1.407043821		Wilkins (2004)
Post-secondary qualification probability ratio underemployed vs population	0.86282872		Wilkins (2004)
Effect of moderate to very high distress on employment	0.8396596		Frijters et al. (2014)
Moderate distress prevalence ratio unemployed by age 15-24, 25+	15-24 years	1.34	Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
	25 years and older	1.73	
Moderate distress prevalence ratio participation by age 15-24, 25+	15-24 years	0.981	Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
	25 years and older	0.924	

Effect of post-secondary qualification on participation	1.435808		Australian Bureau of Statistics (2014-2022)
Post-secondary qualifications prevalence ratio participation vs population	1.08		Australian Bureau of Statistics (2014-2022)
Effect of post-secondary qualification on employment vs low educational attainment	1.512015		Australian Bureau of Statistics (2014-2022)
Post-secondary qualifications prevalence ratio unemployed vs population	0.822		Australian Bureau of Statistics (2014-2022)
Effect of secondary qualification only on participation	1.281302		Australian Bureau of Statistics (2014-2022)
Secondary qualifications only prevalence ratio participation vs population	0.964		Australian Bureau of Statistics (2014-2022)
Effect of secondary qualification only on employment vs low educational attainment	1.305415		Australian Bureau of Statistics (2014-2022)
Secondary qualifications only prevalence ratio unemployed vs population	1.29		Australian Bureau of Statistics (2014-2022)
NEET			
Proportion of population NEET ratio 15-17 / 15-24	0.2893055		Australian Bureau of Statistics (2015-2022)
Coefficient for students aged 15-24 and not employed initial	1.711780643		Estimated with constrained optimisation
Coefficient for students aged 15-24 and not employed increase per year	0.046446351		Estimated with constrained optimisation
Psychological distress / disorder			
Prevalence of moderate to very high distress initial by age 12+	12-14 years	0.307415879	Estimated with constrained optimisation
	15-17 years	0.506342413	
	18-24 years	0.19807616	
	25 years and older	0.336014894	
Coefficient Social cohesion on Distress onset per year per base rate by age 12+	12-14 years	-0.107442807	Estimated with constrained optimisation
	15-17 years	-0.019644493	
	18-24 years	-0.028448839	
	25 years and older	-0.032940071	
Intercept social cohesion on Distress onset per year per base rate by age 12+	12-14 years	0.049399265	Estimated with constrained optimisation
	15-17 years	0.060668244	
	18-24 years	-0.002286305	
	25 years and older	0.034026888	
Coefficient social cohesion on Disorder incidence per year base rate by age 12+	12-14 years	-0.116738035	Estimated with constrained optimisation
	15-17 years	-0.027401149	
	18-24 years	-0.027628572	
	25 years and older	-0.026413605	
Intercept social cohesion on Disorder incidence per year base rate by age 12+	12-14 years	0.974258794	Estimated with constrained optimisation
	15-17 years	0.993189929	
	18-24 years	1.014336705	
	25 years and older	0.979776148	
Death rate ratio Moderate distress vs Low distress	1.16		Russ et al. (2012)
Death rate ratio High distress vs Low distress	1.37		Russ et al. (2012)
Prevalence of low distress ratio Australia vs QLD by age 12+	12-14 years	1	Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
	15-17 years	1	
	18-24 years	1.01	
	25 years and older	1.02	
Prevalence of disorder ratio Australia vs QLD by age 12+	12-14 years	1	Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
	15-17 years	1	
	18-24 years	0.983	
	25 years and older	0.958	
Effect of unemployment on distress	15-24 years	1.43	Australian Bureau of Statistics (2007a)
	25 years and older	1.81	

Unemployment rate ratio of low distress vs population by age 15-24, 25+	15-24 years	0.759	Australian Bureau of Statistics (2007a)
	25 years and older	0.666	
Effect of homelessness on distress	2.14		Australian Bureau of Statistics (2007a)
Homelessness prevalence ratio of low distress vs population	0.567		Australian Bureau of Statistics (2007a)
Effect of underemployment on distress	1.132448		Dooley et al. (2000)
Underemployment ratio of low distress vs population	1.003201		Griffiths et al. (2021)
Effect of substance abuse on distress	2.63		Marmorstein et al. (2010)
Substance misuse prevalence ratio of low distress vs population	0.6595638		Australian Bureau of Statistics (2012)
Distress recovery per year base rate by age 12+	0.06833333		Jokela et al. (2011)
Disorder recovery per year base rate by age 12+	0.06833333		Jokela et al. (2011)
Proportion of disorder recovery to no disorder, moderate to very high distress through treatment	0.8		Assumes that 80% of people with a mental disorder who recover through accessing services will recover to a state of moderate to very high psychological distress and that 20% will recover into a state of low psychological distress.
Proportion of Close to average SDQ to Low distress	0.468		Australian Institute of Family Studies (2022)
Proportion of Close to average SDQ to Disorder, Moderate to Very high distress	0.238		Australian Institute of Family Studies (2022)
Proportion of Slightly raised SDQ to Low distress	0.182		Australian Institute of Family Studies (2022)
Proportion of Slightly raised SDQ to Disorder, Moderate to Very high distress	0.62		Australian Institute of Family Studies (2022)
Proportion of High SDQ to Low distress	0.112		Australian Institute of Family Studies (2022)
Proportion of High SDQ to Disorder, Moderate to Very high distress	0.72		Australian Institute of Family Studies (2022)
Strengths and Difficulties			
Coefficient Social cohesion on Close to average to Slightly raised SDQ per year base rate by age <12	0-4 years	-0.042484533	Estimated with constrained optimisation
	5-11 years	-0.044012565	
Intercept social cohesion on Close to average to Slightly raised SDQ per year base rate by age <12	0-4 years	1.242650711	Estimated with constrained optimisation
	5-11 years	1.041291164	
Coefficient Social cohesion on Slightly raised to High SDQ per year base rate by age <12	0-4 years	-0.017355267	Estimated with constrained optimisation
	5-11 years	-0.038128501	
Intercept social cohesion on Slightly raised to High SDQ per year base rate by age <12	0-4 years	0.360948024	Estimated with constrained optimisation
	5-11 years	2.28262466	
Proportion of High SDQ recovery to Slightly raised through treatment	0.8		Assumes that 80% of people with High levels of SDQ who recover through accessing services will recover to a state of Slightly raised SDQ and that 20% will recover into a state of Close to average SDQ

Prevalence of slightly raised SDQ ratio rest of Australia vs BSPHN by age <12	0-4 years	1.06	Australian Institute of Family Studies (2022)
	5-11 years	0.824	
Prevalence of high SDQ ratio rest of Australia vs BSPHN by age <12	0-4 years	0.918	Australian Institute of Family Studies (2022)
	5-11 years	0.874	
Slightly raised to Close to average SDQ per year base rate by age <12	0.06833333		Jokela et al. (2011)
High to Slightly raised SDQ per year base rate by age <12	0.06833333		Jokela et al. (2011)
Homelessness			
Homeless by age initial	0–4 years	230.3500687	Estimated with constrained optimisation
	5–11 years	258.4868751	
	12-14 years	101.3063039	
	15-17 years	167.9467548	
	18-24 years	716.0155577	
	25 years and older	2298.728691	
Entering homelessness per week base rate by age	0–4 years	0.000027358	Estimated with constrained optimisation
	5–11 years	0.000015254	
	12-14 years	0.000012205	
	15-17 years	0.000014189	
	18-24 years	0.000023220	
	25 years and older	0.000011581	
Mean duration of homelessness	239.8571		Ranney (2023)
Death rate ratio homeless vs non-homeless	1.6		Morrison (2009)
Effect of unemployment on entering homelessness	2.6		Nilsson et al. (2019)
Effect of mental illness on entering homelessness	1.7		Nilsson et al. (2019)
Effect of substance misuse on entering homelessness	2.3		Nilsson et al. (2019)
Substance misuse			
Waiting for substance misuse treatment by age 15-24, 25+ initial	15-24 years	980.4253188	Estimated with constrained optimisation
	25 years and older	974.8870492	
Substance misuse seeking treatment per capita per week rate initial	15-24 years	0.002209145	Estimated with constrained optimisation
	25 years and older	0.001545306	
Substance misuse seeking treatment per capita per week increase per year	15-24 years	0.000131204	Estimated with constrained optimisation
	25 years and older	0.000485677	
Substance misuse onset per capita per week base rate by age 15-24, 25+	15-24 years	0.000159647	Estimated with constrained optimisation
	25 years and older	0.000022895	
Substance misuse natural recovery per capita per week base rate by age 15-24, 25+	15-24 years	0.000914274	Estimated with constrained optimisation
	25 years and older	0.002283660	
Substance misuse treatment capacity per week initial	76.20995643		Estimated with constrained optimisation
Substance misuse treatment capacity per week increase per year	8.648468568		Estimated with constrained optimisation
Substance misuse treatment mean duration	4.140022		Australian Institute of Health and Welfare (2023)
Prevalence of substance misuse ratio rest of Australia vs BSPHN by age 15-24, 25+	1		This sector was calibrated with national prevalence data, hence the prevalence ratio will be one. Australian Bureau of Statistics (2008, 2020-22)
Death rate ratio substance misuse vs no substance misuse	1.95		Roerecke and Rehm (2013)
Effect of homelessness on substance misuse	1.65		Johnson et al. (1997)

Prevalence of homelessness in the non substance misuse population vs total population		0.8683555	Slade et al. (2009)
Effect of moderate to very high distress on substance misuse		2.505036	Australian Institute of Health and Welfare (2017)
Prevalence of distress in the non substance misuse population vs total population		0.9916363	Australian Institute of Health and Welfare (2017)
Effect of NEET substance misuse		1.43	Gariépy et al. (2022)
Prevalence of NEET in the non substance misuse population vs total population		1.012717083	Australian Bureau of Statistics (2020-22)
QLD average number of closed treatment episodes per client		1.3	Australian Institute of Health and Welfare (2016-21)
Recovery rate from substance misuse treatment		0.359	Manning et al. (2017)
Suicidal behaviours			
Suicide attempt lethality 0-24		0.023634286	Estimated with constrained optimisation
Index suicide attempt base rate by age 12+	12-14 years	0.000014123825	Estimated with constrained optimisation
	15-17 years	0.000024350493	
	18-24 years	0.000025232155	
	25 years and older	0.000016279156	
Repeat suicide attempts per week base rate		0.006285649	Estimated with constrained optimisation
Suicide attempt lethality ratio 0-24 vs 25+		3.217148569	Australian Institute of Health and Welfare (2021d, 2021e)
Suicide rate ratio substance misuse disorder vs no substance misuse disorder		4.1	Too et al. (2019)
Suicide attempt rate ratio by distress	No distress	1 (Reference)	Hockey et al. (2022)
	Distress No Disorder	1.41	
	Distress Disorder	3.57	
Mental health services			
Effect of disengagement on increasing psychological distress		1.271517	Australian Bureau of Statistics (2012)
Baseline disengagement rate waiting per year		0.2620284	Tyrer et al. (1995)
Baseline disengagement rate hospital care		0.051642558	Australian Institute of Health and Welfare (2016-17)
Baseline disengagement rate non-hospital care		0.03909747	Australian Institute of Health and Welfare (2016-17)
Effect of distress on hospitalisation	No distress	0	Australian Bureau of Statistics (2007a)
	Distress No Disorder	1 (Reference)	
	Distress Disorder	1.773723	
Mean treatment duration psychiatric hospital care		1.997143	Australian Institute of Health and Welfare (2021b)
Mean treatment duration non-specialised hospital care		0.7142857	Australian Institute of Health and Welfare (2021b)
Mean treatment duration online services		6	Christensen, Griffiths, and Jorm (2004)
Seeking help to online services rate by age	0–4 years	0.0440037	Australian Bureau of Statistics (2020-22)
	5–11 years	0.0440037	
	12-14 years	0.079675	
	15-17 years	0.079675	
	18-24 years	0.079675	
	25 years and older	0.027663	
Referral rate from GP to headspace	0–4 years	0	Australian Institute of Health and Welfare (2022); KPMG (2022)
	5–11 years	0	
	12-14 years	0.07415457	
	15-17 years	0.07415457	
	18-24 years	0.07415457	
	25 years and older	0	

Referral rate from GP to other services	0.046749		Australian Institute of Health and Welfare (2015-16)
Effect of distress on help-seeking with GP	No distress	0	Australian Bureau of Statistics (2007a)
	Distress No Disorder	1	
	Distress Disorder	3.287037	
Proportion of post-discharge referrals to non-CMHC services to GP	0.5		Assumes half of patients not referred to CMHC services after discharge from hospital care are referred to a general practitioner. The remaining patients (i.e., those not referred to CMHC services or a general practitioner) are referred to a psychiatrist or allied mental health professional
Effect of distress on referral rate	No distress	0	Australian Bureau of Statistics (2007a)
	Distress No Disorder	1	
	Distress Disorder	1.786096	
Effect of distress on seeking help psychiatrist or allied health services	No distress	0	Australian Bureau of Statistics (2007a)
	Distress No Disorder	1	
	Distress Disorder	4.398422	
Baseline recovery rate psychiatric hospital care	No distress	0	Thase et al. (1997)
	Distress No Disorder	0.4241071	
	Distress Disorder	0.3712737	
Baseline recovery rate headspace	0.050295858		KPMG (2022)
Baseline recovery rate CMHC services	0.02332282		Australian Institute of Health and Welfare (2016)
Recovery rate ratio GP services	No distress	0	Cuijpers, Smits, Donker, ten Have, and de Graaf (2009)
	Distress No Disorder	1	
	Distress Disorder	0.4626866	
Baseline recovery rate mental health treatment	No distress	0	Thase et al. (1997)
	Distress No Disorder	0.09525994	
	Distress Disorder	0.08339287	
Psychological treatment rate GP services	0.48343875		Australian Institute of Health and Welfare (2016)
Recovery rate online services	No distress	0	Christensen et al. (2004); Cuijpers, Straten, Schaik, and Andersson (2009)
	Distress No Disorder	0.4	
	Distress Disorder	0.1850746	
Perceived needs for services per capita per week rate initial	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	0.001805767	
	Distress Disorder	0.012469428	
Perceived needs for services rate increase per year	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	-3.32927E-05	
	Distress Disorder	7.80161E-05	
Re-engaging excluding ED per capita per week rate initial	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	0.113266016	
	Distress Disorder	0.095776677	
Re-engaging excluding ED per capita per week rate increase per year	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	0.002808987	
	Distress Disorder	0.085153265	
Proportion of population in distress seeking help initial by distress	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	0.195389983	
	Distress Disorder	0.652438251	
Disengaged initial total	0		Estimated with constrained optimisation
GP services capacity per week initial	2058.304273		Estimated with constrained optimisation
GP services capacity per week increase per year	140.5472373		Estimated with constrained optimisation
Psychiatrist and allied health services capacity per week initial	5342.906405		Estimated with constrained optimisation

Psychiatrist and allied health services capacity per week increase per year	298.2331118		Estimated with constrained optimisation
CYMHS services capacity per week initial	1147.346		Estimated with constrained optimisation
CYMHS services capacity per week increase per year	89.01923		Estimated with constrained optimisation
CMHC services (adult) capacity per week initial	4816.154		Estimated with constrained optimisation
CMHC services (adult) capacity per week increase per year	222.3462		Estimated with constrained optimisation
Psychiatric hospitalisation capacity per week initial	90.5		Estimated with constrained optimisation
Psychiatric hospitalisation capacity per week increase per year	4.412692		Estimated with constrained optimisation
Non-specialised hospital care services capacity per week initial	206.883489		Estimated with constrained optimisation
Non-specialised hospital care services capacity capacity per week increase per year	35.86016039		Estimated with constrained optimisation
headspace services capacity per week initial	1		Estimated with constrained optimisation
headspace services capacity capacity per week increase per year	45.39721129		Estimated with constrained optimisation
ED presentations per capita per week rate by age initial	0–4 years	0.00000620315	Estimated with constrained optimisation
	5–11 years	0.00003095921	
	12-14 years	0.00018241607	
	15-17 years	0.00030566461	
	18-24 years	0.00062163940	
	25 years and older	0.00048565391	
ED presentations rate by age increase per year	0–4 years	0.00000614195	Estimated with constrained optimisation
	5–11 years	0.00000703190	
	12-14 years	0.00001119396	
	15-17 years	0.00000543526	
	18-24 years	-0.00001699589	
	25 years and older	-0.00001301185	
ED presentation rate ratio help seeker	1		Estimated with constrained optimisation
ED to admission rate initial by age	0–4 years	0.218855977	Estimated with constrained optimisation
	5–11 years	0.125828686	
	12-14 years	0.191485232	
	15-17 years	0.249542276	
	18-24 years	0.08105427	
	25 years and older	0.145228354	
ED to admission rate increase per year	0–4 years	-0.011687394	Estimated with constrained optimisation
	5–11 years	0.004505288	
	12-14 years	0.010480664	
	15-17 years	-0.001778161	
	18-24 years	0.072187184	
	25 years and older	0.086166213	
Proportion of admissions into psychiatric hospitalisation by age 0-17, 18-24, 25+	0-17 years	0.414161436	Estimated with constrained optimisation
	18-24 years	0.547643051	
	25 years and older	0.377282299	
Additional non-specialised hospitalisations per capita per week by age 0-17, 18-24, 25+	0-17 years	0.00023579	Estimated with constrained optimisation
	18-24 years	0.000773031	
	25 years and older	0.00189995	
Referral rate from ED to CMHC	0.074017861		Estimated with constrained optimisation
Waiting for psychiatric hospitalisation initial total	0		Estimated with constrained optimisation
Seeking help GP services rate by age 0-14, 15-24, 25+ initial	0-14 years	0.003158381	Estimated with constrained optimisation
	15-24 years	0.005169437	

	25 years and older	0.007613575	
Seeking help GP services rate by age 0-14, 15-24, 25+ increase per year	0-14 years	2.99577E-06	Estimated with constrained optimisation
	15-24 years	0.000307391	
	25 years and older	1.00601E-05	
Waiting for GP initial total	4260.483118		Estimated with constrained optimisation
Referral rate from GP to psychiatrist and allied health service initial	0.045365473		Estimated with constrained optimisation
Referral rate from GP to psychiatrist and allied health service increase per year	0.004929958		Estimated with constrained optimisation
Referral rate from GP to CMHC	0.003341101		Estimated with constrained optimisation
Additional psychiatrist or allied health services per capita per week initial by age 0-14, 15-24, 25+	0-14 years	0.014226087	Estimated with constrained optimisation
	15-24 years	0.008226495	
	25 years and older	0.027601801	
Additional psychiatrist or allied health services per capita per week increase per year by age 0-14, 15-24, 25+	0-14 years	-0.000439327	Estimated with constrained optimisation
	15-24 years	0.00126023	
	25 years and older	-0.000438443	
Referral rate from psychiatrist and allied health to psychiatric hospital care services by age 0-17, 18-24, 25+	0-17 years	0.003455588	Estimated with constrained optimisation
	18-24 years	0.008682608	
	25 years and older	0.007059504	
Waiting for psychiatrist and allied health initial total	41729.37681		Estimated with constrained optimisation
Referral rate from post-discharge to CMHC services initial	0–4 years	0.735839126	Estimated with constrained optimisation
	5–11 years	0.66178922	
	12-14 years	0.721061818	
	15-17 years	0.697091783	
	18-24 years	0.701704305	
	25 years and older	0.777140465	
Referral rate from post-discharge to CMHC services increase per year	0–4 years	0.003500216	Estimated with constrained optimisation
	5–11 years	0.053376831	
	12-14 years	0.010040507	
	15-17 years	0.023416686	
	18-24 years	0.02094671	
	25 years and older	-0.0006888	
Additional CMHC per capita per week initial by age AIHW	0–4 years	0.006479574	Estimated with constrained optimisation
	5–11 years	0.034805066	
	12-17 years	0.092108971	
	18-24 years	0.042861193	
	25 years and older	0.046489093	
Additional CMHC per capita per week increase per year by age AIHW	0–4 years	-0.000243268	Estimated with constrained optimisation
	5–11 years	0.000392489	
	12-17 years	0.002132025	
	18-24 years	0.000638724	
	25 years and older	-0.001044554	
Waiting for CMHC initial total	35055.52948		Estimated with constrained optimisation
Seeking help headspace rate by age 12+ initial	12-14 years	0.000001012955	Estimated with constrained optimisation
	15-17 years	0.000001331976	
	18-24 years	0.000000968132	
	25 years and older	0.000004073255	
Seeking help headspace rate by age 12+ increase per year	12-14 years	0.000509271129	Estimated with constrained optimisation
	15-17 years	0.000408177488	
	18-24 years	0.000215692733	
	25 years and older	-0.000000055495	
Waiting for headspace initial total	0		Estimated with constrained optimisation

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Supplementary Material Part B

Modelled estimates of the health outcomes and economic value of improving the social determinants of mental health

Nature Mental Health

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Contents

Additional results

Table S1: Cumulative cost impacts of improvements to social determinants by payer and degree of improvement

	HEALTH CARE PERSPECTIVE				SOCIETAL PERSPECTIVE				
Scenarios	Australian Government ($)	Queensland Government ($)	Non-government incl. individuals ($)	Total costs ($)	Australian Government ($)	Queensland Government ($)	Non-government incl. individuals ($)	Economy ($)	Total costs ($)
5% improvement									
Business as usual	-	-	-	-	-	-	-	-	-
Social cohesion	-470,455	-15,407,688	-459,144	-16,337,288	-7,283,947	-16,344,095	6,241,397	-20,627,248	-38,013,893
Childhood difficulties	-312,646	-11,055,063	-310,409	-11,678,118	-1,841,487	-11,484,421	1,176,135	-4,800,977	-16,950,750
Homelessness	-6,988,228	-4,650,838	-4,806,364	-16,445,430	-13,604,802	-19,145,236	-4,716,035	-521,478	-37,987,550
Unemployment	-137,509	-490,866	-98,154	-726,529	-707,257	-1,834,956	265,062	-95,033,724	-97,310,874
Discontinue secondary ed.	-3,606	-75,447	-3,127	-82,179	-160,745	-866,581	84,462	-302,431	-1,245,293
Discontinue tertiary ed.	-3,803	-82,990	-3,329	-90,122	-163,094	-886,704	85,242	-646,839	-1,611,395
Substance misuse	-147,137	-791,403	-107,373	-1,045,914	-10,360,971	-107,847,593	672,496	-157,298,402	-274,834,469
Underemployment	-21,309	-224,124	-16,544	-261,977	-209,478	-130,397	163,138	-10,776,591	-10,953,326
10% improvement									
Business as usual	-	-	-	-	-	-	-	-	-
Social cohesion	-939,150	-30,756,351	-916,558	-32,612,060	-14,544,965	-32,627,439	12,463,607	-41,190,763	-75,899,560
Childhood difficulties	-630,654	-22,297,968	-626,116	-23,554,739	-3,738,379	-23,171,915	2,395,656	-9,725,430	-34,240,067
Homelessness	-13,978,197	-9,303,469	-9,613,931	-32,895,597	-27,213,186	-38,296,158	-9,432,877	-1,043,732	-75,985,952
Unemployment	-276,029	-985,976	-197,034	-1,459,039	-1,420,238	-3,683,838	532,634	-190,821,348	-195,392,789
Discontinue secondary ed.	-7,252	-151,752	-6,289	-165,293	-323,580	-1,744,086	170,054	-610,503	-2,508,113
Discontinue tertiary ed.	-7,646	-166,859	-6,693	-181,198	-328,054	-1,783,319	171,481	-1,301,946	-3,241,838
Substance misuse	-294,612	-1,584,910	-214,996	-2,094,518	-20,749,455	-215,976,995	1,347,334	-314,995,803	-550,374,919
Underemployment	-42,745	-449,931	-33,188	-525,864	-420,399	-262,383	327,418	-21,619,820	-21,975,184

All figures are in 2020-21 Australian dollars, cumulative over 11 years, 2024 to 2034, discounted at 5%.
Negative figures indicate a reduction in cost compared with business as usual.
Childhood difficulties = early life and childhood behavioural and emotional difficulties; ed. = education

Table S2: Incremental net monetary benefit vs. business as usual, by degree of improvement, time horizon and perspective (AUD$ million)

	Health care perspective		Societal perspective	
	Time horizon		Time horizon	
Scenario	3 years	11 years	3 years	11 years
5% improvement				
Business as usual	-	-	-	-
Social cohesion	3.44	124.96	3.99	146.64
Childhood difficulties	27.48	229.23	27.60	234.50
Homelessness	2.24	17.21	5.10	38.75
Unemployment	0.27	3.84	45.44	100.43
Discontinue secondary ed.	0.02	0.72	0.07	1.88
Discontinue tertiary ed.	0.03	0.75	0.11	2.27
Substance misuse	0.23	7.88	30.92	281.67
Underemployment	0.13	1.89	5.83	12.58
10% improvement				
Business as usual	-	-	-	-
Social cohesion	6.88	249.41	7.98	292.69
Childhood difficulties	55.09	462.56	55.33	473.24
Homelessness	4.48	34.42	10.20	77.51
Unemployment	0.55	7.72	91.14	201.65
Discontinue secondary ed.	0.04	1.44	0.14	3.79
Discontinue tertiary ed.	0.06	1.50	0.23	4.56
Substance misuse	0.45	15.78	61.88	564.06
Underemployment	0.26	3.78	11.67	25.23

All figures are in 2020-21 AUD$ million, cumulative over 11 years, 2024 to 2034, discounted at 5%.
Quality-adjusted life years have been monetised using a willingness-to-pay of $83,004 per quality-adjusted life year. Source: Shiroiwa et al. [1] , indexed to 2020-21 financial year using the Australian Consumer Price Index.
Incremental net monetary benefit (INMB) = (incremental quality-adjusted life years * willingness-to-pay per quality-adjusted life year) – incremental costs. The cost of interventions is excluded from this calculation of INMB because the changes in social determinants are hypothetical and interventions that would need to be implemented to achieve these changes have not been included here.
Childhood difficulties = early life and childhood behavioural and emotional difficulties; ed. = education

Table S3: Incremental health outcomes vs. business as usual, 5% and 10% improvement, 3 year and 11 year time horizons

	Incremental QALYs gained vs. BAU (n)		Incremental suicide deaths avoided vs. BAU (n)		Incremental self-harm hospitalisations avoided vs. BAU (n)		Incremental MH ED presentations avoided vs. BAU (n)	
	Time horizon		Time horizon		Time horizon		Time horizon	
Scenario	**3 years**	**11 years**	**3 years**	**11 years**	**3 years**	**11 years**	**3 years**	**11 years**
5% improvement								
Business as usual	-	-	-	-	-	-	-	-
Social cohesion	38	1,309	0	5	1	74	12	648
Childhood difficulties	324	2,621	0	1	1	31	42	814
Homelessness	0	9	0	0	0	1	0	4
Unemployment	3	38	0	0	0	4	1	18
Discontinue secondary ed.	0	8	0	0	0	2	0	5
Discontinue tertiary ed.	0	8	0	0	0	2	0	5
Substance misuse	2	82	0	6	11	140	1	40
Underemployment	1	20	0	0	0	1	0	8
10% improvement								
Business as usual	-	-	-	-	-	-	-	-
Social cohesion	76	2,612	0	9	3	148	24	1,294
Childhood difficulties	650	5,289	0	3	2	63	83	1,646
Homelessness	1	18	0	0	0	2	0	9
Unemployment	6	75	0	0	0	7	2	37
Discontinue secondary ed.	0	15	0	0	0	4	0	10
Discontinue tertiary ed.	1	16	0	0	0	4	0	10
Substance misuse	5	165	1	13	22	281	2	79
Underemployment	3	39	0	0	0	1	1	17

All figures are cumulative over 11 years, 2024 to 2034.
QALYs are discounted at 5%. Other health outcomes are not.
QALY: quality-adjusted life year; BAU: business as usual; MH ED: mental health-related emergency department presentations
Childhood difficulties = early life and childhood behavioural and emotional difficulties; ed. = education

Costs

Table S4: Individual cost items for health services, homelessness and substance use disorder

Cost group (Level 1)	Cost category (Level 2)	Cost item (Level 3)	Unit of measure 2020-21 AUD	Unit cost (total of all payers)	State	Common wealth	Non-governme nt incl. individuals	Economy	Perspective	Method	Sources	Assumptions
Health care	Specialised mental health services	Mental health-related hospitalisation	per admitted episode	15,624.00	14,775.19	423.80	425.02	0.00	Health Care and Societal	Unit cost provided directly by IHACPA Payer split derived from total funding of MH expenditure	IHACPA, National Benchmarking Portal, https://benchmarking.ihacpa.gov.au Filter: Year 2020-21, Stream: Mental Health, State: QLD, LHN: Metro South (Qld) and Children's Health Queensland combined Funder split: AIHW Mental health services in Australia: Expenditure on mental health services, Table EXP.32 2020-21	
Health care	Specialised mental health services	Community mental health care services (same for CYMHS & CMHS)	per service contact	272.41	257.61	7.39	7.41	0.00	Health Care and Societal	Total cost of CMHS divided by number of service contacts, both for QLD Payer split derived from total funding of MH expenditure	Service contacts: AIHW Mental health services in Australia: State and territory community mental health services, Table CMHC.1 (2020-21) Total expenditure on CMHS: AIHW Mental Health services in Australia: Expenditure on mental health services, Table EXP.1: Recurrent expenditure on state and territory specialised mental health services, states and territories, 2020-21 Funder source split from AIHW Mental Health Expenditure 2020-21, Table EXP.32 https://www.aihw.gov.au/reports/mental-health-services/mental-health-services-in-australia/	Assume same cost for adults and child/adolescent community services

Health care	Medicare-subsidised services	Non-GP mental health professional consultations (psychiatrists, psychologists, allied health)	per service contact	165.14	0.00	118.89	46.25	0.00	Health Care and Societal	Total Australian Government funded cost of Medicare-subsidised non-GP MH services for QLD divided by number of non-GP MH MBS services provided for QLD for Commonwealth split. OOP additional gap payment estimated by calculating the proportion of gap between total fees charged and benefits paid by Medicare for each service type (weighted average for all non-GP MH professionals) based on national data because this is not provided by state. This approach has the advantage of effectively being a weighted average of all relevant MBS item numbers rather than having to pick a specific item/s from the MBS schedule.	Mental health services in Australia: Expenditure on mental health services, Table EXP.18 for total expenditure by service for QLD Mental health services in Australia: Medicare-subsidised mental health-specific services, Table MBS.11 for service counts Mental health services in Australia: Expenditure on mental health services, Table EXP.23 for derived gap proportions https://www.aihw.gov.au/reports/mental-health-services/mental-health-services-in-australia/	% gap payment for Australian national average is generalisable to QLD
Health care	Medicare-subsidised services	General practitioner	per service contact	89.87	0.00	84.54	5.33	0.00	Health Care and Societal	Same as above but for GPs only	Same as non-GP MH professionals but for GPs only	% gap payment for Australian national average is generalisable to QLD
Health care	PBS-subsidised prescriptions	Where the prescriber is a GP	per patient per year	109.32	0.00	96.35	12.97	0.00	Health Care and Societal	Total PBS-subsidised expenditure on any MH-related medication prescribed by GPs divided by number of patients with at least 1 MH-related prescription filled in 2020-21. Proportion of OOP spend derived from general PBS expenditure on all subsidised medicines.	Total expenditure on MH-related medicines by all type of prescribers from AIHW Mental Health Expenditure Table EXP.26 Number of patients with prescription per prescriber from Table PBS.2, where fully subsidised or co-payment involved Proportion of OOP contribution to PBS medicines derived from AIHW general Health Expenditure Table A3	% gap payment for all medicines is generalisable to MH-related prescriptions
Health care	PBS-subsidised prescriptions	Where the prescriber is a non-GP	per patient per year	205.19	0.00	180.85	24.34	0.00	Health Care and Societal	As per methods for GPs but for psychiatrists and psychologists	As per sources for GPs but for psychiatrists and psychologists	% gap payment for all medicines is generalisable to MH-related prescriptions

		mental health professional										
Health care	Emergency care	Ambulance cost weighted average	per attendance	641.00	641.00	0.00	0.00	0.00	Health Care and Societal	Unit cost given	Queensland Ambulance Service https://www.ambulance.qld.gov.au/docs/Public-Performance-Indicators-Fourth-Quarter-2020-21.pdf Cost per incident for Metro South	
Health care	Emergency care	Emergency department presentation	per presentation	662.99	662.99	0.00	0.00	0.00	Health Care and Societal	Unit cost given	IHACPA NHCDC Round 25 2020-21 Appendix Table 8 ED by Jurisdiction, average cost per presentation for QLD, all presentation types https://www.ihacpa.gov.au/resources/national-hospital-cost-data-collection-nhcdc-public-hospitals-report-2020-21	
Health care	Specialised mental health services	Online services currently available	per person per year	0.00	0.00	0.00	0.00	0.00	Health Care and Societal	Various services are currently available at no cost, or accessible at not cost after a referral by a health care professional.		Assume that the cost of maintaining existing online services do not change between interventions and therefore excluded from analysis.
Homelessness	Youth homelessness 15-24yo	Specialised homelessness services	per person	3,695.00	3,695.00	0.00	0.00	0.00	Societal only	Unit cost given	Department of Communites, Housing and Digital Economy, 2020-2021 annual report, Queensland; page 44 https://www.chde.qld.gov.au/__data/assets/pdf_file/0020/18722/annual-report-2010-21.pdf	Assumes all costs borne by State
Homelessness	Youth homelessness 15-24yo	Criminal justice costs	per person per year	10,774.45	10,774.45	0.00	0.00	0.00	Societal only	Unit cost given Indexed from 2011-12 to 2020-21 using GNE IPD	CSI report - MacKenzie 2016 - The cost of youth homelessness - Research Briefing, page 3 https://www.csi.edu.au/media/uploads/CYHA_FINAL_REPORT_18April2016_v0dqGpT.pdf Indexation from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	Assumes all criminal justice costs paid by the state

Homelessness	Youth homelessness 15-24yo	Additional health care costs	per person per year	10,112.96	2,820.24	4,321.19	2,971.53	0.00	Health Care and Societal	Unit cost given Payer split derived from total funding of general health care expenditure Indexed from 2011-12 to 2020-21 using AIHW health price index	CSI report - MacKenzie 2016 - The cost of youth homelessness - Research Briefing, page 2 https://www.csi.edu.au/media/uploads/CYHA_FINAL_REPORT_18April2016_v0dqGpT.pdf Funder splits from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	
Homelessness	Adult homelessness	Specialised homelessness services	per person per year	3,695.00	3,695.00	0.00	0.00	0.00	Societal only	Same as youth homelessness	Same as youth homelessness	Assume same as youth homelessness
Homelessness	Adult homelessness	Additional health care costs	per person per year	17,541.72	4,891.92	7,495.44	5,154.35	0.00	Health Care and Societal	Unit cost given Payer split derived from total funding of general health care expenditure Indexed from 2010-11 to 2020-21 using AIHW health price index	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	
Homelessness	Adult homelessness	Criminal justice costs	per person per year	6,915.69	6,915.69	0.00	0.00	0.00	Societal only	Unit cost given Indexed from 2010-11 to 2020-21 using GNE IPD	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	Assumes all criminal justice costs fall to the state

Homelessness	Adult homelessness	Welfare and taxation forgone	per person per year	8,395.64	0.00	8,395.64	-8,395.64	0.00	Societal only (transfer payment, expense for Commonwealth but income for non-government)	Unit cost given Indexed from 2010-11 to 2020-21 using wage price inflator derived from ABS	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from Australian Bureau of Statistics Wage Price Index, table 2a https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/wage-price-index-australia/jun-2022#data-downloads	Assumes all welfare and taxation forgone incurred by Commonwealth gov
Homelessness	Adult homelessness	Children placed in care	per person per year	2,742.39	2,742.39	0.00	0.00	0.00	Societal only	Unit cost given Indexed from 2010-11 to 2020-21 using GNE IPD	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	Assumes all childcare protection services funded by state
Substance Misuse	Alcohol dependency	Healthcare cost	per person with alcohol dependence per year	5,562.77	1,551.31	2,376.93	1,634.53	0.00	Health Care and Societal	Total cost of health care due to alcohol addiction from KPMG report divided by estimated prevalence of alcohol use disorder. Payer split derived from total funding of general health care expenditure.	Total cost attributable to aclohol dependence: A KPMG and Rethink Addiction report in 2022 https://www.rethinkaddiction.org.au/understanding-the-cost-of-addiction-in-australia Number of people with alcohol use disorder from ABS National Study of Mental Health and Wellbeing 2020-2022 https://www.abs.gov.au/statistics/health/mental-health/national-study-mental-health-and-wellbeing/2020-2022/Table 2 - 12-month mental disorders and severity by sex.xlsx Payer split for general health care costs: https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	
Substance Misuse	Alcohol dependency	Justice and law enforcement	per person with alcohol dependence per year	12,662.34	12,662.34	0.00	0.00	0.00	Societal only	As above but for justice and law enforcement	As above	

Substance Misuse	Alcohol dependency	Workplace productivity	per person with alcohol dependence per year	8,020.46	0.00	0.00	0.00	8,020.46	Societal only	As above but for workplace productivity	As above
Substance Misuse	Alcohol dependency	Household productivity	per person with alcohol dependence per year	8,744.59	0.00	0.00	0.00	8,744.59	Societal only	As above but for household productivity	As above
Substance Misuse	Alcohol dependency	Social services	per person with alcohol dependence per year	1,721.76	0.00	1,721.76	-1,721.76	0.00	Societal only	As above but for social services	As above
Substance Misuse	Alcohol dependency	Engaging in harmful consumption	per person with alcohol dependence per year	6,369.54	0.00	0.00	0.00	6,369.54	Societal only	As above but for harmful consumption	As above
Substance Misuse	Illicit drugs dependency	Healthcare cost	per person with illicit drug dependence per year	5,803.52	1,618.45	2,479.80	1,705.27	0.00	Health Care and Societal	Total cost of health care attributable to addiction to other drugs from KPMG report divided by estimated prevalence of dependence on illicit drugs. Payer split derived from total funding of general health care expenditure.	Total cost attributable to illicit drug dependence: A KPMG and Rethink Addiction report in 2022 https://www.rethinkaddiction.org.au/understanding-the-cost-of-addiction-in-australia Prevalence of drug use disorder from ABS National Study of Mental Health and Wellbeing 2020-2022 https://www.abs.gov.au/statistics/health/mental-health/national-study-mental-health-and-wellbeing/2020-2022/Table 2 - 12-month mental disorders and severity by sex.xlsx Payer split for general health care costs: https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data
Substance Misuse	Illicit drugs dependency	Justice and law enforcement	per person with illicit drug dependence per year	33,083.48	33,083.48	0.00	0.00	0.00	Societal only	As above	As above
Substance Misuse	Illicit drugs dependency	Workplace productivity	per person with illicit drug dependence per year	13,594.55	0.00	0.00	0.00	13,594.55	Societal only	As above	As above

Substance Misuse	Illicit drugs dependency	Household productivity	per person with illicit drug dependence per year	8,586.03	0.00	0.00	0.00	8,586.03	Societal only	As above	As above	
Substance Misuse	Illicit drugs dependency	Social services	per person with illicit drug dependence per year	1,130.04	0.00	1,130.04	-1,130.04	0.00	Societal only	As above	As above	
Substance Misuse	Illicit drugs dependency	Engaging in harmful consumption	per person with illicit drug dependence per year	9,716.07	0.00	0.00	0.00	9,716.07	Societal only	As above	As above	
Headspace		Overall headspace services	per occasion of service	234.45	0.00	234.45	0.00	0.00	Health Care and Societal	Unit cost provided directly by KPMG evaluation, indexed to 2020-21 financial year	KPMG 2022 - National headspace evaluation final report June 2022	Assume fully funded by Commonwealth Assume national average applies to BSPHN
Alcohol & other drug treatment services		Overall AOD treatment services	per episode of care	10,122.72	4,960.13	3,138.04	2,024.54	0.00	Health Care and Societal	Total cost of AOD treatment services $1.26 billion divided by 145,226 episodes of care, then indexed to 2020-21	National Drug and Alcohol Research Centre, UNSW - New Horizons: The review of alcohol and other drug treatment services in Australia, Final Report July 2014 https://ndarc.med.unsw.edu.au/sites/default/files/ndarc/resources/New%20Horizons%20Final%20Report%20July%202014.pdf	The total cost of AOD treatment services is incurred by people that actually gain access to those services and have closed episodes of care. Assume national average applies to BSPHN
Child and Youth Mental Health Services		Overall CYMH services	per patient day	2,597.35	2,456.24	70.45	70.66	0.00	0.00	Unit cost provided by AIHW reprot, indexed to 2020-21	AIHW - Expenditure on mental health services 2019-20, page 5 https://www.aihw.gov.au/getmedia/030bb981-9de2-4520-8831-d9ddff1f6c4a/expenditure-on-mental-health-related-services-2019-20.pdf.aspx	Assume national average applies to BSPHN

Table S5: Individual cost items for productivity-related categories

Productivity item	Unit of measure	Amount <25 years	Amount 25+ years	Payer	Perspective	Method	Sources	Assumptions
Absenteeism from paid work due to medium & high distress	per person per year	1,327.23	2,945.42	Economy	Societal only	Days absent for people with MH disorders (11 days) x weighted average weekly earnings for age group (converted to days)	Days off work due to psychological distress for people with MH from Productivity Commission Inquiry, Appendix H https://www.pc.gov.au/inquiries/completed/mental-health/report Median weekly earnings from Australian Bureau of Statistics, Characteristics of employment, August 2021 https://www.abs.gov.au/statistics/labour/earnings-and-working-conditions/employee-earnings/aug-2021#data-downloads	Absenteeism and presenteeism costs are the same for all people with high or medium distress, regardless of whether they are diagnosed with a disorder.
Presenteeism at paid work due to medium & high distress	per person per year	965.26	2,142.12	Economy	Societal only	Days working at reduced activity (8 days) x 50% productivity for those days x weighted average weekly earnings for age group (converted to days)	Days at reduced capacity and 50% productivity for those days from Productivity Commission Inquiry, Appendix H, link as above.	
Absenteeism from paid work due to MH-related hospitalisation	per person per day in hospital	121.00	268.00	Economy	Societal only	weighted average weekly earnings for age group (converted to days)	Average weekly earnings as per absenteeism	
Paid work productivity lost due to premature mortality, human capital approach	per death	31,370.84	69,618.95	Economy	Societal only	Weighted average weekly earnings x 52 weeks x years of productive life lost (67 less age at death) discounted	Average weekly earnings as per absenteeism	Person would have otherwise remained alive and employed to the age of 67
Paid work productivity lost due to high distress, human capital approach	per person per year	31,370.84	69,618.95	Economy	Societal only	Annual cost of lost productivity incurred each year a person remains unemployed due to high distress	As above	
Absenteeism from unpaid work due to medium & high distress	per person per year	688.46	1,104.61	Economy	Societal only	Time spent on unpaid work per day (minutes) / 60 minutes per hour x weighted average hourly earnings for age group x 11 days absent from normal duties Opportunity cost method to value hours of unpaid work using median hourly earnings	Time spent on unpaid work: How Australians Use Their Time (ABS) https://www.abs.gov.au/statistics/people/people-and-communities/how-australians-use-their-time/latest-release#data-downloads Median hourly earnings from Characteristics of Employment (ABS) https://www.abs.gov.au/statistics/labour/earnings-and-working-conditions/employee-earnings/aug-2021#data-downloads	Assume presenteeism does not apply to unpaid work. Assume same unpaid work time lost for all ages. (data not available from time use survey by age AND employment status) Assume days absent from unpaid work is the same as paid work reported by Productivity Commission.

Unpaid work productivity lost due to premature mortality, human capital approach	per death	22,844.37	36,653.00	Economy	Societal only	As above but multiplied by 365 days per year x years of productive life lost (67 less age at death) discounted	As above	Assume unpaid work occurs every day of the year
Absenteeism from unpaid work due to medium & high distress	per person per year	792.81	1,272.04	Economy	Societal only	As above but for unemployed daily time use	As above	
Unpaid work productivity lost due to premature mortality, human capital approach	per death	26,307.03	42,208.73	Economy	Societal only	As above but for unemployed daily time use	As above	
Absenteeism from unpaid work due to medium & high distress	per person per year	860.38	1,380.46	Economy	Societal only	As above but for NILF time use	As above	
Unpaid work productivity lost due to premature mortality, human capital approach	per death	28,549.11	45,806.07	Economy	Societal only	As above but for NILF time use	As above	
Absenteeism for carers (days off due to caring for someone with medium or high distress, with or without disorder)	per person per year	637.07	1,413.80	Economy	Societal only	0.44 x 12 days x average weekly earnings (converted to days)	90% of people with high or very high distress, regardless of diagnosis, have 1 carer. 44% carers experience 1 day absent from work every 30 days Mental health productivity draft report 2019: https://apo.org.au/sites/default/files/resource-files/2019-10/apo-nid265801_5.pdf table page 467	Assumes only absenteeism, no presenteeism for carers because they are not ill. Assumes every person with medium or high distress has 1 carer (but only 44% of those carers experience absenteeism).
Carers payment allowance (to be applied to each person with medium or high distress with diagnosed disorder)	$ per person per year	12,557.15	12,557.15	Commonwealth (income households)	Societal only	Dividing total carer welfare expenditure (allowance, payment and supplement) by carer recipients where main condition is psychological or psychiatric	24% of carer receive a carer's allowance. Productivity Commission Inquiry Report, Mental Health, Volume 3, pages 912 and 913	Assume one carer per person with medium or high distress and a diagnosed disorder

Utilities

Table S6: Utilities used to calculate quality-adjusted life years, ages 12 years and greater

	General population without distress	Low distress	Moderate, high, v. high without disorder	Moderate, high, v. high with disorder
12-14	0.9600	0.9264	0.8880	0.8223
15-17	0.9600	0.9235	0.8785	0.7983
18-24	0.9600	0.9185	0.8573	0.8073
25+	0.9125	0.8772	0.7914	0.7279

Table S7: Utilities used to calculate quality-adjusted life years, ages 11 years and less

Age group	General population without distress	Close to average	Slightly raised	High and very high
0-4 years	0.96	0.8678	0.7602	0.6808
5-11 years	0.96	0.8659	0.7595	0.6750

Projected social determinants, business as usual vs. improvements

Figure S1: Social cohesion projection

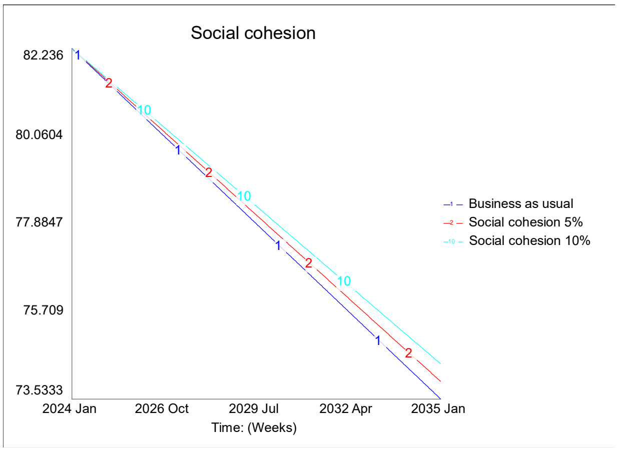
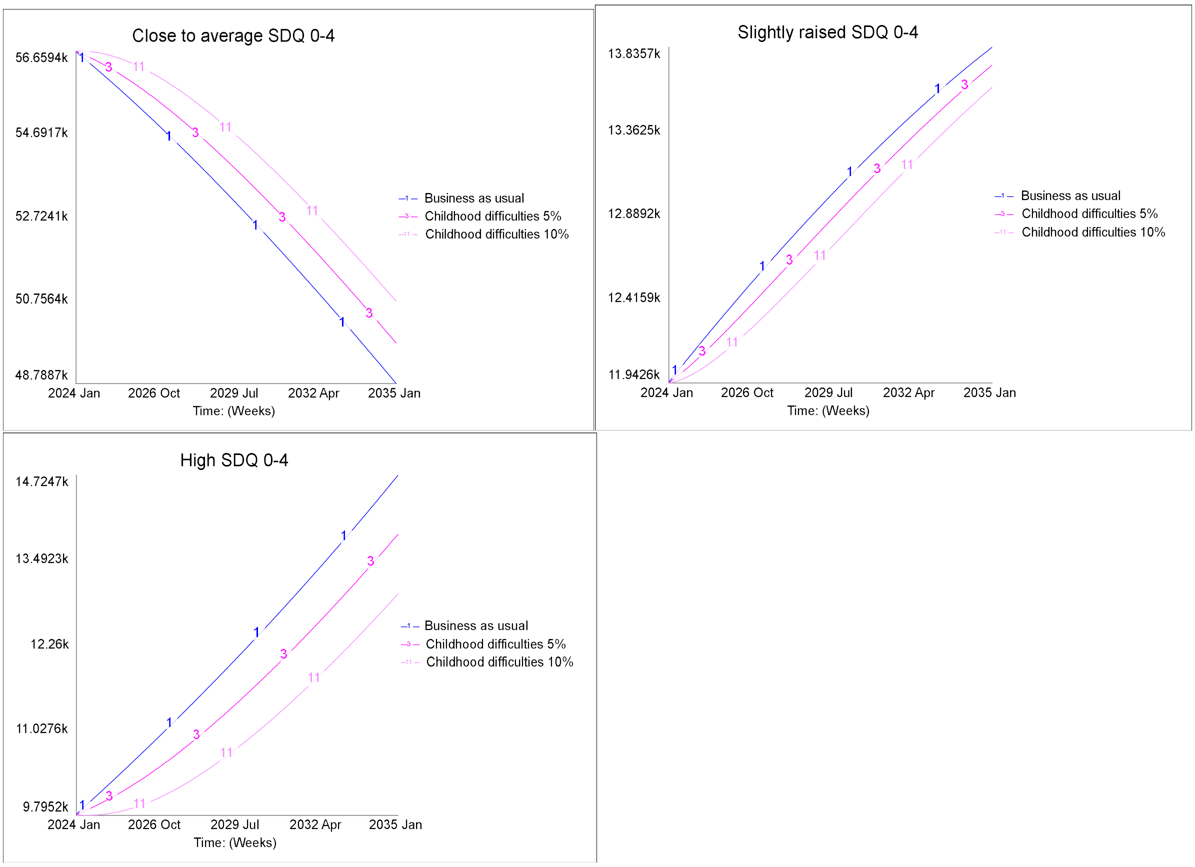


Figure S2: Childhood difficulties projection



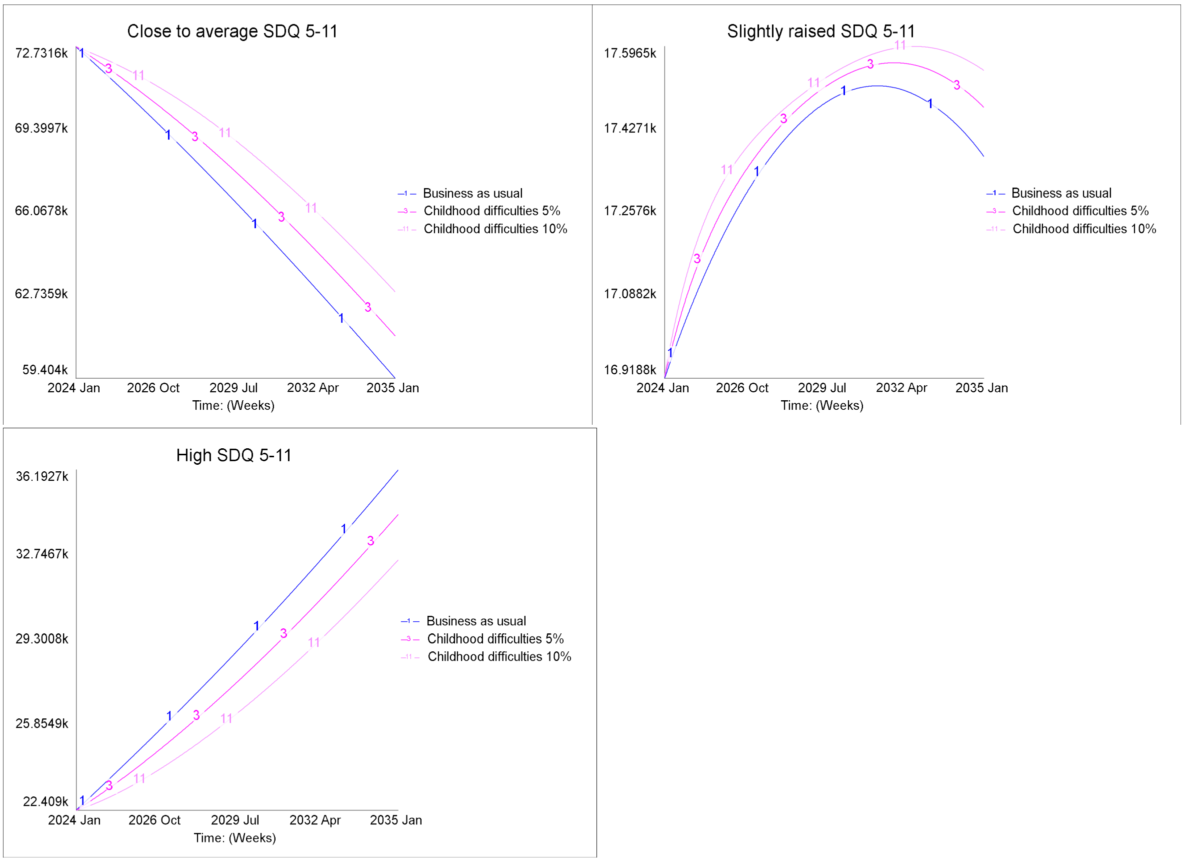
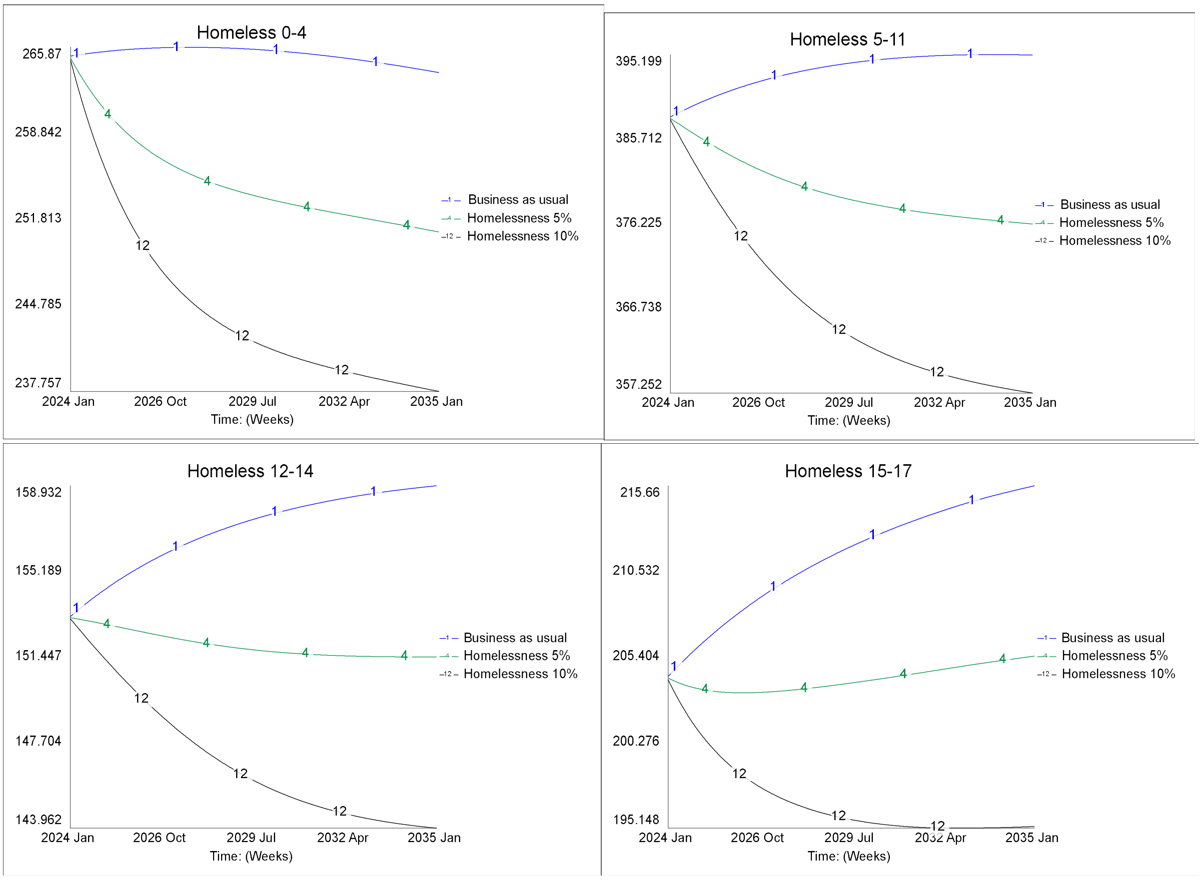


Figure S3: Homelessness projection



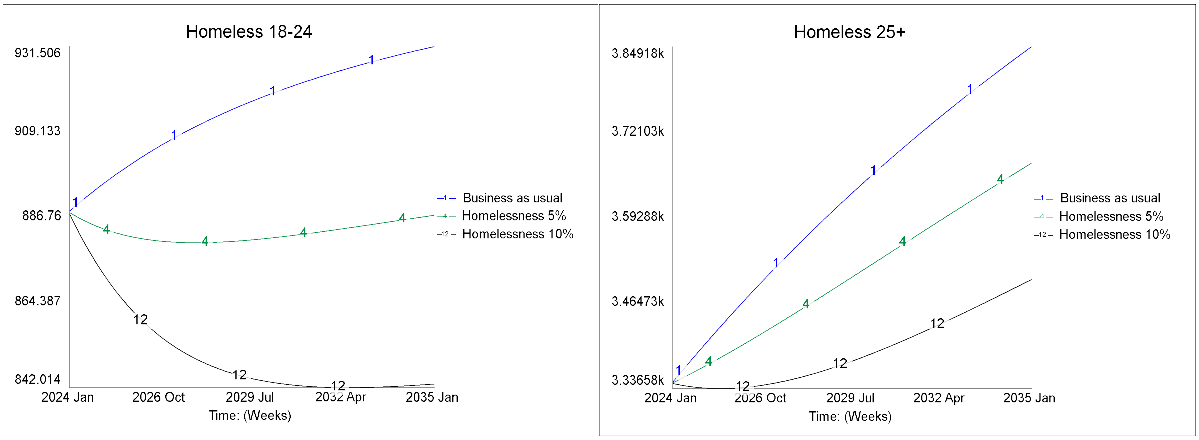


Figure S4: Unemployment projection

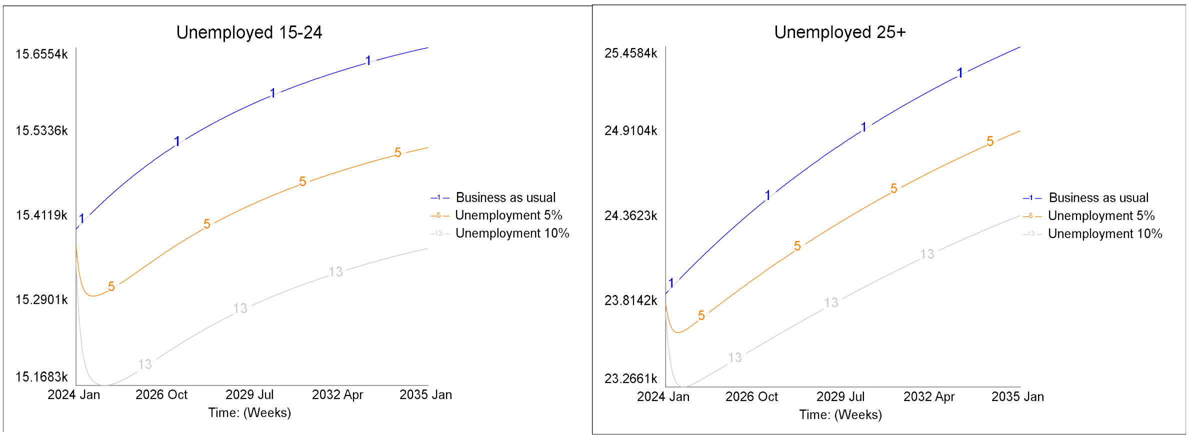


Figure S5: Underemployment projection

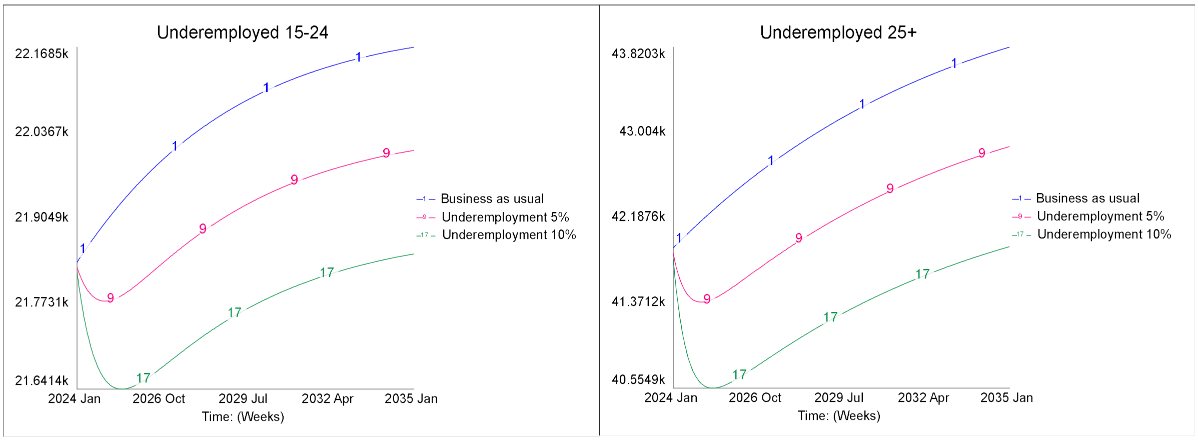


Figure S6: Discontinuing secondary education projection

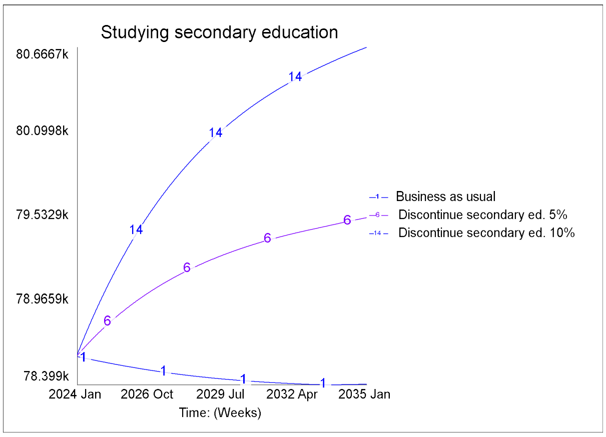


Figure S7: Discontinuing tertiary education projection

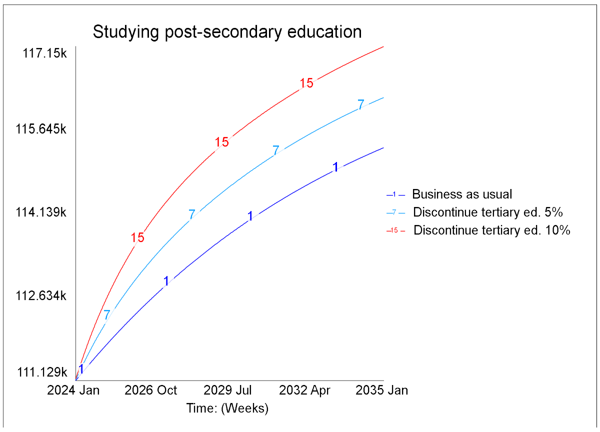
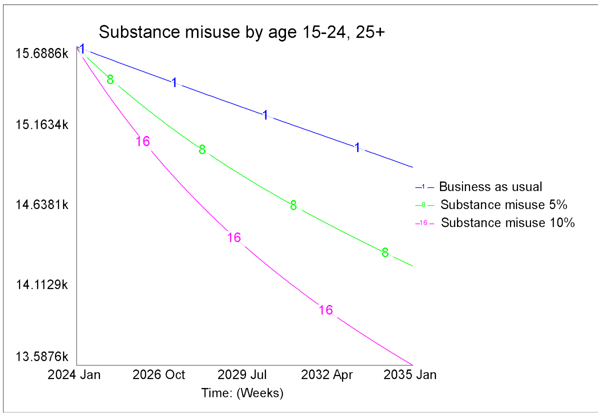


Figure S8: Substance misuse projection



Sensitivity analysis

Both 5% and 10% improvements in social determinants are reported in the main results. Alternative time horizons also form part of the main results. Further univariate sensitivity analysis was performed on selected parameters that may have a material impact on the rank ordering of social determinants and overall conclusions:

1. Utility values for ages 12 and above were varied -/+ 10%. Utilities are used to calculate quality-adjusted life years.
2. Utility values for ages 0 to 11 were varied -/+ 10%.
3. Costs incurred by people who experience homelessness additional to the general population were varied -/+ 20%.
4. Costs incurred by people who experience substance misuse disorder additional to the general population were varied -/+ 20%.

The results of the sensitivity analysis are reported in Table S8 and Table S9 in terms of incremental net monetary benefit for the societal perspective. INMB shifts in the expected direction for each sensitivity analysis but not enough to alter the rank ordering of social determinants based on this measure.

Table S8: Sensitivity analysis, incremental net monetary benefit (societal perspective, $M)

		Utilities ages 12+		Utilities up to age 11		Homelessness costs		Substance misuse costs	
Scenario	Base case analysis	-10%	+10%	-10%	+10%	-20%	+20%	-20%	+20%
Business as usual	-	-	-	-	-	-	-	-	-
Social cohesion	146.6	138.3	155.0	144.1	149.2	146.6	146.7	146.6	146.7
Childhood difficulties	234.5	231.8	237.2	215.5	253.5	234.5	234.5	234.5	234.5
Homelessness	38.7	38.7	38.8	38.7	38.7	31.3	46.2	38.7	38.8
Unemployment	100.4	100.1	100.7	100.4	100.4	100.3	100.6	100.4	100.5
Discontinue secondary ed.	1.9	1.8	1.9	1.9	1.9	1.9	1.9	1.8	1.9
Discontinue tertiary ed.	2.3	2.2	2.3	2.3	2.3	2.3	2.3	2.2	2.3
Substance misuse	281.7	281.0	282.3	281.7	281.7	281.5	281.8	275.1	288.2
Underemployment	12.6	12.4	12.7	12.6	12.6	12.6	12.6	12.6	12.6

Table S9: Sensitivity analysis, rank order of incremental net monetary benefit (societal perspective)

		Utilities ages 12+		Utilities up to age 11		Homelessness costs		Substance misuse costs	
Scenario	Base case analysis	-10%	+10%	-10%	+10%	-20%	+20%	-20%	+20%
Business as usual	-	-	-	-	-	-	-	-	-
Social cohesion	3	3	3	3	3	3	3	3	3
Childhood difficulties	2	2	2	2	2	2	2	2	2
Homelessness	5	5	5	5	5	5	5	5	5
Unemployment	4	4	4	4	4	4	4	4	4
Discontinue secondary ed.	8	8	8	8	8	8	8	8	8
Discontinue tertiary ed.	7	7	7	7	7	7	7	7	7
Substance misuse	1	1	1	1	1	1	1	1	1
Underemployment	6	6	6	6	6	6	6	6	6

Assumptions

Assumption	Justification	Implications
Structure, including scope & population		
The model focuses on youth mental health but includes the entire Brisbane South population. Ages below 25 years old are grouped based on advice from the model development group using developmental stages and progression through school. The adult population is represented by a single group of those aged 25 and over.	The whole population was included to capture health and other impacts as young people age, more relevant for longer time horizons, and whole-system representation of mental health service use and other indirect impacts, such as the influence of social determinants.	Economic outcomes are based on all age groups to capture whole-system representation in resource allocation decisions. Stratification of age groups may over or under estimate the impact of interventions in practice that might be targeted at more specific ages. The aggregation of all adults into a single group requires the use of the same average weekly earnings (applied to non-fatal productivity impacts) and the same number of years of productive life lost due to premature mortality for anyone aged 25 and over.
Population is modelled in aggregated stocks rather than individuals	Inherent to system dynamics approach to modelling at the population level and data availability	Individual heterogeneity is not represented at the level of individual trajectories in this system dynamics model
Psychological distress and disorder is represented using 3 categories based on the K10 and proportion of people in distressed health states that had a diagnosable disorder	Adopts categories specified by the Australian Bureau of Statistics and simplifies complexity of a greater number of health states	Fails to account for individual complexity and nuance within distress-based health states, potentially oversimplifying clinical reality
Linear continuation of trends assumed for business as usual scenario	Simplifying assumption to enable model development	Future states of the world may be very different to what has occurred in the past, creating uncertainty around results.
Time horizon and discounting		
Default time horizon set to 11 years	Balances the need for decision-maker and political relevance, capturing some degree of long term effects, and computational feasibility	11 years is shorter than conventional economic evaluation where lifetime time horizon is common. The cost effectiveness of interventions may change beyond this timeframe.
5% discount rate adopted based on guidance issued by Pharmaceutical Benefits Advisory Committee	Common practice in economic evaluation to take account of time preference for money and opportunity cost of capital	Reduces the value of health and cost consequences that occur in future years
Social determinants		
Any changes to social determinants are hypothetical. The analysis is naïve to whether such change are achievable by interventions and at what cost.	Underlying premise of the analysis.	The health and economic value of improvements to social determinants do not take into account the cost of achieving those changes or if those improvements are even achievable. This is not a cost-effectiveness analysis.
Only selected social determinants are included in the model based on stakeholder feedback and data availability.	Boundaries are necessary to keep the modelling exercise tractable	There may be other social determinants not included in the model that may be more valuable to improve
Behavioural assumptions		
Transition rates between distress states depends on socio-economic factors, such as unemployment and homelessness	Reflects evidence on social determinants of mental health	Relationships may be mis-specified or incomplete
Services were assumed to be operating at 100% based on their	Key system feedback identified in participatory modelling and	Critical driver of unintended consequences

current activity levels, and service capacity constraints affect waiting times and outcomes	assumption checked with model development group	
Calibration		
Where data were unavailable, parameters were estimated via calibration to historical trends using Powell's method of optimisation	Ensures internal consistency with observed data	May over or underestimate actual relationships between system components
Quality-adjusted life years		
For people aged 12 and over, utilities were derived by mapping average K10 scores for distressed health states to the EQ-5D using a published mapping algorithm	Necessary for cost-utility analysis	Uncertainty is introduced, both by the underlying mapping algorithm and the representativeness of the resulting K10-EQ-5D QALY changes to actual quality of life changes in practice as a result of some system change
For children aged under 15 years, utilities were derived by mapping average SDQ scores to CHU-9D using a published mapping algorithm	Necessary for cost-utility analysis	Uncertainty is introduced, both by the underlying mapping algorithm and the representativeness of the resulting CHU-9D based QALY changes to actual quality of life changes in practice as a result of some system change
Costs		
Inflation not explicitly accounted for	Costs are indexed to the same financial year, ensuring consistent financial units, but inflation levels in future years is unknown	May under or over estimate actual cash costs that are incurred in any category in future years
Societal perspective includes productivity, selected non-health sector costs	Captures broader economic impact based on judgement of categories most relevant to the decision context	Excludes many cost categories that technically fall within a societal perspective, like environmental impacts. Likely to enhance the cost effectiveness of interventions
Intervention costs informed by stakeholder feedback and model development group, informed by resource use mentioned in literature	Reflects most likely resource use and costs if the intervention were implemented in the region	May over or under estimate actual costs incurred by implementing an intervention
Uncertainty		
Only parameter uncertainty was explored, not structural uncertainty	Resource and time constraints	Alternative model structures may yield different results
Effects are assumed to be homogenous for all age groups to which they were applied	Simplifies modelling development given data limitations	May obscure differential impacts experienced by subgroups in practice, such as, socioeconomic group, gender, sexual orientation, race or geography

References

1 Shiroiwa, T. *et al.* International survey on willingness-to-pay (WTP) for one additional QALY gained: what is the threshold of cost effectiveness? *Health Econ* **19**, 422-437 (2010). https://doi.org/10.1002/hec.1481

Appendix 4: Supplementary material for Chapter 4 (Modelling Study 3 as published in *Value in Health*)

Supplementary Material Part A

The health and economic benefits of mental health system reform: exploring the optimal mix of interventions and service capacity through simulation modelling

Model structure

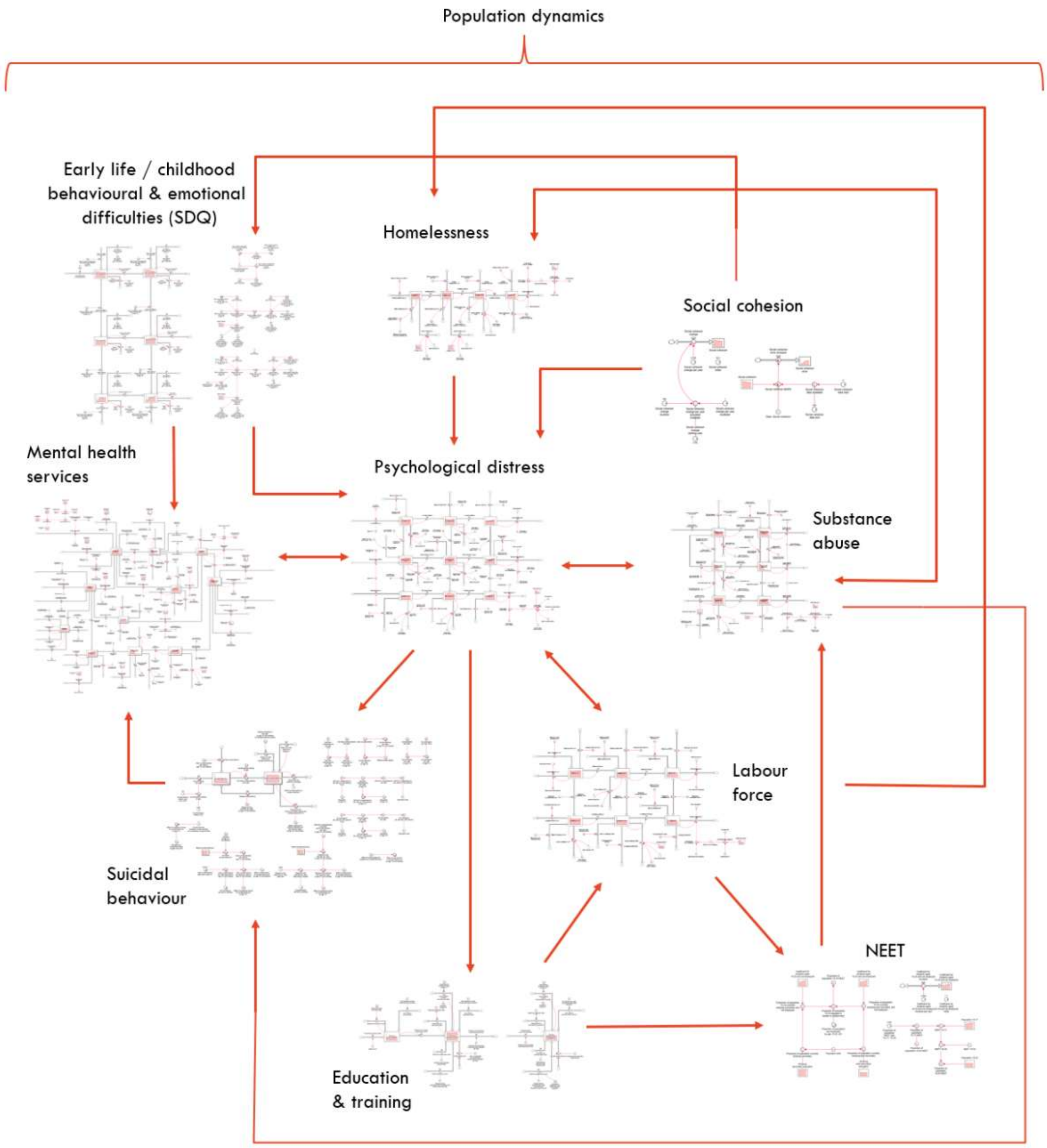
Overview

This system dynamics model was developed for the Brisbane South Primary Health Network (BSPHN) population catchment and consists of multiple sectors that represents different aspects of the population. Supplementary Figure 1 presents an overview of the model structure showing the causal links between different sectors. Supplementary Figures 2 to 22 present the structure of each sector. Please note that for each stock, an inflow representing the suicide deaths prevented through various interventions is included in the model but have been left out of these figures for visual clarity.

The sectors of the model included are:

- **Population** which models the resident population divided into six ages brackets (0-4-year-olds, 5-11, 12-14, 15-17, 18-24, and 25 and older),
- **Education** which models students enrolled in primary, secondary and post-secondary education, and people with different levels of highest qualifications,
- **Labour force** which models unemployment, underemployment and participation rates,
- **Not in education, employment nor training (NEET)** which models the youth population aged 15-24 years not in education, employment nor training,
- **Homelessness** which models the population experiencing homelessness,
- **Substance misuse** which models the prevalence of 12-month substance misuse disorder and substance misuse closed treatment episodes,
- **Psychological distress / disorder** which models the prevalence of low psychological distress and the prevalence of moderate to very high psychological distress. The population with moderate to very high psychological distress is further dichotomised by whether nor not they meet the criteria for any 12-month psychological disorder,
- **Strengths and difficulties** which models the prevalence of behavioural and emotional difficulties among children aged 0-4-years and 5-11-years as measured by the Strengths and Difficulties Questionnaire (SDQ),
- **Social cohesion** which models the population level of social cohesion according to the Scanlon-Monash Index of Social Cohesion,
- **Suicidal behaviours** which models the rates of suicide attempts and suicide deaths, and
- **Mental health services** which models the mental health services delivered by health professionals.

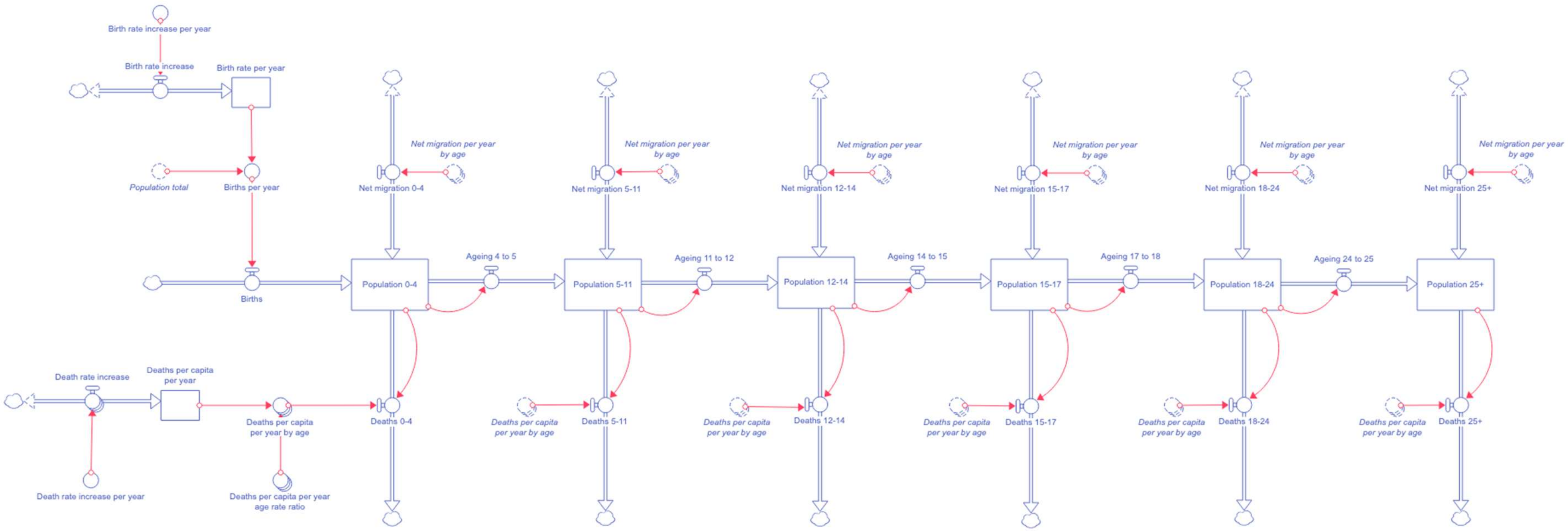
Data used to calibrate each sector are described in figure captions. For any data extracted at the Statistical Area (SA) level of geographic granularity (such as those from the Australian Bureau of Statistics (ABS)), we concorded these data to Primary Health Network (PHN) level estimates through concordance files supplied by the Australian Department of Health and Aged Care (2023).



Supplementary Figure 1. Overview of the causal structure of the system dynamics model

Population

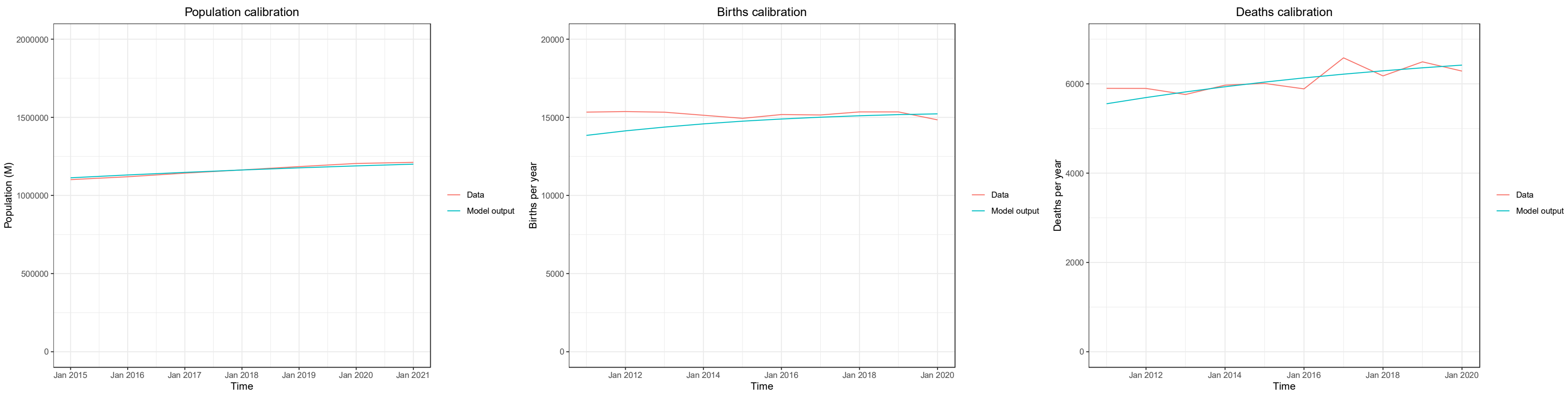
Supplementary Figure 2a. Structure of the population sector



The population sector models the estimated resident population of the BSPHN catchment into six age-specific stocks. The stocks correspond to people aged 0-4 years, 5-11 years, 12-14 years, 15-17 years, 18-24 years, and 25 years and older. Each stock has a mortality outflow and a net migration biflow. Births flow into the stock of 0–4-year-olds and people follow an ageing chain flowing from the younger to older age stocks This sector is calibrated with data based on estimated resident population data from the

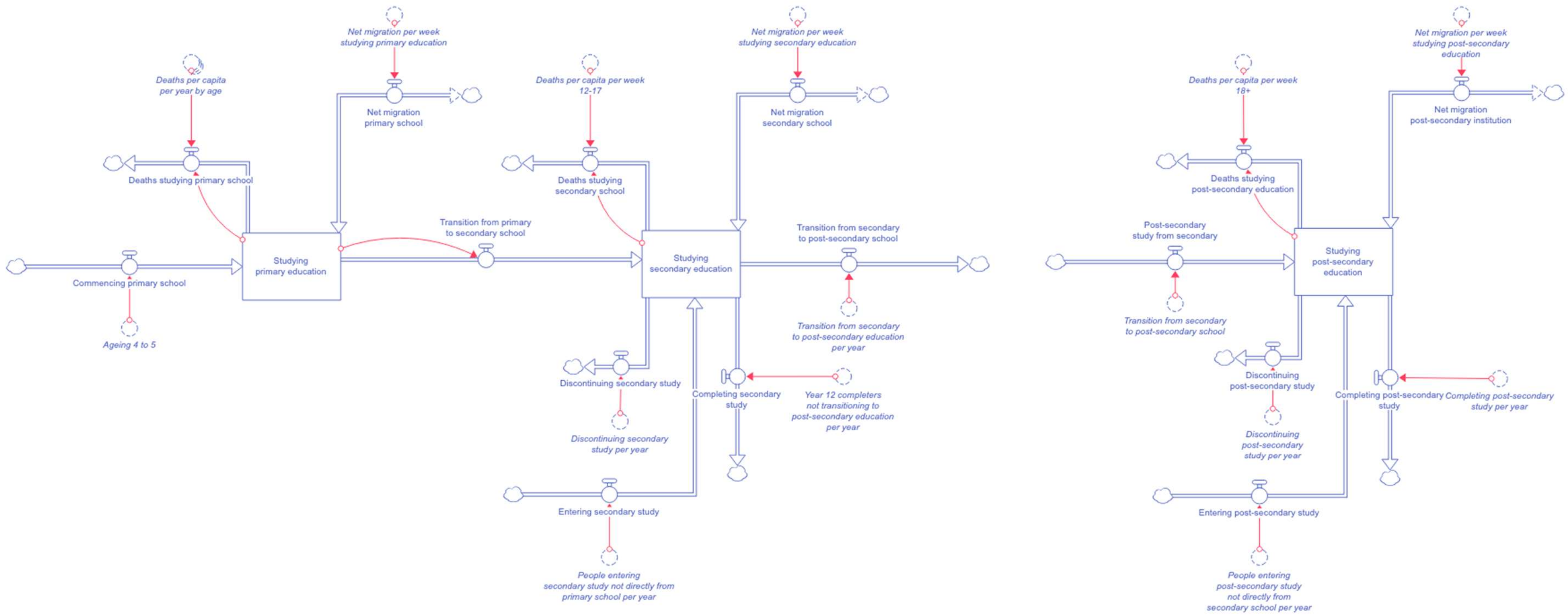
Public Health Information Development Unit (PHIDU) at Torrens University Australia (Public Health Information Development Unit, 2016-2021), and births (Australian Bureau of Statistics, 2021a), deaths (Australian Bureau of Statistics, 2021b), and migration (Australian Bureau of Statistics, 2020) statistics from the ABS.

Supplementary Figure 2b. Calibration plots from the population sector



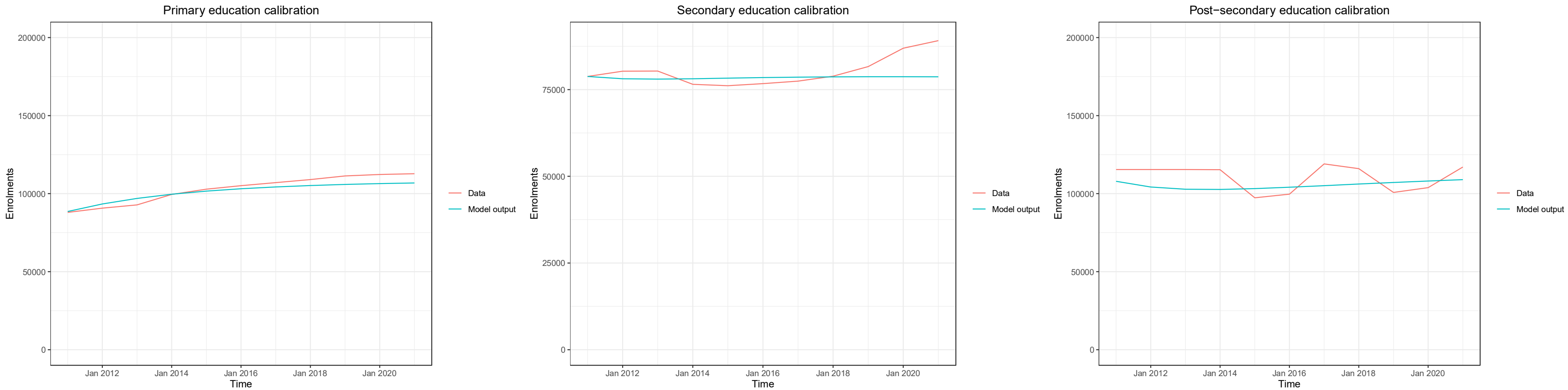
Education (students)

Supplementary Figure 3a. Structure of the education (students) sector



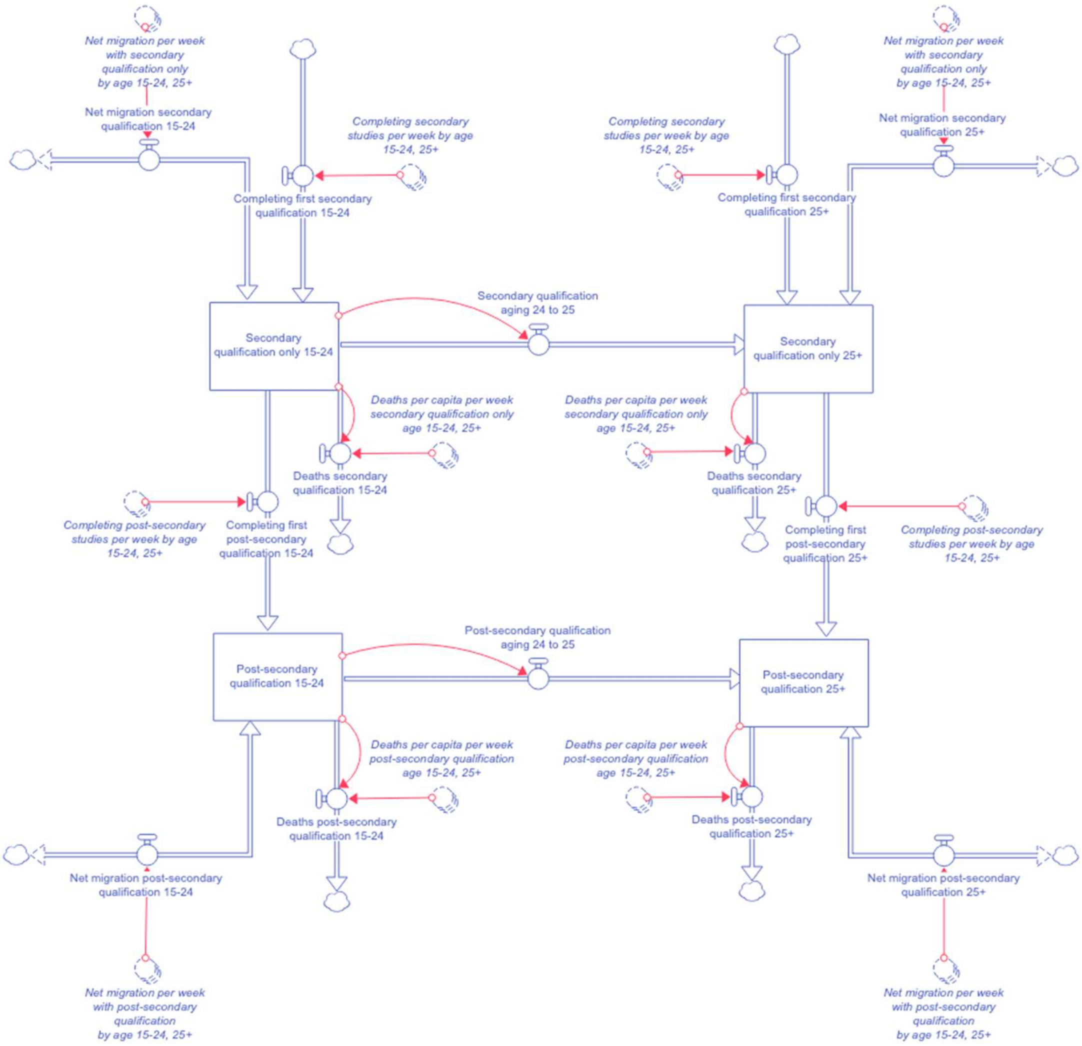
The education (students) sector models students enrolled in education in BSPHN. The stocks correspond to students enrolled in primary education, secondary education and post-secondary education. Each stock has a mortality outflow and a net migration biflow. People flow into the "Studying primary education" stock as they age from 4 to 5 years of age. Graduates of primary education then transition to secondary education, and graduates of secondary education can either transition to post-secondary education or not (e.g. those commencing employment). Students in secondary or post-secondary education may discontinue their studies at rates dependent on the prevalence of psychological distress / disorder (Butterworth & Leach, 2017; Lee et al., 2009). People may enter secondary or post-secondary studies without directly transitioning from primary education or secondary education respectively (e.g. re-enrolling after discontinuation, people enrolled in both secondary and post-secondary studies). This sector is calibrated using student enrolment (Australian Curriculum Assessment and Reporting Authority) and completion (Australian Curriculum Assessment and Reporting Authority) data from the Australian Curriculum Assessment and Reporting Authority (ACARA), post-secondary education destinations data from the Queensland Department of Education (Queensland Department of Education, 2023), and education and work statistics from the ABS (Australian Bureau of Statistics, 2014-2022).

Supplementary Figure 3a. Calibration plots from the education (students) sector



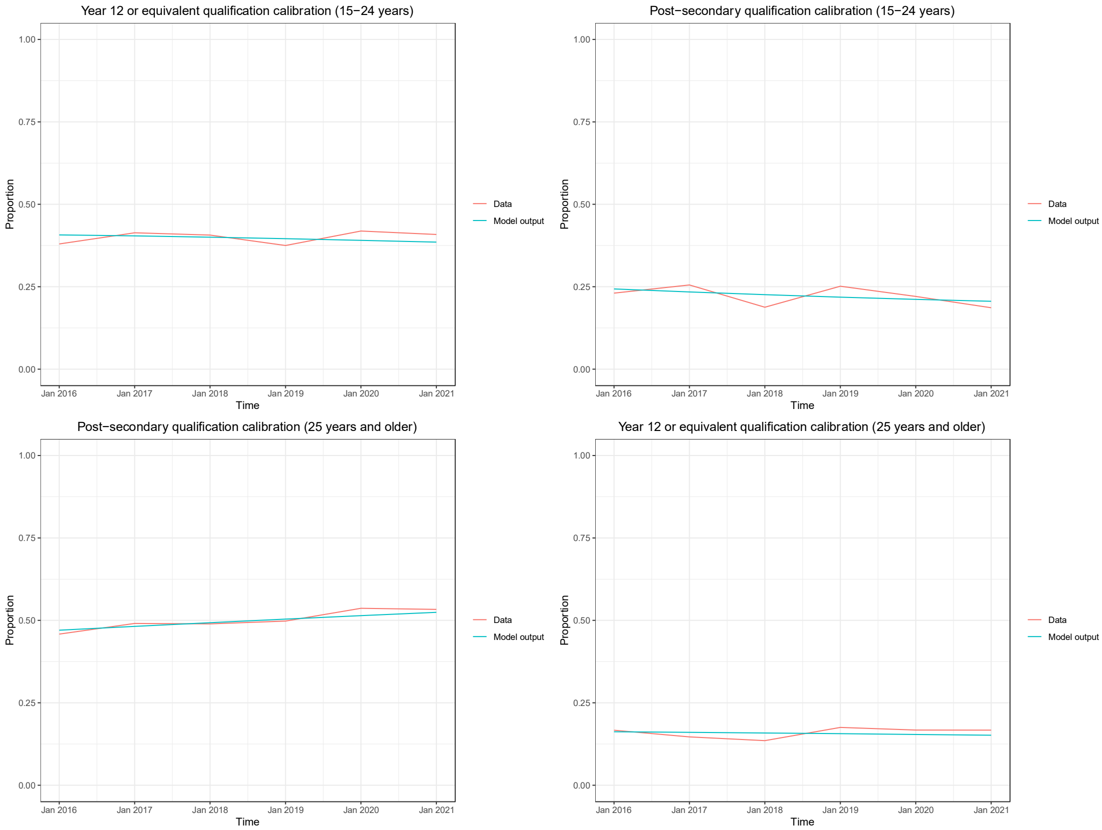
Education (highest level of qualification)

Supplementary Figure 4a. Structure of the education (highest level of qualification) sector



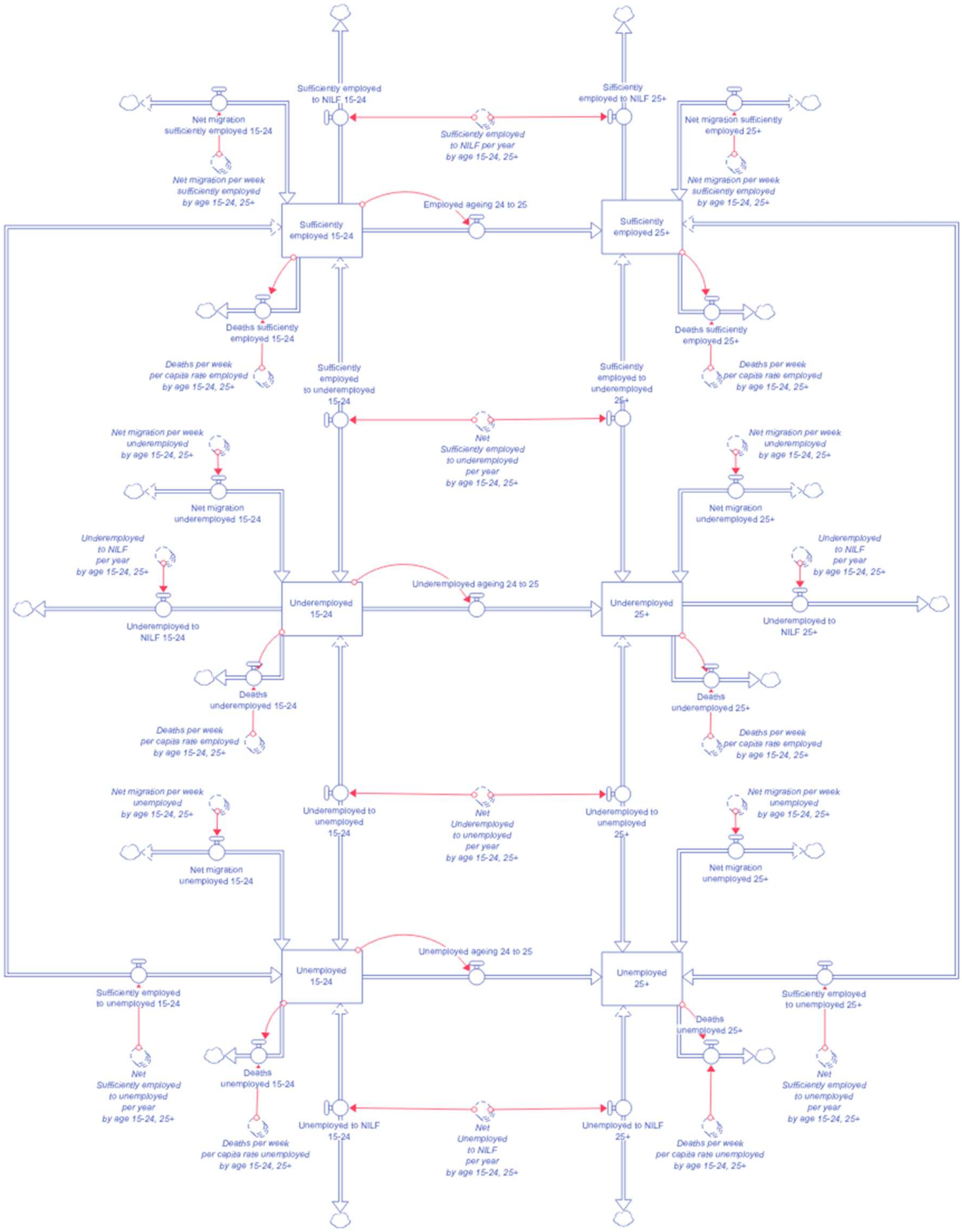
The education (highest level of qualification) sector models holders of different qualifications in BSPHN. The stocks correspond to people aged 15-24 years and 25 years and older, and by their highest level of qualification. More specifically, the stocks correspond to people whose highest level of qualification is Year 12 or equivalent completion, and to people whose highest level of qualification is Certificate III or above. People not in any of these two qualification stocks correspond to people whose highest level of qualification is below Year 12 or equivalent. Each stock has a mortality outflow (Welsh et al., 2021) and a net migration biflow. People who complete secondary education then flow into the "Secondary qualification only" stocks. People who then complete their first post-secondary qualification flow into the "Post-secondary qualification" stocks. People also follow the ageing chain from 15-24 years to 25 years and older. This sector is calibrated using qualifications, education and work statistics from the ABS (Australian Bureau of Statistics, 2014-2022).

Supplementary Figure 4b. Calibration plots from the education (highest level of qualification) sector



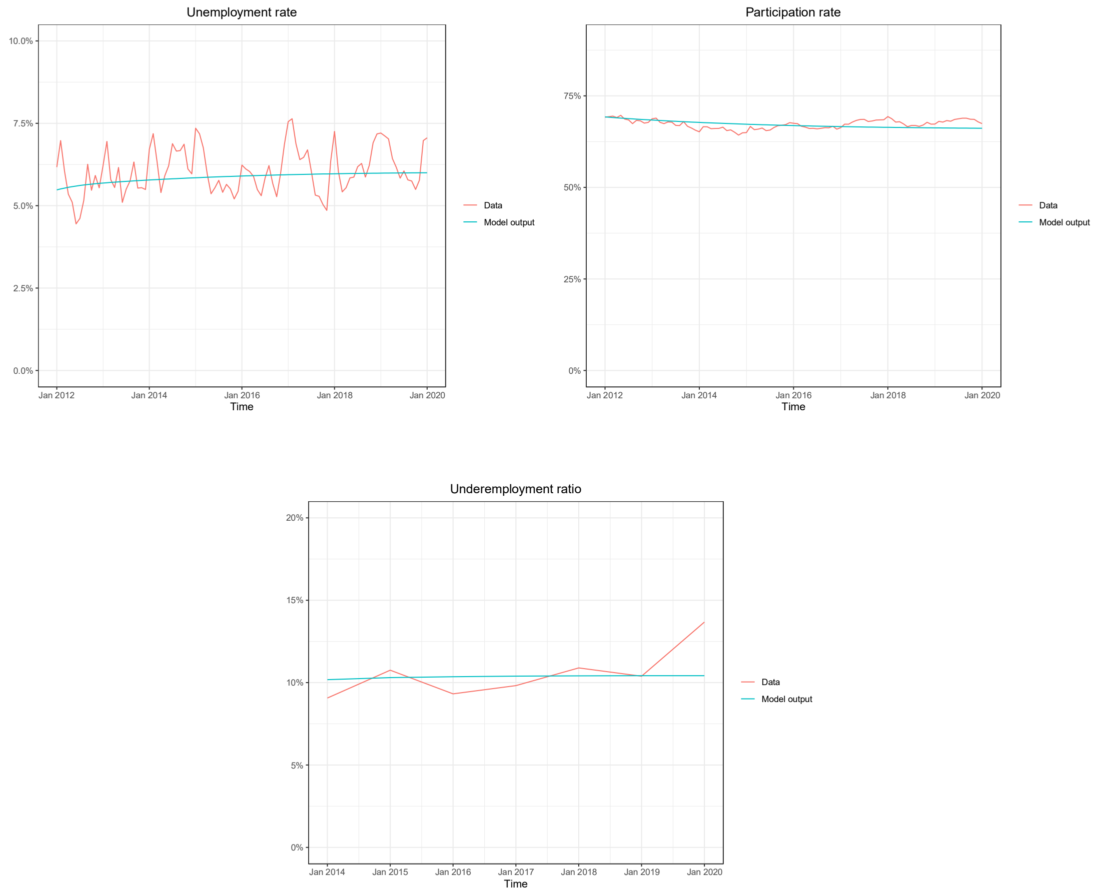
Labour force

Supplementary Figure 5a. Structure of the labour force sector



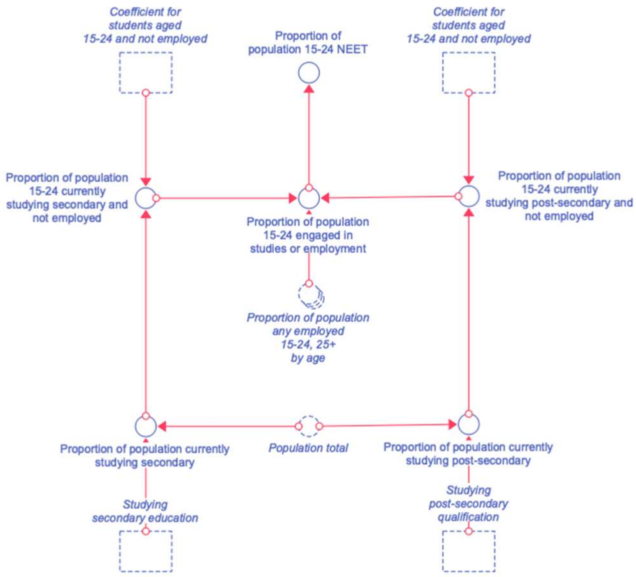
This labour force sector models the employment statuses and flow between these statuses of the BSPHN resident population. The stocks correspond to people aged 15-24 years and 25 years and older, and by their labour force status. More specifically, people can be either sufficiently employed, underemployed or unemployed. People who are not in either of these stocks are deemed to be not in the labour force (NILF) (e.g. retirees). Each stock has a mortality outflow (Sorlie & Rogot, 1990) and a net migration biflow. People can transition between these four labour force statuses with the exception for the NILF population who must transition into unemployment prior to transitioning into employment to reflect people actively looking for work prior to being employed. The rates of transition between employed and unemployed, and between NILF and unemployed are dependent on age and levels of psychological distress / disorder (Australian Bureau of Statistics, 2011-12, 2014-15, 2017-18; Frijters, Johnston, & Shields, 2014) and highest levels of qualifications (Australian Bureau of Statistics, 2014-2022). The rates of transition between sufficiently employed and underemployed are dependent on age and highest level of qualifications (Wilkins, 2004). This sector is calibrated using labour force statistics from the ABS (Australian Bureau of Statistics, 2014-2022, 2023a, 2023b).

Supplementary Figure 5b. Calibration plots from the labour force sector



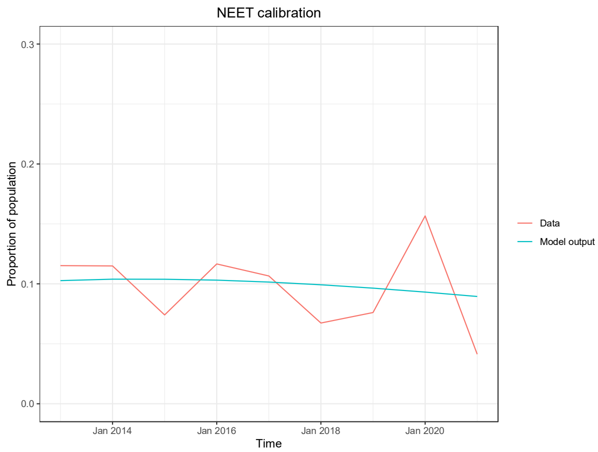
Not in employment nor education (NEET)

Supplementary Figure 6a. Structure of the NEET sector



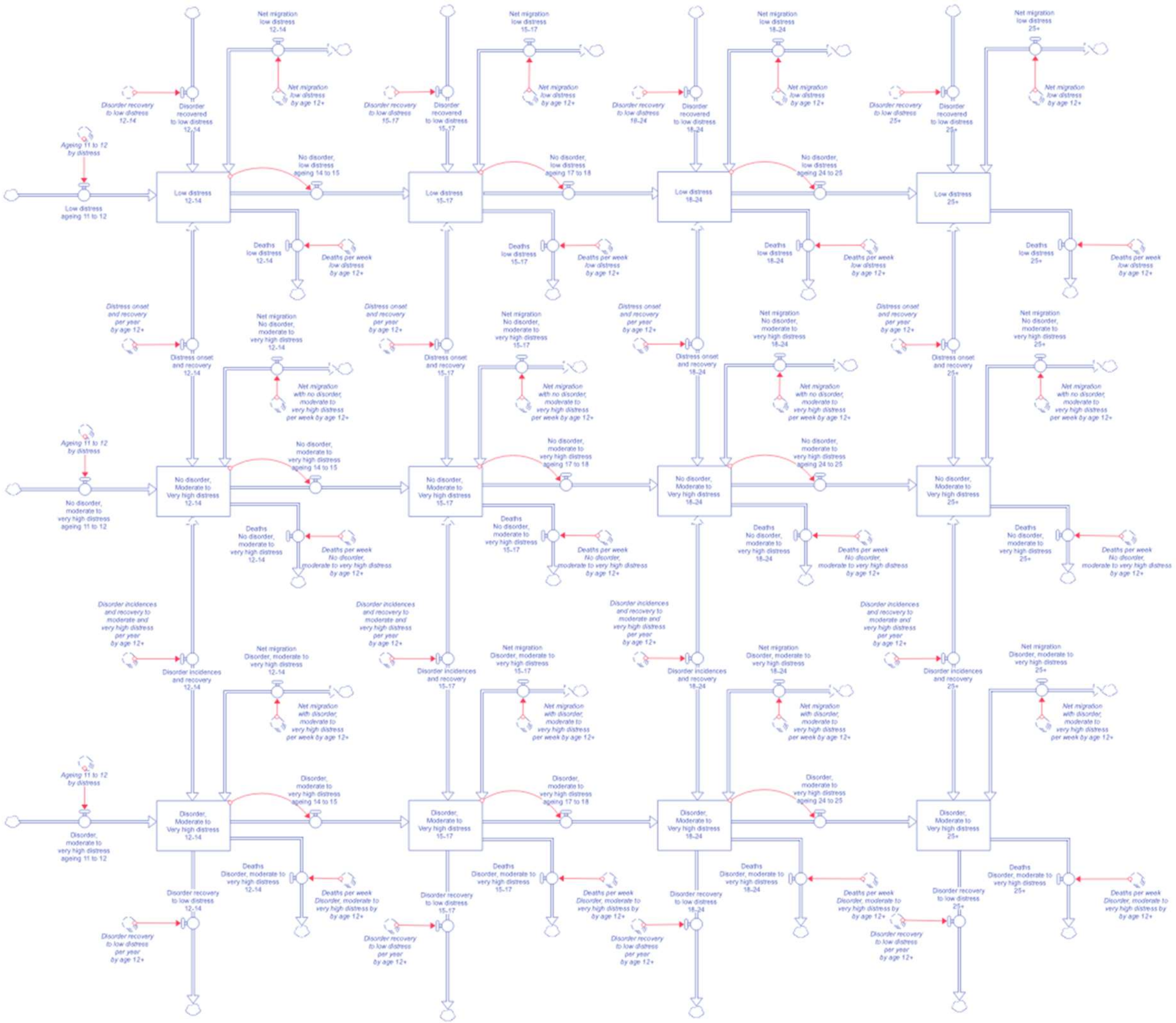
This sector models residents of BSPHN aged 15-24 years who are not in education, employment nor training (NEET). This sector uses model outputs from the labour force and education (students) sectors to calculate the numbers of young people who are NILF and not currently studying. This sector is calibrated using education and work statistics from the ABS (Australian Bureau of Statistics, 2014-2022).

Supplementary Figure 6b. Calibration plot from the NEET sector



Psychological distress / disorder

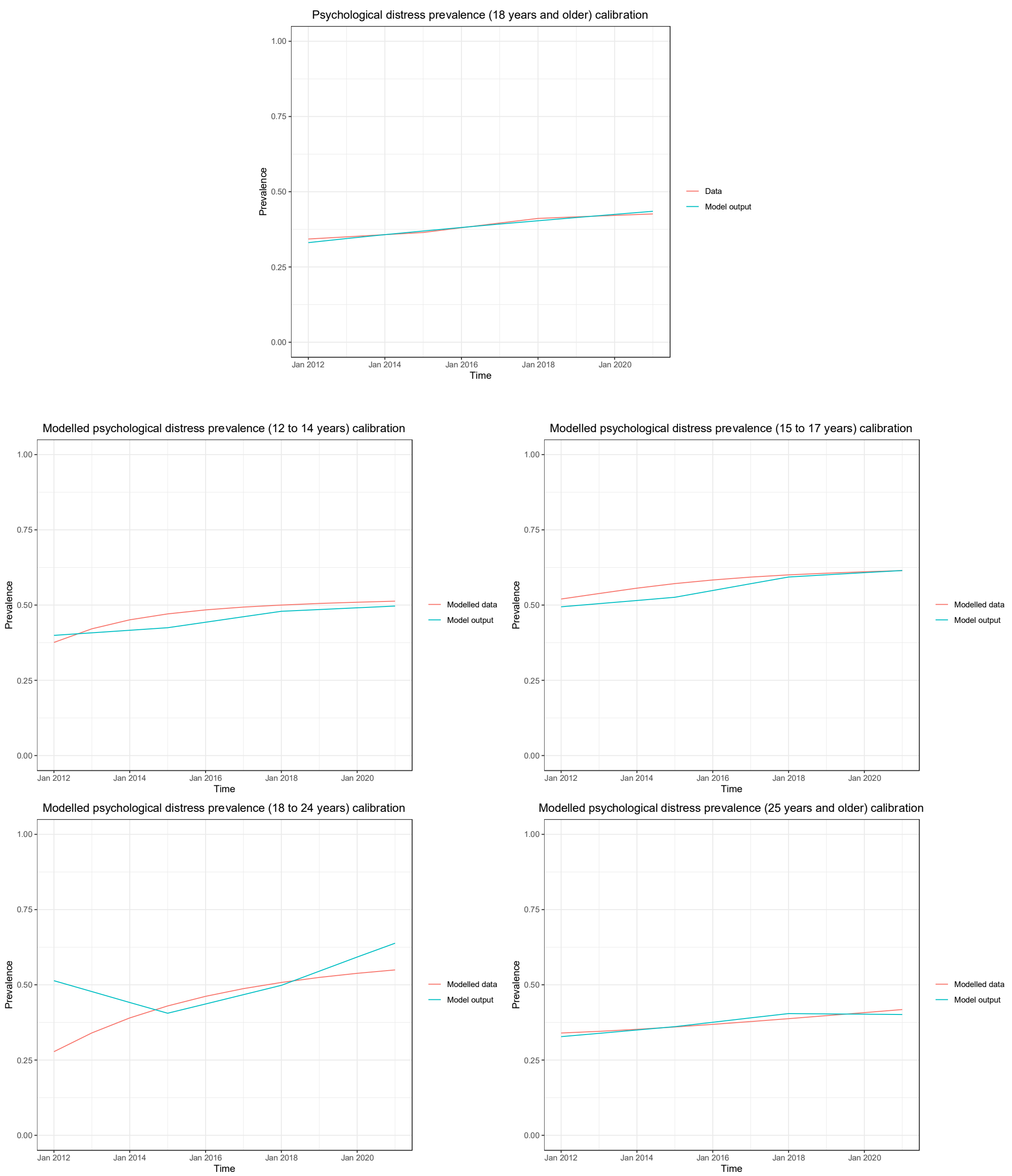
Supplementary Figure 7a. Structure of the psychological distress / disorder sector



This sector models the prevalence of psychological distress and 12-month psychological disorder in people aged 12-14 years, 15-17 years, 18-24 years, and 25 years and older in BSPHN. These stocks model the population with low psychological distress according to the Kessler Psychological Distress Scale (K10) (Kessler et al., 2002), the population with moderate to very high psychological distress who do not meet the criteria for a 12-month psychological disorder, and the population with moderate to very high psychological distress who meet the criteria for a 12-month psychological disorder. Transition rates between these three levels of psychological distress / disorder are dependent on age, rates of homelessness (Australian Bureau of Statistics, 2007a), unemployment (Australian Bureau of Statistics, 2007a), underemployment (Dooley, Prause, & Ham-Rowbottom, 2000; Griffiths et al., 2021), substance misuse (Australian Bureau of Statistics, 2012; Marmorstein, Iacono, & Malone, 2010), engagement and disengagement with the mental health services system and the levels of social cohesion. Each stock has a mortality outflow (Russ et al., 2012) and a net migration biflow, and the population ages following an ageing chain across each level of psychological distress / disorder. This sector is calibrated using psychological distress prevalence data as measured by the K10 from the ABS' National Health

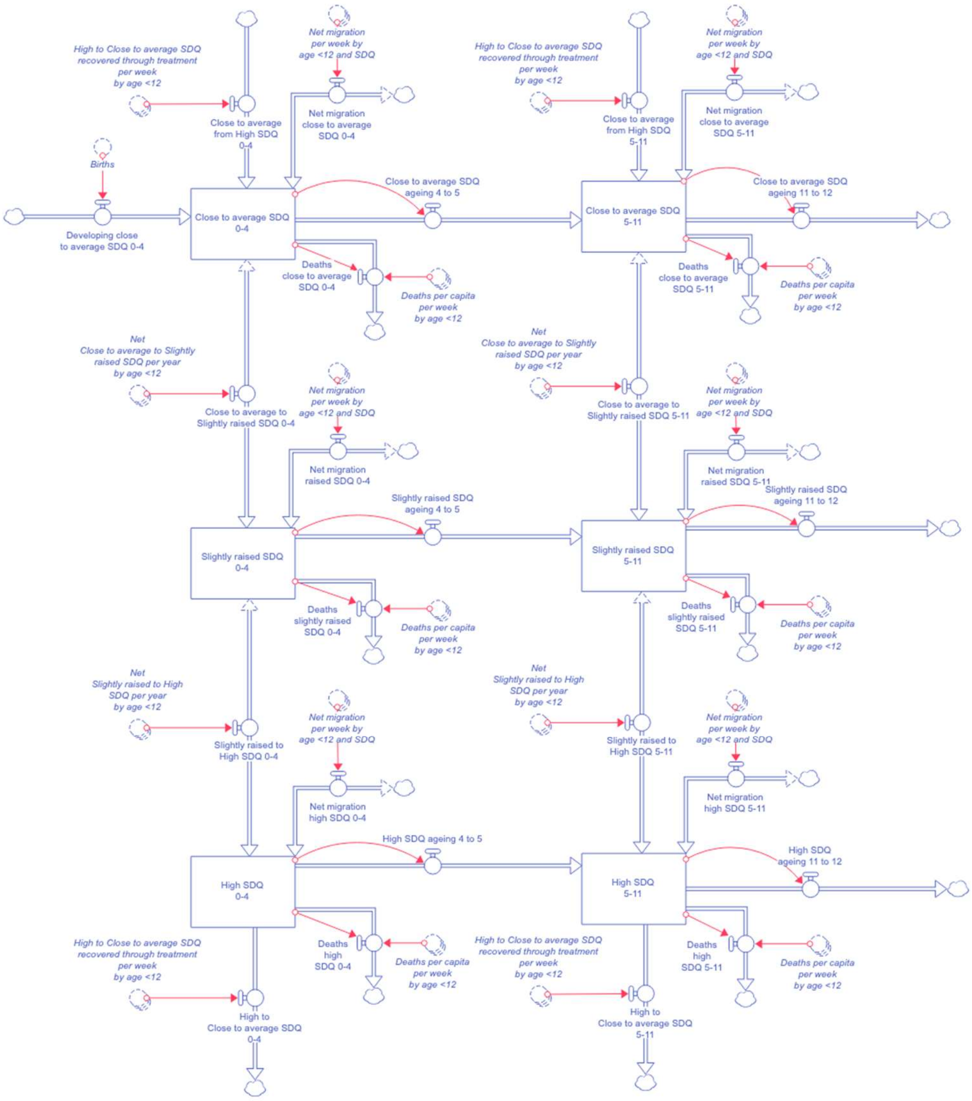
Surveys (Australian Bureau of Statistics, 2011-12, 2013-14, 2017-18, 2011-12, 2014-15, 2017-18, 2020-21) and the Young Minds Matter Survey (Young Minds Matter Survey, 2013-14). The prevalence estimates for 12-month psychological disorder were modelled from data from the ABS' National Study of Mental Health and Wellbeing (Australian Bureau of Statistics, 2007b, 2020-22). Calibration for 12-14-year-olds and 15-17-year-olds used data and modelled estimates inferred using the Young Minds Matter Survey (Young Minds Matter Survey, 2013-14) and the ABS' National Health Surveys (Australian Bureau of Statistics, 2011-12, 2013-14, 2017-18, 2011-12, 2014-15, 2017-18, 2020-21).

Supplementary Figure 7b. Calibration plots from the psychological distress / disorder sector



Strengths and Difficulties

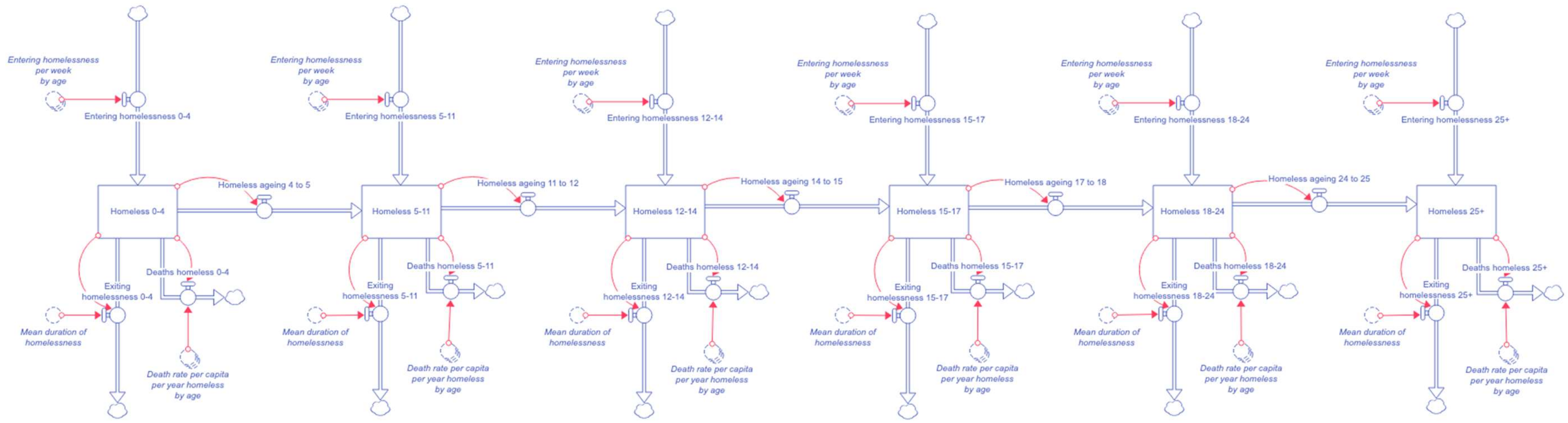
Supplementary Figure 8. Structure of the Strengths and Difficulties sector



This sector models the prevalence of mental health difficulties in children aged 0-4-years and 5-11-years as measured using the Strengths and Difficulties Questionnaire (SDQ). These stocks model the population with "Close to average", "Slightly raised" and "High" SDQ scores. People are assumed to be born with close to average levels of SDQ and hence flow into the "Close to average SDQ" stock for 0-4-year-olds. People can flow between close to average and slightly raised levels of SDQ, and between slightly raised to high levels of SDQ with rates dependent on age and rates of engagement and disengagement with the mental health services systems and the levels of social cohesion. Each stock has a mortality outflow and a net migration biflow, and the population ages following an ageing chain across each level of SDQ stocks. This sector is calibrated using SDQ data from the Longitudinal Study of Australian Children (Australian Institute of Family Studies, 2022). Calibration for 0-4-year-olds used modelled estimates inferred using data for 5-11-year-olds. Please note that, as part of the user agreement between the authors and the Longitudinal Study of Australian Children, SDQ data at the PHN level of geographic granularity cannot be shown. As such, calibration plots for the Strengths and Difficulties sector will not be shown here.

Homelessness

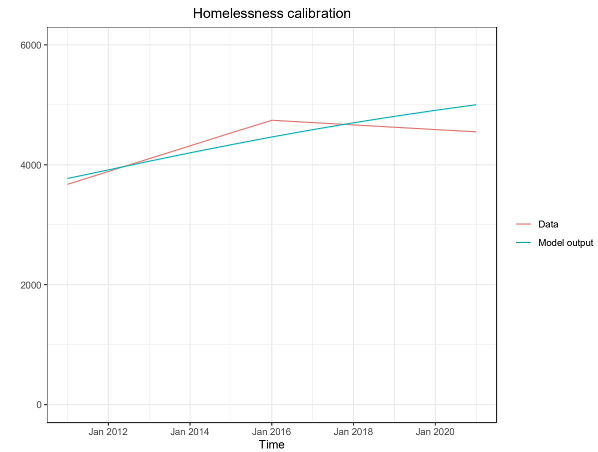
Supplementary Figure 9a. Structure of the homelessness sector



This sector consists of six stocks modelling people experiencing homelessness aged 0-4 years, 5-11 years, 12-14 years, 15-17 years, 18-24 years, and 25 years and older. Each stock has a mortality outflow (Morrison, 2009) and a net migration biflow. People aged 15 and older enter homelessness at rates which are dependent on age, levels of psychological distress / disorder, unemployment rates, and substance misuse rates (Nilsson, Nordentoft, & Hjorthøj, 2019). For people under 15 years of age, rates of entering homelessness are dependent on age. People exit homelessness at rates dependent on the mean duration of homelessness (Ranney, 2023). People age into older stocks following the ageing chain.

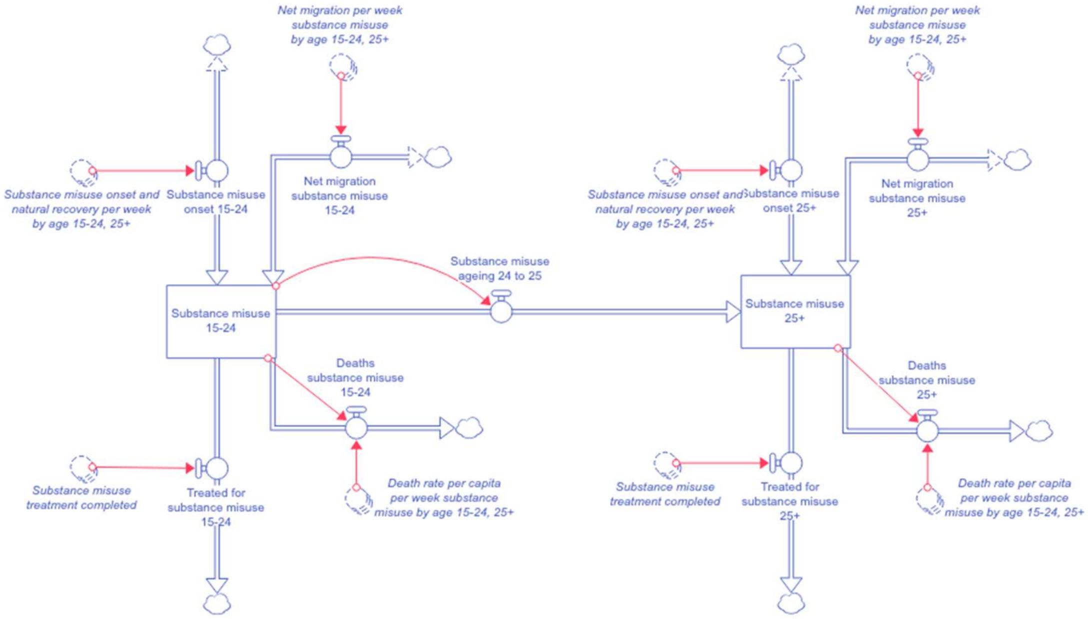
This sector was calibrated using homelessness statistics from the ABS (Australian Bureau of Statistics, 2011, 2016, 2021, 2016, 2021).

Supplementary Figure 9b. Calibration plot from the homelessness sector



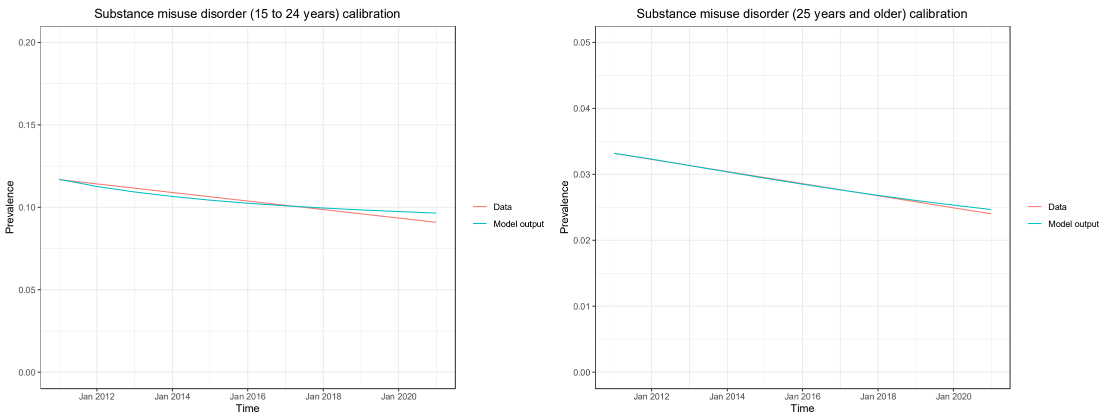
Substance misuse (substance misuse disorder)

Supplementary Figure 10a. Structure of the substance misuse (substance misuse disorder) sector



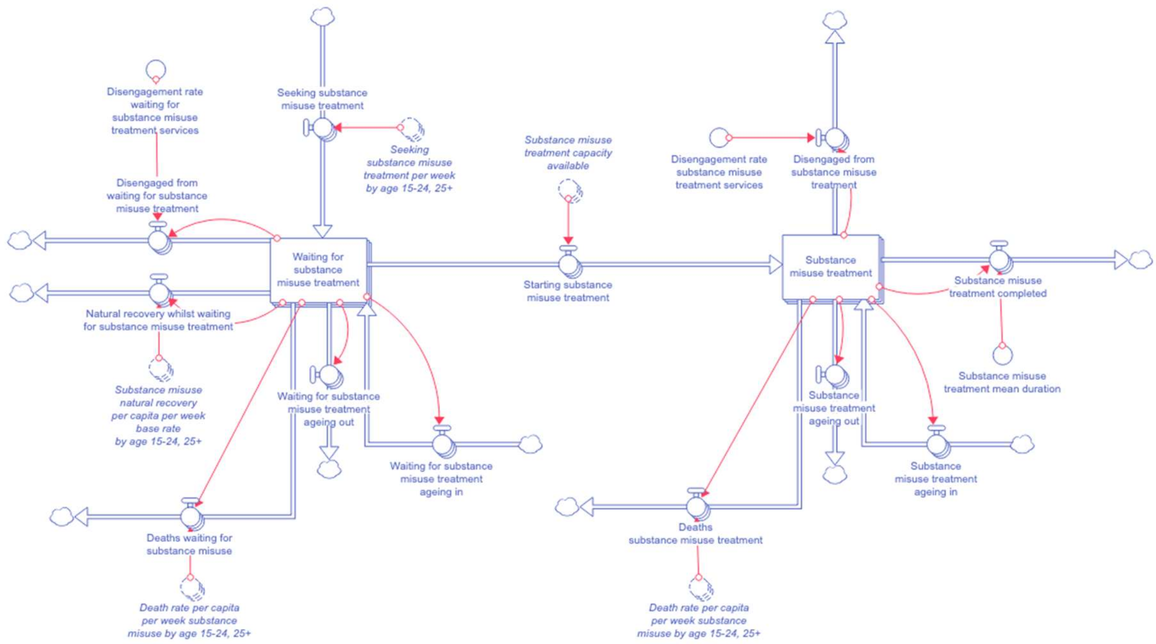
This sector models the prevalence of substance misuse in the BSPHN resident population. The stocks correspond to people aged 15-24 years and 25 years and older who meet the criteria for 12-month substance use disorder. Each stock has a mortality outflow (Roerecke & Rehm, 2013) and a net migration biflow, and the population ages following an ageing chain. Each stock has a disorder onset and recovery biflow which reflect the rates of onset of and the non-treatment based recovery from substance misuse disorder. The onset rates are dependent on age, prevalence of psychological distress / disorder (Australian Institute of Health and Welfare, 2017), homelessness (Johnson, Freels, Parsons, & Vangeest, 1997; Slade et al., 2009) and NEET (Australian Bureau of Statistics, 2020-22; Gariépy, Danna, Hawke, Henderson, & Iyer, 2022). Each stock also has a recovery through treatment outflow representing people who recover from substance misuse disorder through treatment with services. This sector is calibrated using national 12-month substance use disorder data from the ABS' National Study of Mental Health and Wellbeing (Australian Bureau of Statistics, 2007b, 2020-22).

Supplementary Figure 10b. Calibration plots from the substance misuse (substance misuse disorder) sector



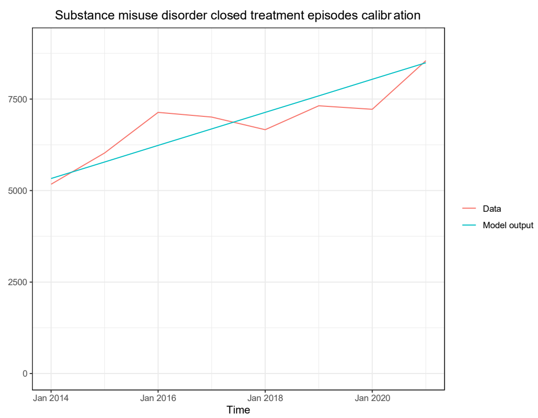
Substance misuse (substance misuse closed treatment episodes)

Supplementary Figure 11a. Structure of the substance misuse (substance misuse closed treatment episodes) sector



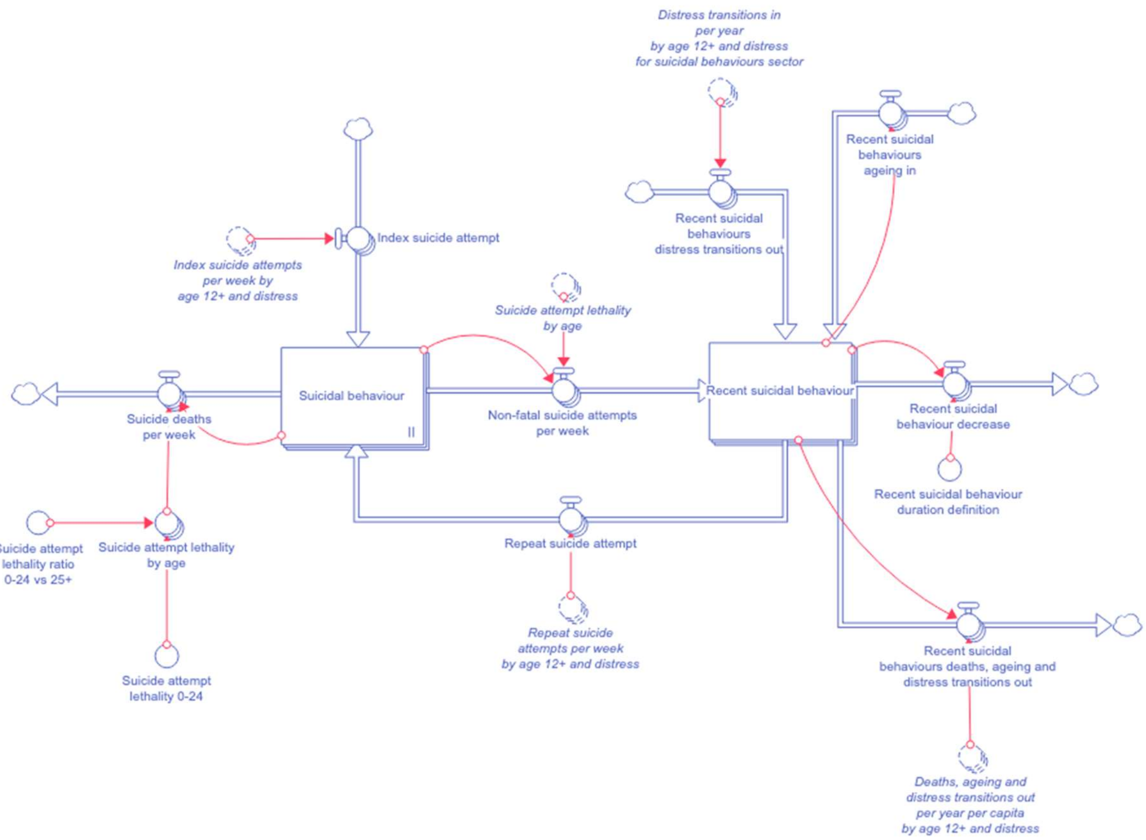
This sector models the flow of people engaging with substance misuse services. People with flow into the substance misuse services waiting stock, representing people on the waitlist for services prior to commencing substance misuse treatment (Brisbane South Primary Health Network, 2016). From the waiting stock, people flow out if they recover without treatment required, if they disengage with services (due to, for example, excessive wait times), through death or, if there are sufficient capacity, through commencing treatment with substance misuse services. From the treatment stock, people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), through death or through the completion of treatment. The remaining flows model ageing, distress / disorder transitions and mortality (Roerecke & Rehm, 2013). This sector was calibrated with substance misuse services data from the AIHW (Australian Institute of Health and Welfare, 2016-21, 2023).

Supplementary Figure 11b. Calibration plots from the substance misuse (substance misuse closed treatment episodes) sector



Suicidal behaviours

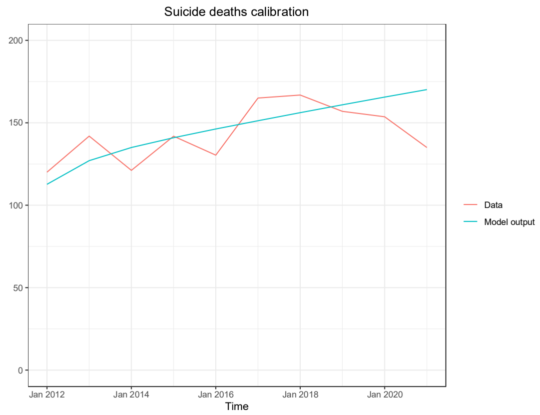
Supplementary Figure 12a. Structure of the suicidal behaviours sector

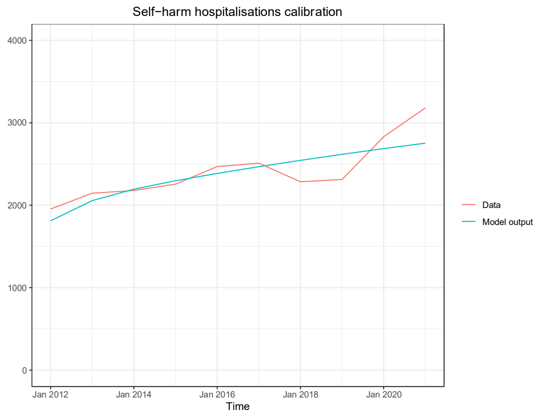


This sector models suicide deaths and attempts in the BSPHN population. The “Suicidal behaviour” stock represents people currently exhibiting suicidal behaviours. People can flow into this stock with an index suicide attempt and people can flow out of this stock depending on whether the attempt was fatal or non-fatal. People who had a non-fatal suicide attempt then flow into the “Recent suicidal behaviour” stock and either remain in this stock for 12 months, representing the duration of which people are at higher risk of exhibiting further suicidal behaviours, or flow back into the “Suicidal behaviours” stock if they have a repeat suicide attempt. The rates of suicide attempts are dependent on age, prevalence of psychological distress / disorder (Hockey et al., 2022) and prevalence of substance misuse disorder (Too et al., 2019). The remaining flows model ageing, distress / disorder transitions and mortality excluding suicide deaths. This sector was calibrated using suicide deaths statistics from the AIHW (Australian Institute of Health and Welfare, 2021c) and intentional self-harm hospitalisations statistics provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023).

Please note that we calibrated non-fatal suicide attempts with intentional self-harm hospitalisations data. We acknowledge that these data do not fully capture the number of non-fatal suicide attempts (for example, those events not resulting in hospitalisation) and that these data may not accurately record the intention of the event.

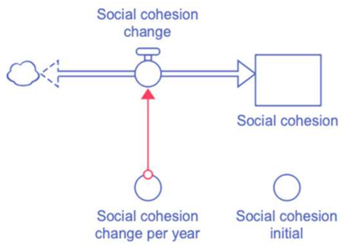
Supplementary Figure 12b. Structure of the suicidal behaviours sector





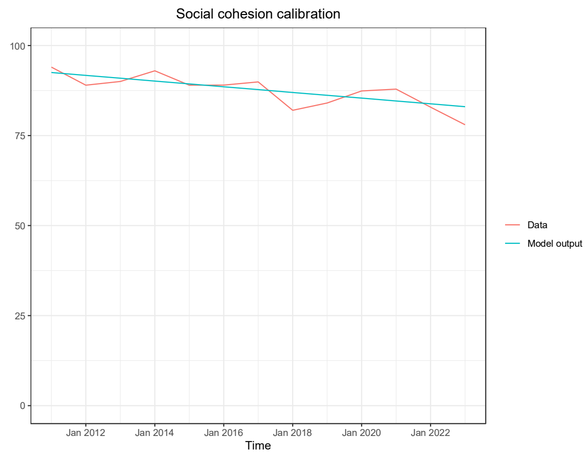
Social cohesion

Supplementary Figure 13a. Structure of the social cohesion sector



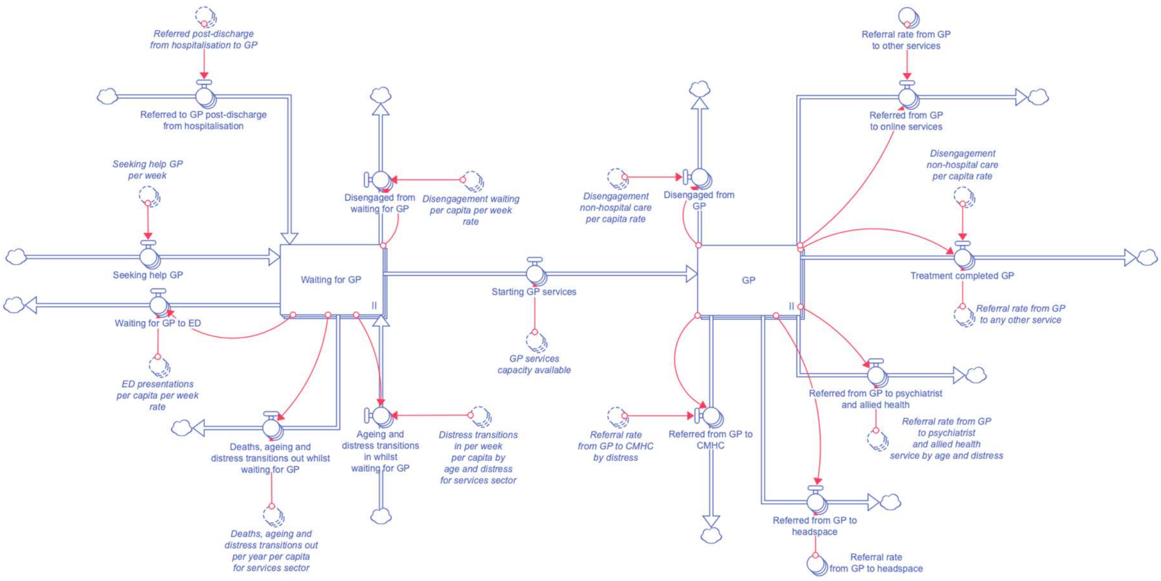
This sector models the level of social cohesion in the population. Social cohesion consists of five domains: belonging, worth, social justice, participation and acceptance and rejection. Social cohesion is a stock and flow structure allowing the level of social cohesion to change at a constant rate per year. This sector was calibrated with the Scanlon-Monash Index of Social Cohesion data from the Scanlon Foundation Research Institute (Scanlon Foundation Research Institute, 2023).

Supplementary Figure 13b. Calibration plot the social cohesion sector



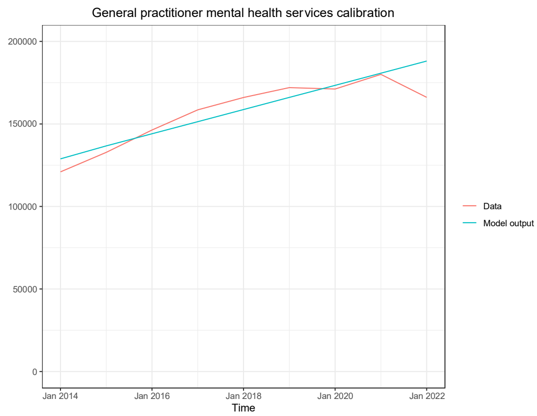
General Practitioner (GP)

Supplementary Figure 14a. Structure of the GP sector



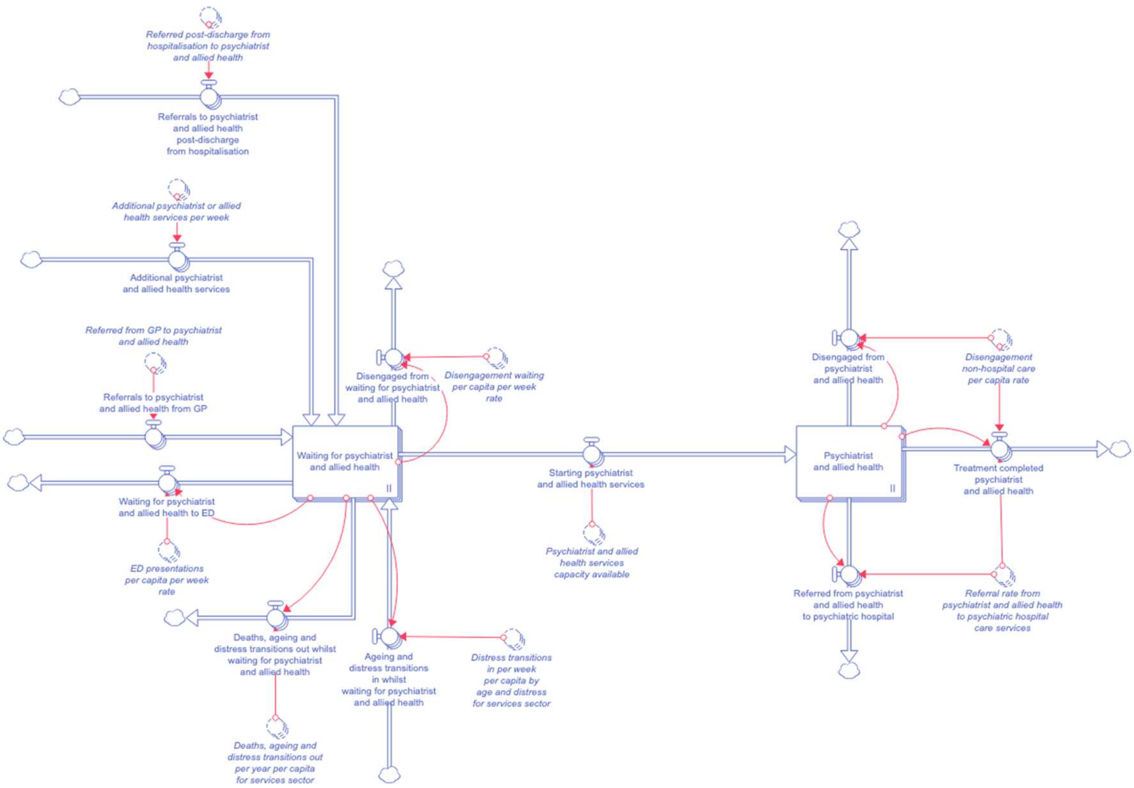
This sector models the flow of people engaging with a GP for their mental health. People flow into waiting stock "Waiting for GP", representing people on the waitlist for GP mental health services. The two inflows into the waiting stock are people in psychological distress who perceive a need for service and commence help-seeking with their GP, and people who have been referred to their GP post-discharge from a mental health related hospitalisation. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their consult with the GP, if services capacity allows. From the service stock "GP", people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), they are referred to other mental health services (e.g. online mental health services) or if their consult is completed without further referrals. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with Medicare-subsidised GP mental health services data from the AIHW (Australian Institute of Health and Welfare, 2022) and from data provided by BSPHN.

Supplementary Figure 14b. Calibration plot from the GP sector



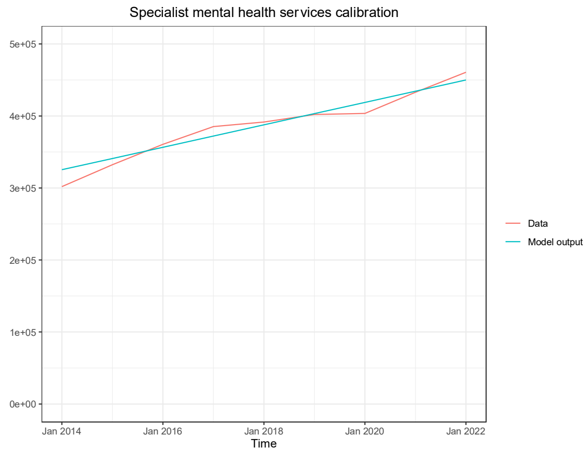
Specialist services

Supplementary Figure 15a. Structure of the specialist services sector



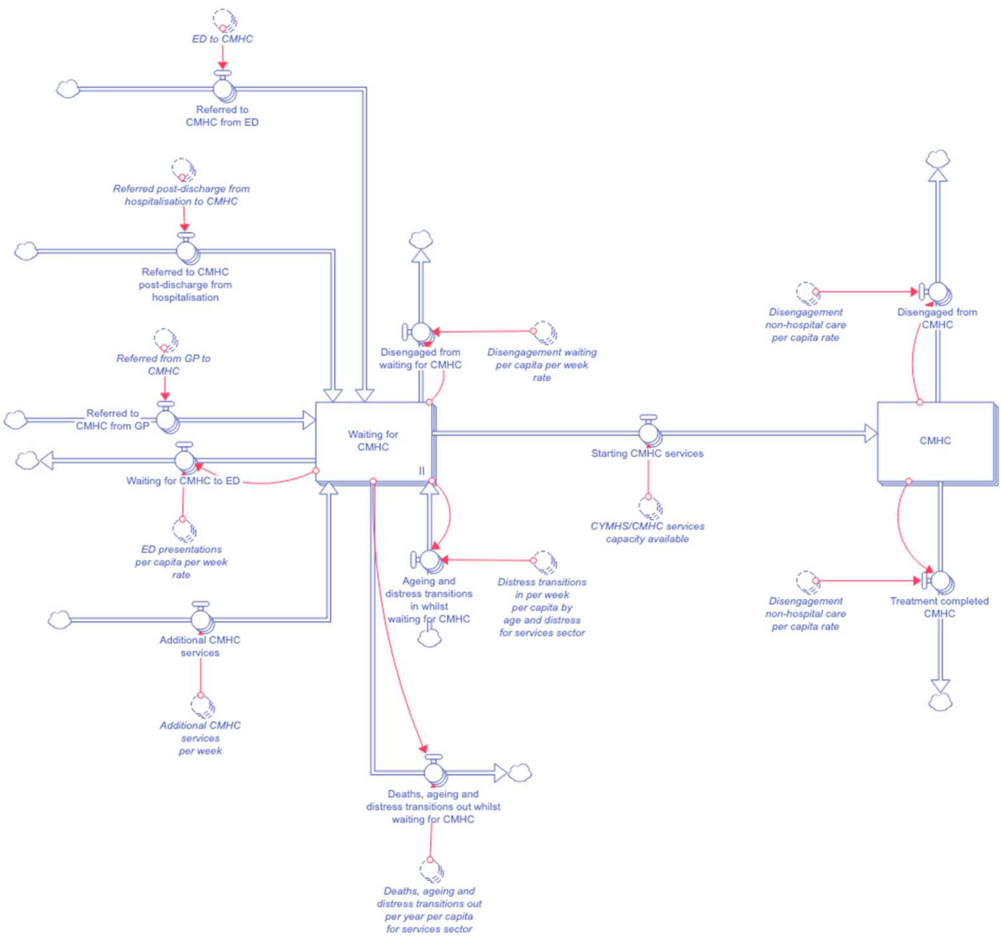
This sector models the flow of people engaging with specialist services (psychiatrists and allied mental health professionals such as psychologists, social worker and occupational therapists). People flow into the waiting stock “Waiting for psychiatrist and allied health”, representing people on the waitlist for services. The inflows into the waiting stock are people referred by their GP, people referred post-discharge from a mental health related hospitalisation and people with follow-up appointments. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their consult with specialised services, if services capacity allows. From the service stock “Psychiatrist and allied health”, people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), they are referred to inpatient psychiatric care or if their consult is completed without further referrals. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with Medicare-subsidised Psychiatrists and Allied Mental Health mental health services data from the AIHW (Australian Institute of Health and Welfare, 2022) and from data provided by BSPHN.

Supplementary Figure 15b. Calibration plot from the specialist services sector



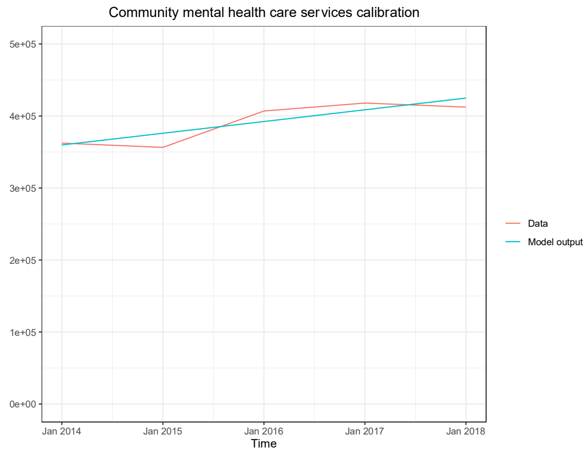
Community mental health care services

Supplementary Figure 16a. Structure of the community mental health care services sector



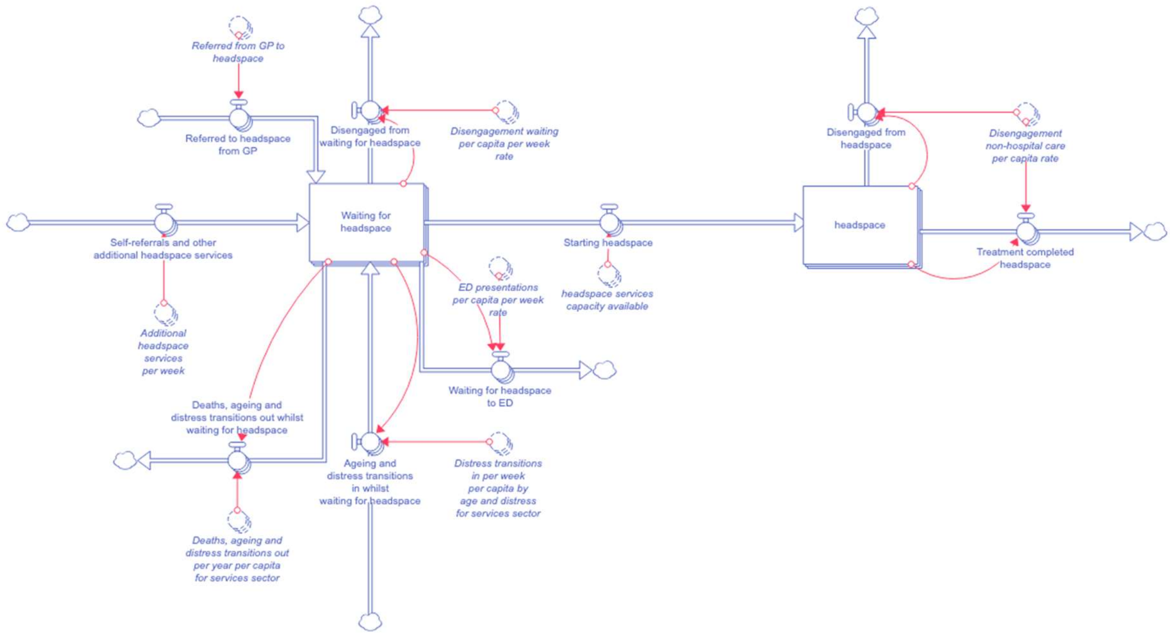
This sub-sector models the flow of people engaging with child and youth mental health services and community mental health care (CMHC). People flow into the waiting stock "Waiting for CMHC", representing people on the waitlist for services. The inflows into the waiting stock are people referred by their GP, people referred post-discharge from a mental health related hospitalisation, people referred post-discharge from a mental health related emergency department presentation and people with follow-up appointments. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their consult with the CYMHS/CMHC, if services capacity allows. From the service stock "CMHC", people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), or if their consult is completed. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with service contacts data from the AIHW (Australian Institute of Health and Welfare, 2017-18).

Supplementary Figure 16b. Calibration plot from the community mental health care services sector



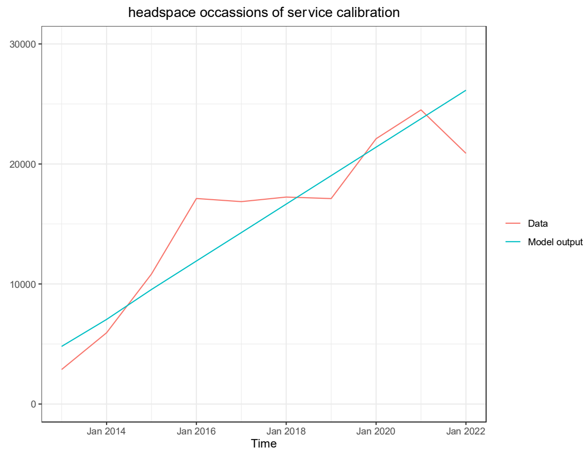
headspace

Supplementary Figure 17a. Structure of the headspace sector



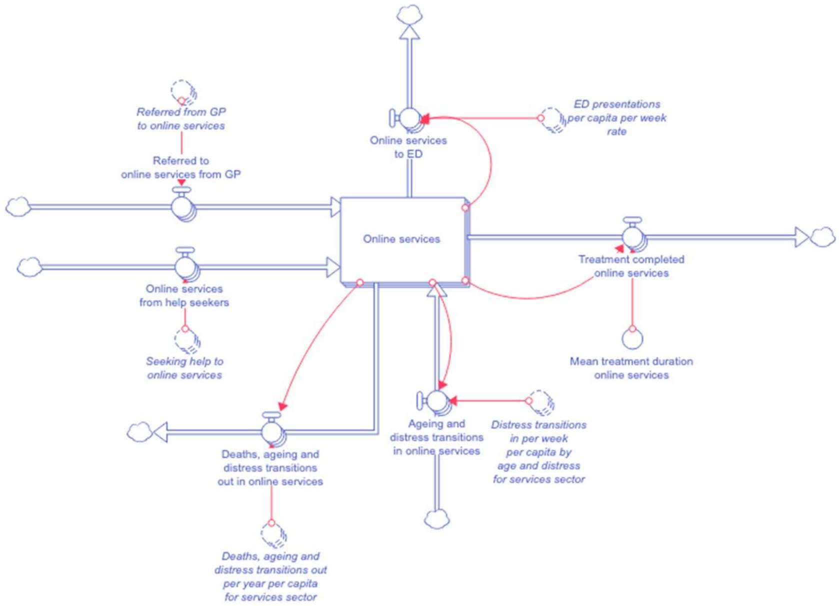
This sector models the flow of young people engaging with youth mental health service provider, headspace. Only people aged 12 and older flow into headspace stocks. People flow into the waiting stock "Waiting for headspace", representing people on the waitlist for services. The two inflows into the waiting stock are people in psychological distress who perceive a need for service and commence help-seeking with headspace, and people who have been referred by their GP. The first inflow reflects people self-referring to headspace, people referred to headspace by family or friends and people with follow-up appointments. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their consult with headspace, if services capacity allows. From the service stock "headspace", people flow out if they disengage with services (due to, for example, dissatisfaction with services provided), or if their consult is completed without further referrals. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with occasions of service data provided by BSPHN.

Supplementary Figure 17b. Calibration plot from the headspace sector



Online mental health services

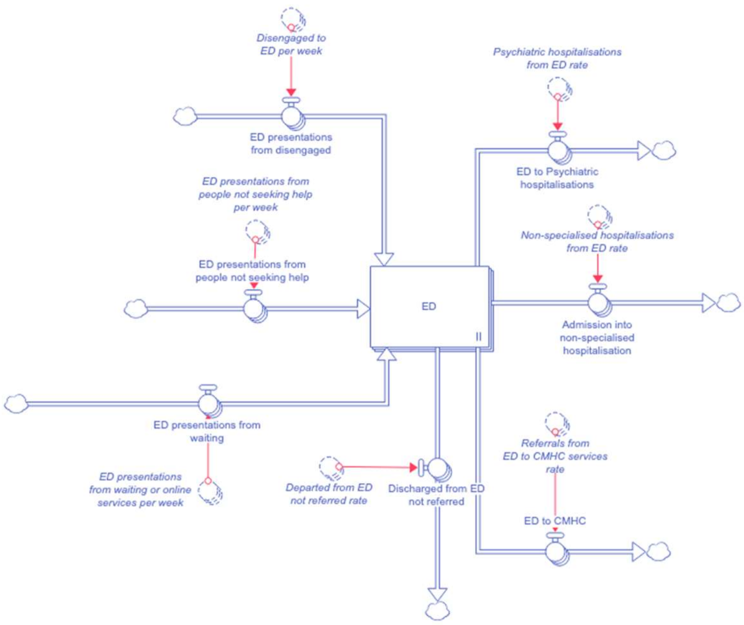
Supplementary Figure 18. Structure of the online mental health services sector



This sector models the flow of people engaging online mental health services. The two inflows into the stock are people in psychological distress who perceive a need for service and commence help-seeking with online services, and people who have been referred by their GP. People flow out when their online course of treatment is completed. The remaining flows model ageing, distress / disorder transitions and mortality.

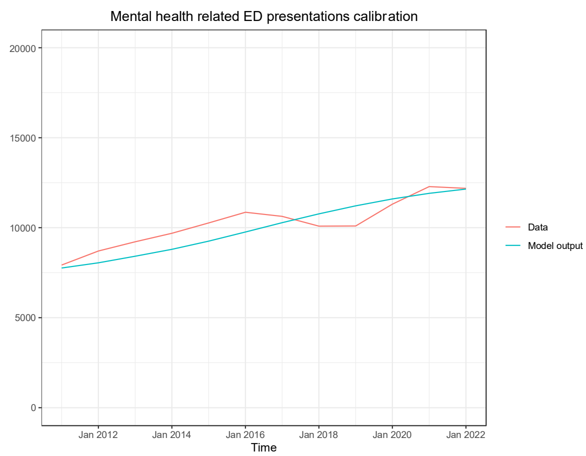
Mental health related emergency department (ED) presentations

Supplementary Figure 19a. Structure of the mental health related ED presentations sector



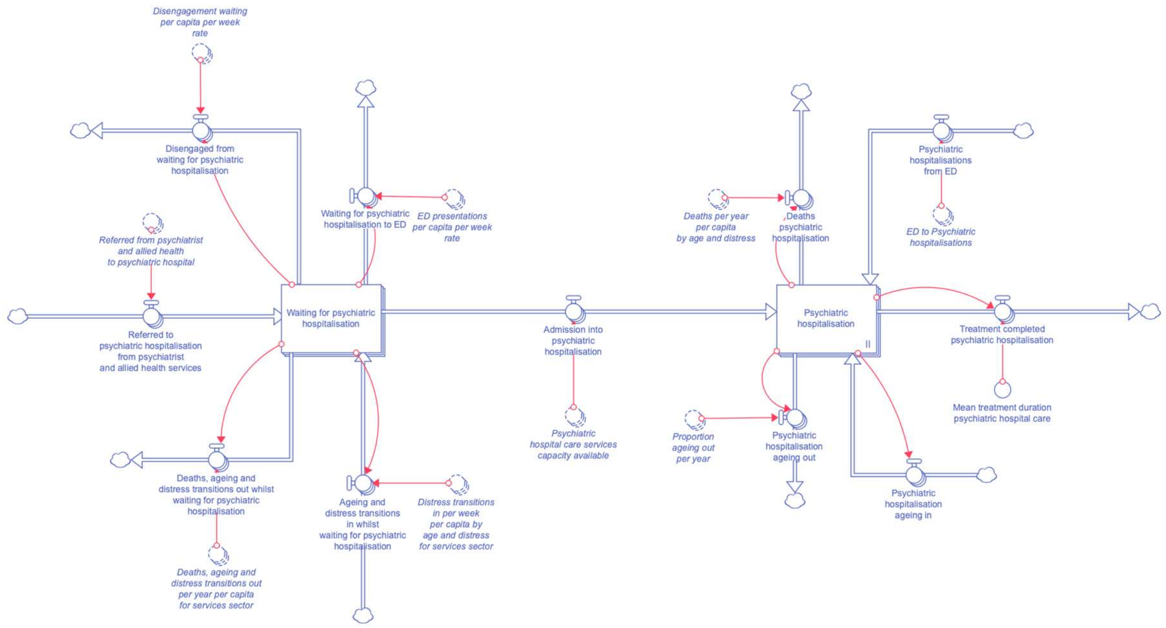
This sector models people presenting to the ED for mental health related presentations. People that flow into the stock are people who are distressed and are currently help-seeking with other services (e.g., whilst waiting for a consult with a psychologist), are not currently help-seeking (e.g., people whose family or friends take them to ED) and people who are disengaged from services. From the stock, people flow out if they are admitted into either psychiatric admitted care or non-specialised admitted care, discharged and referred to CMHC, or discharged without further referrals. This sector was calibrated with mental health related ED presentations data provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023).

Supplementary Figure 19b. Calibration plot from the mental health related ED presentations sector



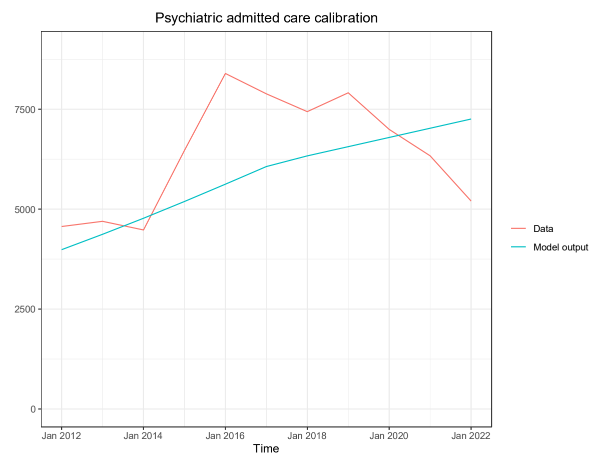
Psychiatric admitted care

Supplementary Figure 20a. Structure of the psychiatric admitted care sector



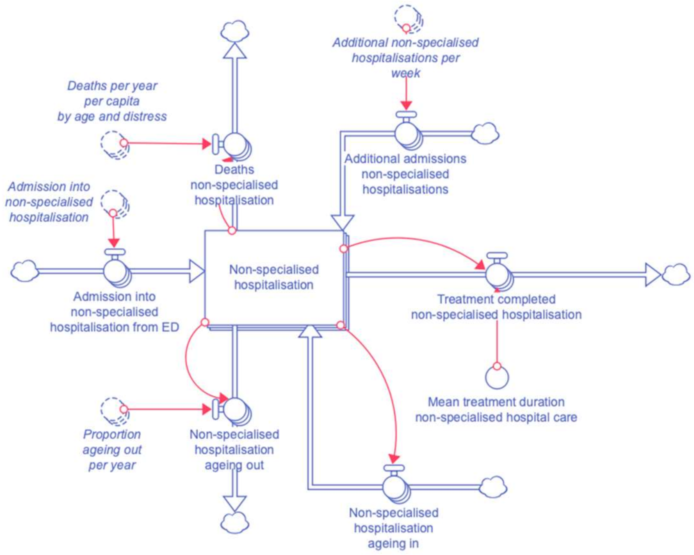
This sector models the flow of people into psychiatric admitted care. People flow into the waiting stock "Waiting for psychiatric hospitalisation", representing people on the waitlist for services. The inflow into the waiting stock are people referred by their specialist. From the waiting stock, people flow out if they disengage with services (due to, for example, excessive wait times), they present to an emergency department (due to, for example, high levels of distress) or they commence their psychiatric admitted care, if services capacity allows. People can directly flow into the service stock if the admission is from the ED. From the service stock "Psychiatric hospitalisation", people flow out once they are discharged. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with episodes of admitted care data provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023).

Supplementary Figure 20b. Calibration from the psychiatric admitted care sector



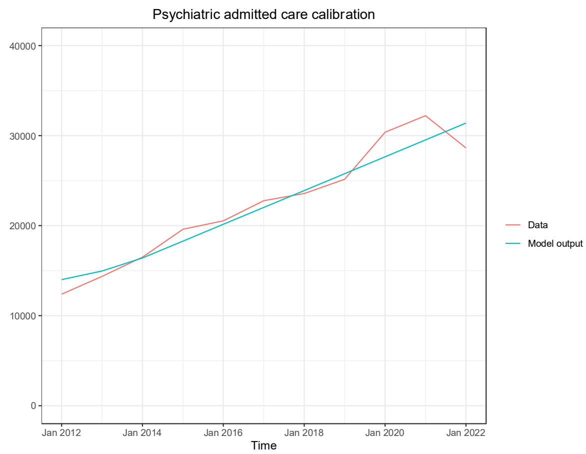
Non-specialised admitted care

Supplementary Figure 21a. Structure of the non-specialised admitted care sector



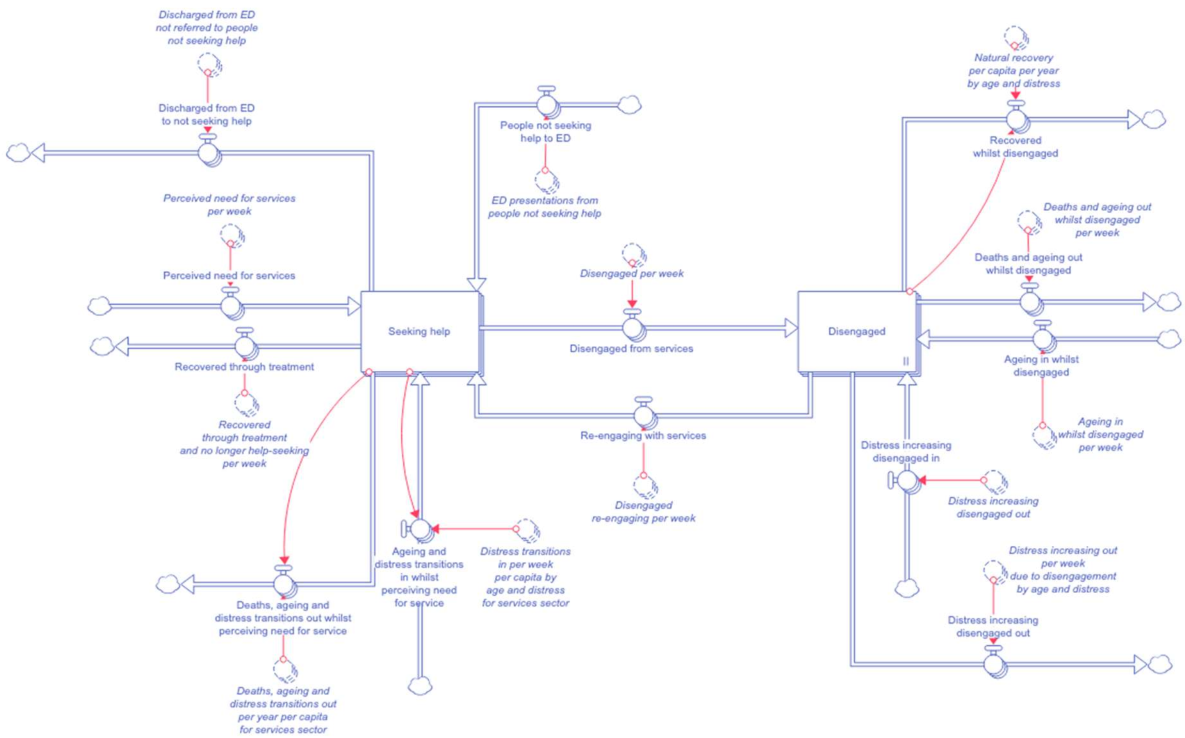
This sector models the flow of people into non-specialised, mental health related admitted care. People that flow into the stock are people who are admitted from ED and any other additional admissions. From the service stock, people flow out once they are discharged. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with episodes of admitted care data provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023).

Supplementary Figure 21b. Calibration plot from the non-specialised admitted care sector



Help-seeking and disengaged

Supplementary Figure 22. Structure of seeking-help and disengaged



This models the flow of people in distress who perceive a need for service and are either seeking help or are disengaged from services. People in distress may develop a perceive need for service and flow into the ”Seeking help” stock. The other inflows are people who present to ED without a perceived need for service (e.g., people whose family or friends take them to ED) and people who were disengaged then re-engaging with services. People who present to ED without a perceived need for service will flow out of the “Seeking help” stock once they are discharged. The flow from “Seeking help” to “Disengaged” models people who disengage from services whilst waiting for services or from their treatment. Whilst disengaged, people develop psychological disorders at a higher rate than the total population’s per-capita rate. The remaining flows model ageing, distress / disorder transitions and mortality. This sector was calibrated with perceived need for service data from ABS’ National Survey of Mental Health and Wellbeing 2007 (Australian Bureau of Statistics, 2007a) and the AIHW’s Mental health performance indicators 2021 (Australian Institute of Health and Welfare, 2021a). More specifically, we used the ABS’ National Survey of Mental Health and Wellbeing 2007 Microdata to estimate the national rates of “Perceived need for any mental health services” disaggregated by K10 and 12-month mental health disorder. We then used AIHW’s Mental health performance indicators 2021 (Table KPI.8.2) to calculate the proportion of the QLD population who received clinical mental health care disaggregated by age for the years 2007-08 to 2020-21. This state-level proportion was multiplied by the population of the BSPHN catchment disaggregated by age to estimate the proportion of people in the BSPHN catchment receiving mental health care for the same years. The average annual change in this region-specific estimated proportion was calculated and used as a proxy for the change in demand for mental health services from 2007 onwards. Finally, the rates of perceived need for service for the region disaggregated by K10 and 12-month mental health disorder was inferred from 2007 onwards using the proxy and the national rates of “Perceived need for any mental health services” disaggregated by K10 and 12-month mental health disorder calculated in the first step. While the ABS 2007 survey is the most recent national source containing the required disaggregation by both K10 and disorder status, we acknowledge that the data are dated. The use of more recent AIHW service activity data to estimate change over time helps mitigate this limitation by aligning the perceived-need estimates with contemporary service patterns.

Services capacity growth rate

To reflect a slowing growth rate in services capacity in recent years compared to the longer term historic trend, multipliers have been applied to annual growth rates for forward projections (i.e., from January 2025). These mulipliers can be modified on the user interface.

Service	Growth rate
General practitioner mental health services	Based on Medicare-subsidised services data published by AIHW for the period 2014 to 2022 (Australian Institute of Health and Welfare, 2022), the maximum number of GP mental health services that can be delivered per week has been increasing at an annual rate of 140 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.68) was derived from Medicare-subsidised services data published by AIHW for the period 2017-2020 (pre-pandemic) (Australian Institute of Health and Welfare, 2022) and represents a decrease in the annual growth rate in GP services capacity of 32% from January 2025.
Specialist mental health services	Based on Medicare-subsidised services data published by AIHW for the period 2014 to 2022 (Australian Institute of Health and Welfare, 2022), the maximum number of Psychiatry and allied mental health services that can be delivered per week has been increasing at an annual rate of 298 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.97) was derived from Medicare-subsidised services data published by AIHW for the period 2017-2020 (Australian Institute of Health and Welfare, 2022) and represents a decrease in the annual growth rate from January 2024 onwards.
Child and youth mental health services	Based on Community Mental Health Care Services published by AIHW for the period 2013 to 2018 (Australian Institute of Health and Welfare, 2017-18), the maximum number of child and youth mental health services that can be delivered per week has been increasing at an annual rate of 89 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.41) was derived from Community Mental Health Care Services data published by AIHW (Australian Institute of Health and Welfare, 2017-18) for the period 2016-2018 and represents a decrease in the annual growth rate.

Community mental health care services	Based on Community Mental Health Care Services published by AIHW for the period 2013 to 2018 (Australian Institute of Health and Welfare, 2017-18), the maximum number of community mental health care services that can be delivered per week has been increasing at an annual rate of 222 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.07) was derived from Community Mental Health Care Services data published by AIHW (Australian Institute of Health and Welfare, 2017-18) for the period 2016-2018 and represents a decrease in the annual growth rate.
headspace	Based on headspace occasions of service data provided by BSPHN for the period 2013 to 2022, the maximum number of headspace services that can be delivered per week has been increasing at an annual rate of 45 additional services per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.58) was derived from headspace occasions of service data provided by BSPHN for the period 2017-2022 and represents a decrease in the annual growth rate.
Psychiatric admitted care	Based on episodes of admitted patient care provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023) for the period 2011 to 2022, the maximum number of episodes of admitted patient care that can be delivered per week has been increasing at an annual rate of 4 additional episodes per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.08) was derived from episodes of admitted patient care provided by Queensland Health (Statistical Services Branch (Queensland Health), 2023) for the period 2017-2019 and represents a decrease in the annual growth rate.
Substance misuse treatment services	Based on alcohol and other drug closed treatment episodes published by AIHW (Australian Institute of Health and Welfare, 2016-21) for the period 2013-14 to 2020-2021, the maximum number of closed treatment episodes that can be delivered per week has been increasing at an annual rate of 9 additional episodes per week. This assumes that services were operating at maximum capacity over this period. The default value for the future growth rate multiplier (0.77) was derived from alcohol and other drug closed treatment episodes published by AIHW

	(Australian Institute of Health and Welfare, 2016-21) for the period 2017-18 to 2019-20 and represents a decrease in the annual growth rate.

Numerical inputs

Variable Name	Stratification / Value		Notes
Population			
Population initial by age	0–4 years	73403.32	Estimated with constrained optimisation
	5–11 years	90745.96	
	12-14 years	35261.66	
	15-17 years	42747.12	
	18-24 years	112203	
	25 years and older	662238.1	
Birth rate per year initial	0.013619180		Estimated with constrained optimisation
Birth rate increase per year	-0.0000904897		Estimated with constrained optimisation
Death rate per year initial	0.005606927		Estimated with constrained optimisation
Death rate increase per year	-0.0000030102		Estimated with constrained optimisation
Deaths per capita per year age rate ratio	0–4 years	0.15787930	Australian Bureau of Statistics (2022a)
	5–11 years	0.01387892	
	12-14 years	0.01618564	
	15-17 years	0.05522237	
	18-24 years	0.07360028	
	25 years and older	1.45942	
Arrivals per year by age initial	0–4 years	21364.22826	Estimated with constrained optimisation
	5–11 years	21421.73749	
	12-14 years	3302.189961	
	15-17 years	7339.889174	
	18-24 years	45644.2283	
	25 years and older	61372.53703	
Arrivals increase per year by age	0–4 years	0	Estimated with constrained optimisation
	5–11 years	31.98119806	
	12-14 years	34.44288621	
	15-17 years	0.66163482	
	18-24 years	0	
	25 years and older	16.90088416	
Per capita departure rate by age initial	0–4 years	0.264754914	Estimated with constrained optimisation
	5–11 years	0.188861708	
	12-14 years	0.076197284	
	15-17 years	0.158536797	
	18-24 years	0.360280937	
	25 years and older	0.079111422	
Per capita departure rate by age increase per year	0–4 years	0.000115989	Estimated with constrained optimisation
	5–11 years	0.000067905	
	12-14 years	0	
	15-17 years	0	
	18-24 years	0.000457962	
	25 years and older	0	
Education - Students			
Studying post-secondary education initial	107910.9861		Estimated with constrained optimisation
Proportion of population not currently studying entering secondary education per year	0.000001319		Estimated with constrained optimisation

Proportion of population not currently studying entering post-secondary education per year	0.04781599		Estimated with constrained optimisation
Discontinuing secondary study base rate	0.0394836834639		Estimated with constrained optimisation
Discontinuing post-secondary study base rate	0.083776167		Estimated with constrained optimisation
Completing secondary study rate	0.144451109414		Estimated with constrained optimisation
Completing post-secondary study rate	0.427533386		Estimated with constrained optimisation
Proportion of secondary study completers transitioning to post-secondary education	0.4796904		Queensland Department of Education (2023)
Proportion of population 5-11 studying primary education ratio: rest of Australia vs QLD	0.969		Australian Bureau of Statistics (2022b)
Proportion of population 12-17 studying secondary education ratio: rest of Australia vs QLD	1.08		Australian Bureau of Statistics (2022b)
Proportion of population 18+ studying post-secondary education ratio: rest of Australia vs QLD	1.013012		Australian Bureau of Statistics (2022b)
Prevalence of moderate to very high psychological distress ratio secondary students vs population	1		Assumes that the prevalence of psychological distress in secondary students is the same as population prevalence for 12-17 year olds.
Effect of moderate to very high distress on discontinuation of secondary education	1.99		Butterworth and Leach (2017)
Prevalence of moderate to very high psychological distress ratio post-secondary students vs population	1.3995		Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
Effect of psychological distress on discontinuation of post-secondary education	1.1		Lee et al. (2009)
Education – Highest qualifications			
Proportion of population with secondary qualification only initial by age 15-24, 25+	15-24 years	0.404604512	Estimated with constrained optimisation
	25 years and older	0.172317986	
Proportion of population with post-secondary qualification initial by age 15-24, 25+	15-24 years	0.29891598	Estimated with constrained optimisation
	25 years and older	0.40157251	
Proportion completing first post-secondary qualification by age 15-24, 25+	15-24 years	0.941009619	Estimated with constrained optimisation
	25 years and older	0.273396566	
Proportion of secondary school graduates who are aged 15-24	0.528945706		Estimated with constrained optimisation
Proportion of post-secondary graduates who are aged 15-24	0.081662928		Estimated with constrained optimisation
Death rate ratio post-secondary qualification vs low education	0.3623188		Welsh et al. (2021)
Death rate ratio secondary qualification only vs low education	0.635		Welsh et al. (2021)
Proportion of population with secondary qualification only ratio Australia vs BSPHN	15-24 years	1.1184972	Australian Bureau of Statistics (2014-2022) Australian Department of Health and Aged Care (2023)
	25 years and older	1.0674508	
Proportion of population with post-secondary qualification ratio Australia vs BSPHN	15-24 years	0.8848893	Australian Bureau of Statistics (2014-2022) Australian Department of Health and Aged Care (2023)
	25 years and older	1.0140127	

Labour force			
Proportion of population 15-24, 25+ sufficiently employed proportion initial	15-24 years	0.645484041	Estimated with constrained optimisation
	25 years and older	0.671011922	
Proportion of population 15-24, 25+ underemployed proportion initial	15-24 years	0.000004229	Estimated with constrained optimisation
	25 years and older	0.000610871	
Proportion of population 15-24, 25+ unemployed proportion initial	15-24 years	0.112349271	Estimated with constrained optimisation
	25 years and older	0.033182918	
Sufficiently employed to unemployed per capita per year base rate by age 15-24, 25+	15-24 years	0.188773316	Estimated with constrained optimisation
	25 years and older	0.041900295	
Unemployed to sufficiently employed per capita per year base rate by age 15-24, 25+	15-24 years	1.966435759	Estimated with constrained optimisation
	25 years and older	0.851576955	
Underemployed to unemployed per capita per year base rate by age 15-24, 25+	15-24 years	0.086418873	Estimated with constrained optimisation
	25 years and older	0.533308196	
Unemployed to underemployed per capita per year base rate by age 15-24, 25+	15-24 years	1.499279338	Estimated with constrained optimisation
	25 years and older	2.25377314	
Sufficiently employed to underemployed per capita per year base rate by age 15-24, 25+	15-24 years	0.062465237	Estimated with constrained optimisation
	25 years and older	0.080178673	
Underemployed to sufficiently employed per capita per year base rate by age 15-24, 25+	15-24 years	0.95585229	Estimated with constrained optimisation
	25 years and older	1.378794293	
Unemployed to NILF per capita per year base rate by age 15-24, 25+	15-24 years	3.031715245	Estimated with constrained optimisation
	25 years and older	2.430982644	
NILF to Unemployed per capita per year base rate by age 15-24, 25+	15-24 years	1.435570397	Estimated with constrained optimisation
	25 years and older	0.268136312	
Sufficiently employed to NILF per capita per year base rate by age 15-24, 25+	15-24 years	0.420654638	Estimated with constrained optimisation
	25 years and older	0.065116267	
Underemployed to NILF per capita per year base rate by age 15-24, 25+	15-24 years	0.049159652	Estimated with constrained optimisation
	25 years and older	0.04791504	
Proportion of population sufficiently employed ratio: rest of Australia vs QLD	0.9999229		Australian Bureau of Statistics (2023a)
Proportion of population underemployed ratio: rest of Australia vs QLD	0.9548649		Australian Bureau of Statistics (2023a)
Proportion of population unemployed ratio: rest of Australia vs BSPHN	0.9051092		Australian Bureau of Statistics (2014-2022)
Death rate ratio: unemployed vs employed	1.22		Sorlie and Rogot (1990)
Effect of post-secondary qualification on underemployment to sufficiently employed rate	1.407043821		Wilkins (2004)
Post-secondary qualification probability ratio underemployed vs population	0.86282872		Wilkins (2004)
Effect of moderate to very high distress on employment	0.8396596		Frijters et al. (2014)
Moderate distress prevalence ratio unemployed by age 15-24, 25+	15-24 years	1.34	Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
	25 years and older	1.73	
Moderate distress prevalence ratio participation by age 15-24, 25+	15-24 years	0.981	Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
	25 years and older	0.924	

Effect of post-secondary qualification on participation	1.435808		Australian Bureau of Statistics (2014-2022)
Post-secondary qualifications prevalence ratio participation vs population	1.08		Australian Bureau of Statistics (2014-2022)
Effect of post-secondary qualification on employment vs low educational attainment	1.512015		Australian Bureau of Statistics (2014-2022)
Post-secondary qualifications prevalence ratio unemployed vs population	0.822		Australian Bureau of Statistics (2014-2022)
Effect of secondary qualification only on participation	1.281302		Australian Bureau of Statistics (2014-2022)
Secondary qualifications only prevalence ratio participation vs population	0.964		Australian Bureau of Statistics (2014-2022)
Effect of secondary qualification only on employment vs low educational attainment	1.305415		Australian Bureau of Statistics (2014-2022)
Secondary qualifications only prevalence ratio unemployed vs population	1.29		Australian Bureau of Statistics (2014-2022)
NEET			
Proportion of population NEET ratio 15-17 / 15-24	0.2893055		Australian Bureau of Statistics (2015-2022)
Coefficient for students aged 15-24 and not employed initial	1.711780643		Estimated with constrained optimisation
Coefficient for students aged 15-24 and not employed increase per year	0.046446351		Estimated with constrained optimisation
Psychological distress / disorder			
Prevalence of moderate to very high distress initial by age 12+	12-14 years	0.307415879	Estimated with constrained optimisation
	15-17 years	0.506342413	
	18-24 years	0.19807616	
	25 years and older	0.336014894	
Coefficient Social cohesion on Distress onset per year per base rate by age 12+	12-14 years	-0.107442807	Estimated with constrained optimisation
	15-17 years	-0.019644493	
	18-24 years	-0.028448839	
	25 years and older	-0.032940071	
Intercept social cohesion on Distress onset per year per base rate by age 12+	12-14 years	0.049399265	Estimated with constrained optimisation
	15-17 years	0.060668244	
	18-24 years	-0.002286305	
	25 years and older	0.034026888	
Coefficient social cohesion on Disorder incidence per year base rate by age 12+	12-14 years	-0.116738035	Estimated with constrained optimisation
	15-17 years	-0.027401149	
	18-24 years	-0.027628572	
	25 years and older	-0.026413605	
Intercept social cohesion on Disorder incidence per year base rate by age 12+	12-14 years	0.974258794	Estimated with constrained optimisation
	15-17 years	0.993189929	
	18-24 years	1.014336705	
	25 years and older	0.979776148	
Death rate ratio Moderate distress vs Low distress	1.16		Russ et al. (2012)
Death rate ratio High distress vs Low distress	1.37		Russ et al. (2012)
Prevalence of low distress ratio Australia vs QLD by age 12+	12-14 years	1	Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
	15-17 years	1	
	18-24 years	1.01	
	25 years and older	1.02	
Prevalence of disorder ratio Australia vs QLD by age 12+	12-14 years	1	Australian Bureau of Statistics (2011-12, 2014-15, 2017-18)
	15-17 years	1	
	18-24 years	0.983	
	25 years and older	0.958	
Effect of unemployment on distress	15-24 years	1.43	Australian Bureau of Statistics (2007a)
	25 years and older	1.81	

Unemployment rate ratio of low distress vs population by age 15-24, 25+	15-24 years	0.759	Australian Bureau of Statistics (2007a)
	25 years and older	0.666	
Effect of homelessness on distress	2.14		Australian Bureau of Statistics (2007a)
Homelessness prevalence ratio of low distress vs population	0.567		Australian Bureau of Statistics (2007a)
Effect of underemployment on distress	1.132448		Dooley et al. (2000)
Underemployment ratio of low distress vs population	1.003201		Griffiths et al. (2021)
Effect of substance abuse on distress	2.63		Marmorstein et al. (2010)
Substance misuse prevalence ratio of low distress vs population	0.6595638		Australian Bureau of Statistics (2012)
Distress recovery per year base rate by age 12+	0.06833333		Jokela et al. (2011)
Disorder recovery per year base rate by age 12+	0.06833333		Jokela et al. (2011)
Proportion of disorder recovery to no disorder, moderate to very high distress through treatment	0.8		Assumes that 80% of people with a mental disorder who recover through accessing services will recover to a state of moderate to very high psychological distress and that 20% will recover into a state of low psychological distress.
Proportion of Close to average SDQ to Low distress	0.468		Australian Institute of Family Studies (2022)
Proportion of Close to average SDQ to Disorder, Moderate to Very high distress	0.238		Australian Institute of Family Studies (2022)
Proportion of Slightly raised SDQ to Low distress	0.182		Australian Institute of Family Studies (2022)
Proportion of Slightly raised SDQ to Disorder, Moderate to Very high distress	0.62		Australian Institute of Family Studies (2022)
Proportion of High SDQ to Low distress	0.112		Australian Institute of Family Studies (2022)
Proportion of High SDQ to Disorder, Moderate to Very high distress	0.72		Australian Institute of Family Studies (2022)
Strengths and Difficulties			
Coefficient Social cohesion on Close to average to Slightly raised SDQ per year base rate by age <12	0-4 years	-0.042484533	Estimated with constrained optimisation
	5-11 years	-0.044012565	
Intercept social cohesion on Close to average to Slightly raised SDQ per year base rate by age <12	0-4 years	1.242650711	Estimated with constrained optimisation
	5-11 years	1.041291164	
Coefficient Social cohesion on Slightly raised to High SDQ per year base rate by age <12	0-4 years	-0.017355267	Estimated with constrained optimisation
	5-11 years	-0.038128501	
Intercept social cohesion on Slightly raised to High SDQ per year base rate by age <12	0-4 years	0.360948024	Estimated with constrained optimisation
	5-11 years	2.28262466	
Proportion of High SDQ recovery to Slightly raised through treatment	0.8		Assumes that 80% of people with High levels of SDQ who recover through accessing services will recover to a state of Slightly raised SDQ and that 20% will recover into a state of Close to average SDQ

Prevalence of slightly raised SDQ ratio rest of Australia vs BSPHN by age <12	0-4 years	1.06	Australian Institute of Family Studies (2022)
	5-11 years	0.824	
Prevalence of high SDQ ratio rest of Australia vs BSPHN by age <12	0-4 years	0.918	Australian Institute of Family Studies (2022)
	5-11 years	0.874	
Slightly raised to Close to average SDQ per year base rate by age <12	0.06833333		Jokela et al. (2011)
High to Slightly raised SDQ per year base rate by age <12	0.06833333		Jokela et al. (2011)
Homelessness			
Homeless by age initial	0–4 years	230.3500687	Estimated with constrained optimisation
	5–11 years	258.4868751	
	12-14 years	101.3063039	
	15-17 years	167.9467548	
	18-24 years	716.0155577	
	25 years and older	2298.728691	
Entering homelessness per week base rate by age	0–4 years	0.000027358	Estimated with constrained optimisation
	5–11 years	0.000015254	
	12-14 years	0.000012205	
	15-17 years	0.000014189	
	18-24 years	0.000023220	
	25 years and older	0.000011581	
Mean duration of homelessness	239.8571		Ranney (2023)
Death rate ratio homeless vs non-homeless	1.6		Morrison (2009)
Effect of unemployment on entering homelessness	2.6		Nilsson et al. (2019)
Effect of mental illness on entering homelessness	1.7		Nilsson et al. (2019)
Effect of substance misuse on entering homelessness	2.3		Nilsson et al. (2019)
Substance misuse			
Waiting for substance misuse treatment by age 15-24, 25+ initial	15-24 years	980.4253188	Estimated with constrained optimisation
	25 years and older	974.8870492	
Substance misuse seeking treatment per capita per week rate initial	15-24 years	0.002209145	Estimated with constrained optimisation
	25 years and older	0.001545306	
Substance misuse seeking treatment per capita per week increase per year	15-24 years	0.000131204	Estimated with constrained optimisation
	25 years and older	0.000485677	
Substance misuse onset per capita per week base rate by age 15-24, 25+	15-24 years	0.000159647	Estimated with constrained optimisation
	25 years and older	0.000022895	
Substance misuse natural recovery per capita per week base rate by age 15-24, 25+	15-24 years	0.000914274	Estimated with constrained optimisation
	25 years and older	0.002283660	
Substance misuse treatment capacity per week initial	76.20995643		Estimated with constrained optimisation
Substance misuse treatment capacity per week increase per year	8.648468568		Estimated with constrained optimisation
Substance misuse treatment mean duration	4.140022		Australian Institute of Health and Welfare (2023)
Prevalence of substance misuse ratio rest of Australia vs BSPHN by age 15-24, 25+	1		This sector was calibrated with national prevalence data, hence the prevalence ratio will be one. Australian Bureau of Statistics (2008, 2020-22)
Death rate ratio substance misuse vs no substance misuse	1.95		Roerecke and Rehm (2013)
Effect of homelessness on substance misuse	1.65		Johnson et al. (1997)

Prevalence of homelessness in the non substance misuse population vs total population	0.8683555		Slade et al. (2009)
Effect of moderate to very high distress on substance misuse	2.505036		Australian Institute of Health and Welfare (2017)
Prevalence of distress in the non substance misuse population vs total population	0.9916363		Australian Institute of Health and Welfare (2017)
Effect of NEET substance misuse	1.43		Gariépy et al. (2022)
Prevalence of NEET in the non substance misuse population vs total population	1.012717083		Australian Bureau of Statistics (2020-22)
QLD average number of closed treatment episodes per client	1.3		Australian Institute of Health and Welfare (2016-21)
Recovery rate from substance misuse treatment	0.359		Manning et al. (2017)
Suicidal behaviours			
Suicide attempt lethality 0-24	0.023634286		Estimated with constrained optimisation
Index suicide attempt base rate by age 12+	12-14 years	0.000014123825	Estimated with constrained optimisation
	15-17 years	0.000024350493	
	18-24 years	0.000025232155	
	25 years and older	0.000016279156	
Repeat suicide attempts per week base rate	0.006285649		Estimated with constrained optimisation
Suicide attempt lethality ratio 0-24 vs 25+	3.217148569		Australian Institute of Health and Welfare (2021d, 2021e)
Suicide rate ratio substance misuse disorder vs no substance misuse disorder	4.1		Too et al. (2019)
Suicide attempt rate ratio by distress	No distress	1 (Reference)	Hockey et al. (2022)
	Distress No Disorder	1.41	
	Distress Disorder	3.57	
Mental health services			
Effect of disengagement on increasing psychological distress	1.271517		Australian Bureau of Statistics (2012)
Baseline disengagement rate waiting per year	0.2620284		Tyrer et al. (1995)
Baseline disengagement rate hospital care	0.051642558		Australian Institute of Health and Welfare (2016-17)
Baseline disengagement rate non-hospital care	0.03909747		Australian Institute of Health and Welfare (2016-17)
Effect of distress on hospitalisation	No distress	0	Australian Bureau of Statistics (2007a)
	Distress No Disorder	1 (Reference)	
	Distress Disorder	1.773723	
Mean treatment duration psychiatric hospital care	1.997143		Australian Institute of Health and Welfare (2021b)
Mean treatment duration non-specialised hospital care	0.7142857		Australian Institute of Health and Welfare (2021b)
Mean treatment duration online services	6		Christensen, Griffiths, and Jorm (2004)
Seeking help to online services rate by age	0–4 years	0.0440037	Australian Bureau of Statistics (2020-22)
	5–11 years	0.0440037	
	12-14 years	0.079675	
	15-17 years	0.079675	
	18-24 years	0.079675	
	25 years and older	0.027663	
Referral rate from GP to headspace	0–4 years	0	Australian Institute of Health and Welfare (2022); KPMG (2022)
	5–11 years	0	
	12-14 years	0.07415457	
	15-17 years	0.07415457	
	18-24 years	0.07415457	
	25 years and older	0	

Referral rate from GP to other services	0.046749		Australian Institute of Health and Welfare (2015-16)
Effect of distress on help-seeking with GP	No distress	0	Australian Bureau of Statistics (2007a)
	Distress No Disorder	1	
	Distress Disorder	3.287037	
Proportion of post-discharge referrals to non-CMHC services to GP	0.5		Assumes half of patients not referred to CMHC services after discharge from hospital care are referred to a general practitioner. The remaining patients (i.e., those not referred to CMHC services or a general practitioner) are referred to a psychiatrist or allied mental health professional
Effect of distress on referral rate	No distress	0	Australian Bureau of Statistics (2007a)
	Distress No Disorder	1	
	Distress Disorder	1.786096	
Effect of distress on seeking help psychiatrist or allied health services	No distress	0	Australian Bureau of Statistics (2007a)
	Distress No Disorder	1	
	Distress Disorder	4.398422	
Baseline recovery rate psychiatric hospital care	No distress	0	Thase et al. (1997)
	Distress No Disorder	0.4241071	
	Distress Disorder	0.3712737	
Baseline recovery rate headspace	0.050295858		KPMG (2022)
Baseline recovery rate CMHC services	0.02332282		Australian Institute of Health and Welfare (2016)
Recovery rate ratio GP services	No distress	0	Cuijpers, Smits, Donker, ten Have, and de Graaf (2009)
	Distress No Disorder	1	
	Distress Disorder	0.4626866	
Baseline recovery rate mental health treatment	No distress	0	Thase et al. (1997)
	Distress No Disorder	0.09525994	
	Distress Disorder	0.08339287	
Psychological treatment rate GP services	0.48343875		Australian Institute of Health and Welfare (2016)
Recovery rate online services	No distress	0	Christensen et al. (2004); Cuijpers, Straten, Schaik, and Andersson (2009)
	Distress No Disorder	0.4	
	Distress Disorder	0.1850746	
Perceived needs for services per capita per week rate initial	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	0.001805767	
	Distress Disorder	0.012469428	
Perceived needs for services rate increase per year	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	-3.32927E-05	
	Distress Disorder	7.80161E-05	
Re-engaging excluding ED per capita per week rate initial	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	0.113266016	
	Distress Disorder	0.095776677	
Re-engaging excluding ED per capita per week rate increase per year	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	0.002808987	
	Distress Disorder	0.085153265	
Proportion of population in distress seeking help initial by distress	No distress	0	Estimated with constrained optimisation
	Distress No Disorder	0.195389983	
	Distress Disorder	0.652438251	
Disengaged initial total	0		Estimated with constrained optimisation
GP services capacity per week initial	2058.304273		Estimated with constrained optimisation
GP services capacity per week increase per year	140.5472373		Estimated with constrained optimisation
Psychiatrist and allied health services capacity per week initial	5342.906405		Estimated with constrained optimisation

Psychiatrist and allied health services capacity per week increase per year	298.2331118		Estimated with constrained optimisation
CYMHS services capacity per week initial	1147.346		Estimated with constrained optimisation
CYMHS services capacity per week increase per year	89.01923		Estimated with constrained optimisation
CMHC services (adult) capacity per week initial	4816.154		Estimated with constrained optimisation
CMHC services (adult) capacity per week increase per year	222.3462		Estimated with constrained optimisation
Psychiatric hospitalisation capacity per week initial	90.5		Estimated with constrained optimisation
Psychiatric hospitalisation capacity per week increase per year	4.412692		Estimated with constrained optimisation
Non-specialised hospital care services capacity per week initial	206.883489		Estimated with constrained optimisation
Non-specialised hospital care services capacity capacity per week increase per year	35.86016039		Estimated with constrained optimisation
headspace services capacity per week initial	1		Estimated with constrained optimisation
headspace services capacity capacity per week increase per year	45.39721129		Estimated with constrained optimisation
ED presentations per capita per week rate by age initial	0–4 years	0.00000620315	Estimated with constrained optimisation
	5–11 years	0.00003095921	
	12-14 years	0.00018241607	
	15-17 years	0.00030566461	
	18-24 years	0.00062163940	
	25 years and older	0.00048565391	
ED presentations rate by age increase per year	0–4 years	0.00000614195	Estimated with constrained optimisation
	5–11 years	0.00000703190	
	12-14 years	0.00001119396	
	15-17 years	0.00000543526	
	18-24 years	-0.00001699589	
	25 years and older	-0.00001301185	
ED presentation rate ratio help seeker	1		Estimated with constrained optimisation
ED to admission rate initial by age	0–4 years	0.218855977	Estimated with constrained optimisation
	5–11 years	0.125828686	
	12-14 years	0.191485232	
	15-17 years	0.249542276	
	18-24 years	0.08105427	
	25 years and older	0.145228354	
ED to admission rate increase per year	0–4 years	-0.011687394	Estimated with constrained optimisation
	5–11 years	0.004505288	
	12-14 years	0.010480664	
	15-17 years	-0.001778161	
	18-24 years	0.072187184	
	25 years and older	0.086166213	
Proportion of admissions into psychiatric hospitalisation by age 0-17, 18-24, 25+	0-17 years	0.414161436	Estimated with constrained optimisation
	18-24 years	0.547643051	
	25 years and older	0.377282299	
Additional non-specialised hospitalisations per capita per week by age 0-17, 18-24, 25+	0-17 years	0.00023579	Estimated with constrained optimisation
	18-24 years	0.000773031	
	25 years and older	0.00189995	
Referral rate from ED to CMHC	0.074017861		Estimated with constrained optimisation
Waiting for psychiatric hospitalisation initial total	0		Estimated with constrained optimisation
Seeking help GP services rate by age 0-14, 15-24, 25+ initial	0-14 years	0.003158381	Estimated with constrained optimisation
	15-24 years	0.005169437	

	25 years and older	0.007613575	
Seeking help GP services rate by age 0-14, 15-24, 25+ increase per year	0-14 years	2.99577E-06	Estimated with constrained optimisation
	15-24 years	0.000307391	
	25 years and older	1.00601E-05	
Waiting for GP initial total	4260.483118		Estimated with constrained optimisation
Referral rate from GP to psychiatrist and allied health service initial	0.045365473		Estimated with constrained optimisation
Referral rate from GP to psychiatrist and allied health service increase per year	0.004929958		Estimated with constrained optimisation
Referral rate from GP to CMHC	0.003341101		Estimated with constrained optimisation
Additional psychiatrist or allied health services per capita per week initial by age 0-14, 15-24, 25+	0-14 years	0.014226087	Estimated with constrained optimisation
	15-24 years	0.008226495	
	25 years and older	0.027601801	
Additional psychiatrist or allied health services per capita per week increase per year by age 0-14, 15-24, 25+	0-14 years	-0.000439327	Estimated with constrained optimisation
	15-24 years	0.00126023	
	25 years and older	-0.000438443	
Referral rate from psychiatrist and allied health to psychiatric hospital care services by age 0-17, 18-24, 25+	0-17 years	0.003455588	Estimated with constrained optimisation
	18-24 years	0.008682608	
	25 years and older	0.007059504	
Waiting for psychiatrist and allied health initial total	41729.37681		Estimated with constrained optimisation
Referral rate from post-discharge to CMHC services initial	0–4 years	0.735839126	Estimated with constrained optimisation
	5–11 years	0.66178922	
	12-14 years	0.721061818	
	15-17 years	0.697091783	
	18-24 years	0.701704305	
	25 years and older	0.777140465	
Referral rate from post-discharge to CMHC services increase per year	0–4 years	0.003500216	Estimated with constrained optimisation
	5–11 years	0.053376831	
	12-14 years	0.010040507	
	15-17 years	0.023416686	
	18-24 years	0.02094671	
	25 years and older	-0.0006888	
Additional CMHC per capita per week initial by age AIHW	0–4 years	0.006479574	Estimated with constrained optimisation
	5–11 years	0.034805066	
	12-17 years	0.092108971	
	18-24 years	0.042861193	
	25 years and older	0.046489093	
Additional CMHC per capita per week increase per year by age AIHW	0–4 years	-0.000243268	Estimated with constrained optimisation
	5–11 years	0.000392489	
	12-17 years	0.002132025	
	18-24 years	0.000638724	
	25 years and older	-0.001044554	
Waiting for CMHC initial total	35055.52948		Estimated with constrained optimisation
Seeking help headspace rate by age 12+ initial	12-14 years	0.000001012955	Estimated with constrained optimisation
	15-17 years	0.000001331976	
	18-24 years	0.000000968132	
	25 years and older	0.000004073255	
Seeking help headspace rate by age 12+ increase per year	12-14 years	0.000509271129	Estimated with constrained optimisation
	15-17 years	0.000408177488	
	18-24 years	0.000215692733	
	25 years and older	-0.000000055495	
Waiting for headspace initial total	0		Estimated with constrained optimisation

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Supplementary Material Part B

The health and economic benefits of mental health system reform: exploring the optimal mix of interventions and service capacity through simulation modelling

Contents

Additional results

Figure S1: Incremental net monetary benefit vs. business as usual (health care perspective)

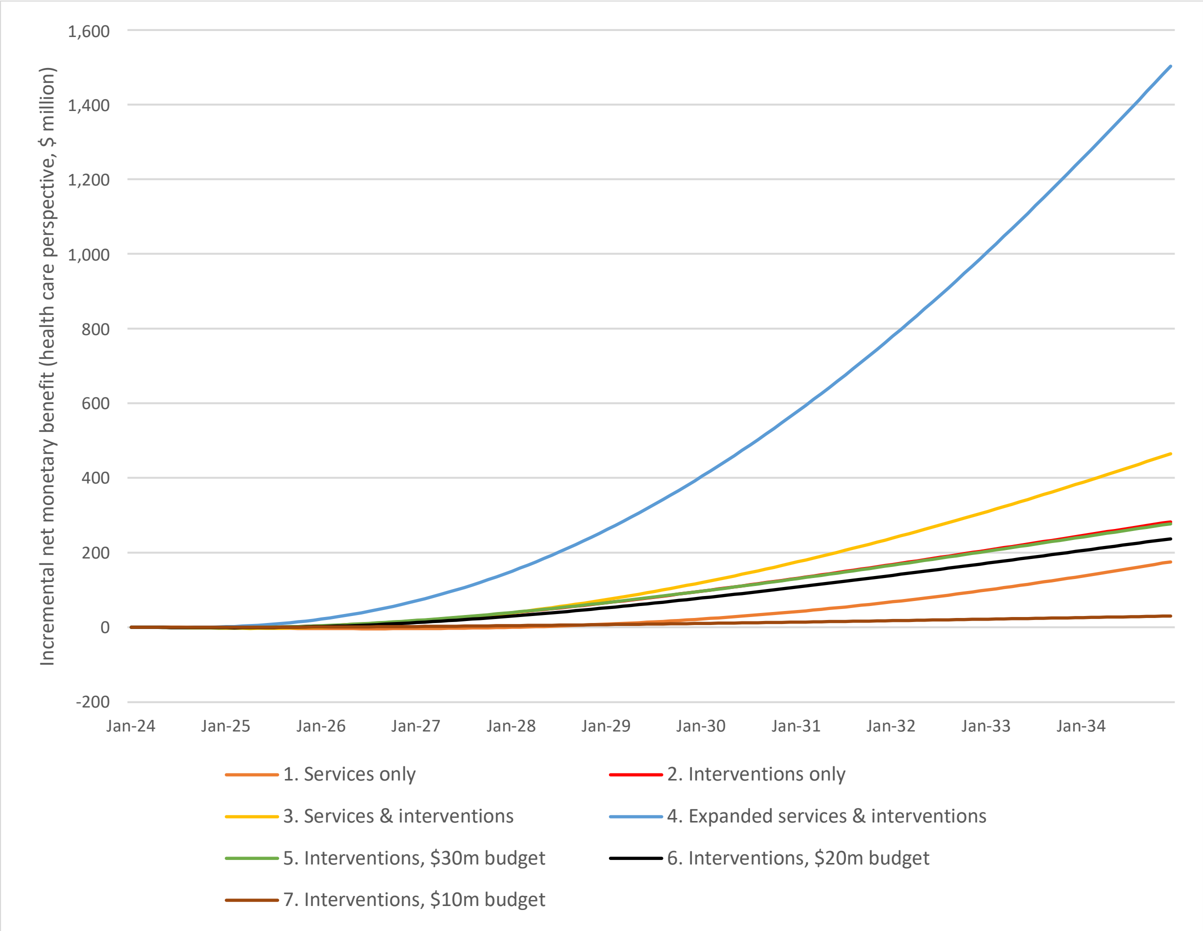


Figure S2: Incremental total cost vs. business as usual (health care perspective)

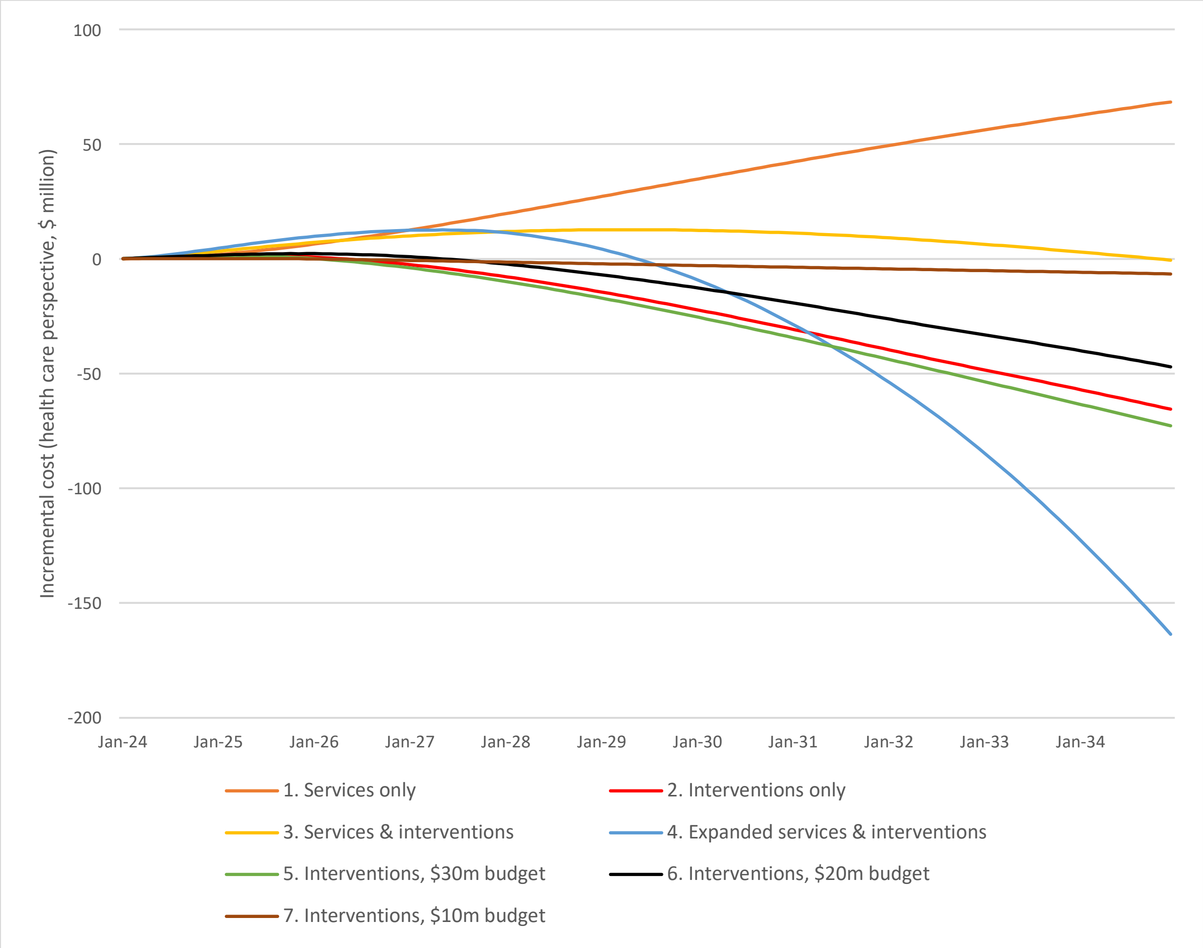
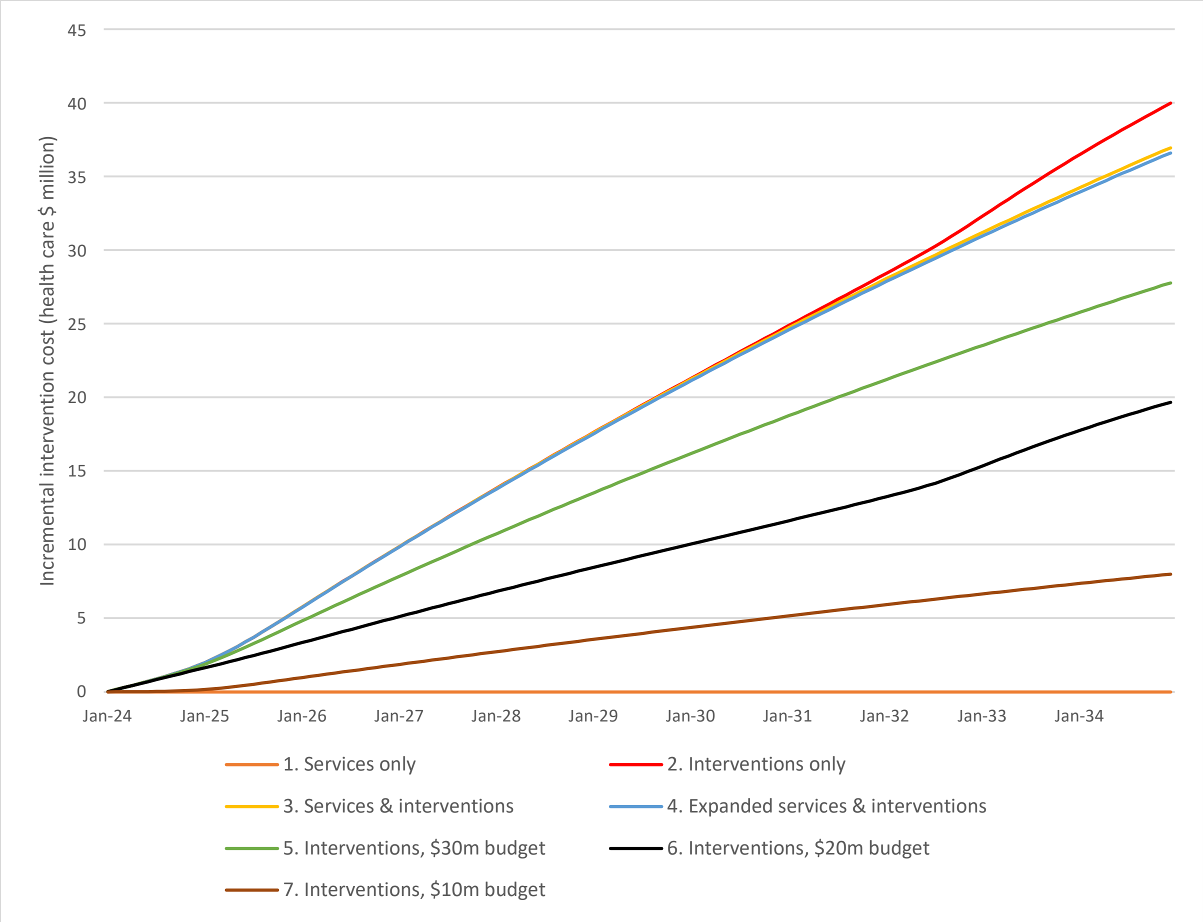


Figure S3: Incremental intervention cost vs. business as usual, health care & societal perspectives (excluding productivity components)



Intervention-related time costs are allocated to the productivity cost category.

Figure S4: Incremental health service cost vs. business as usual, health care & societal perspectives

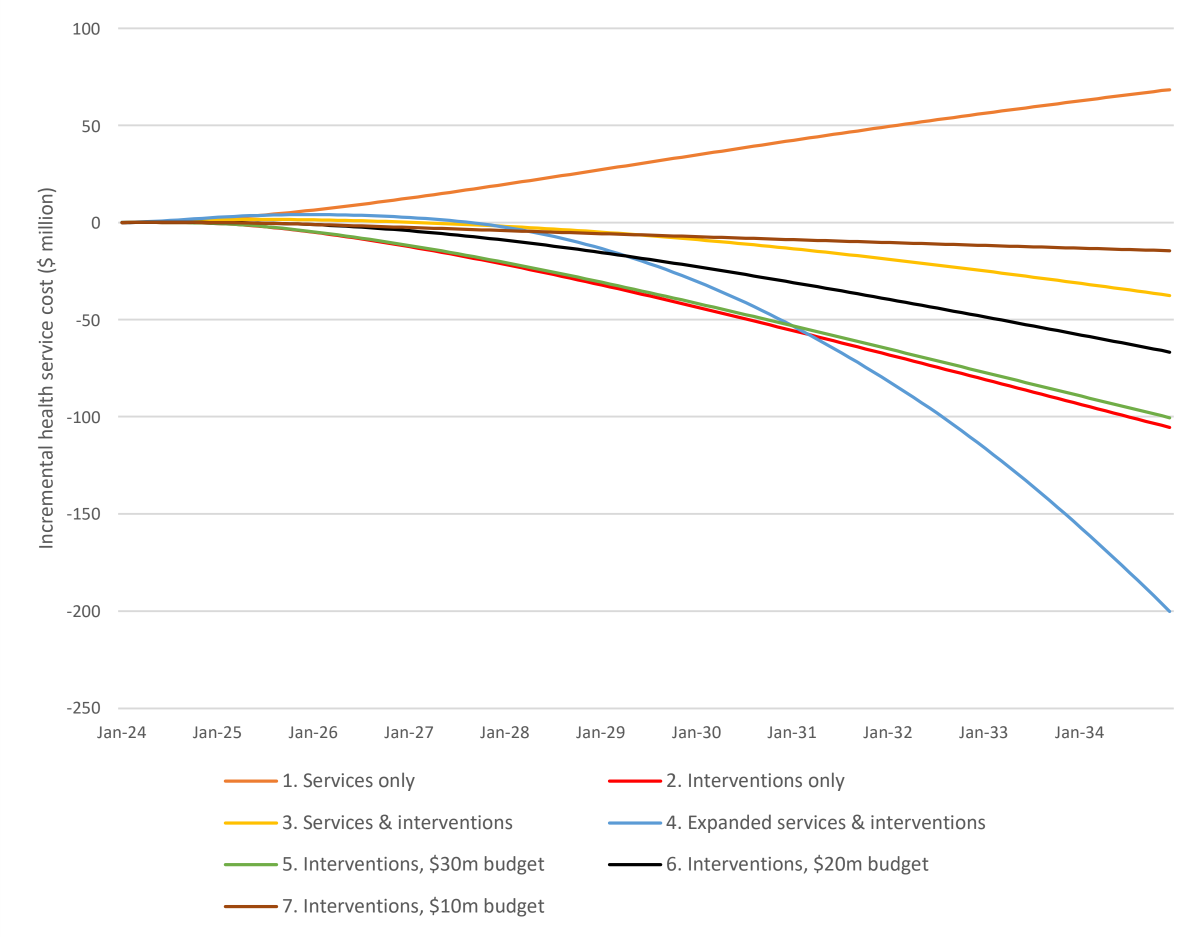
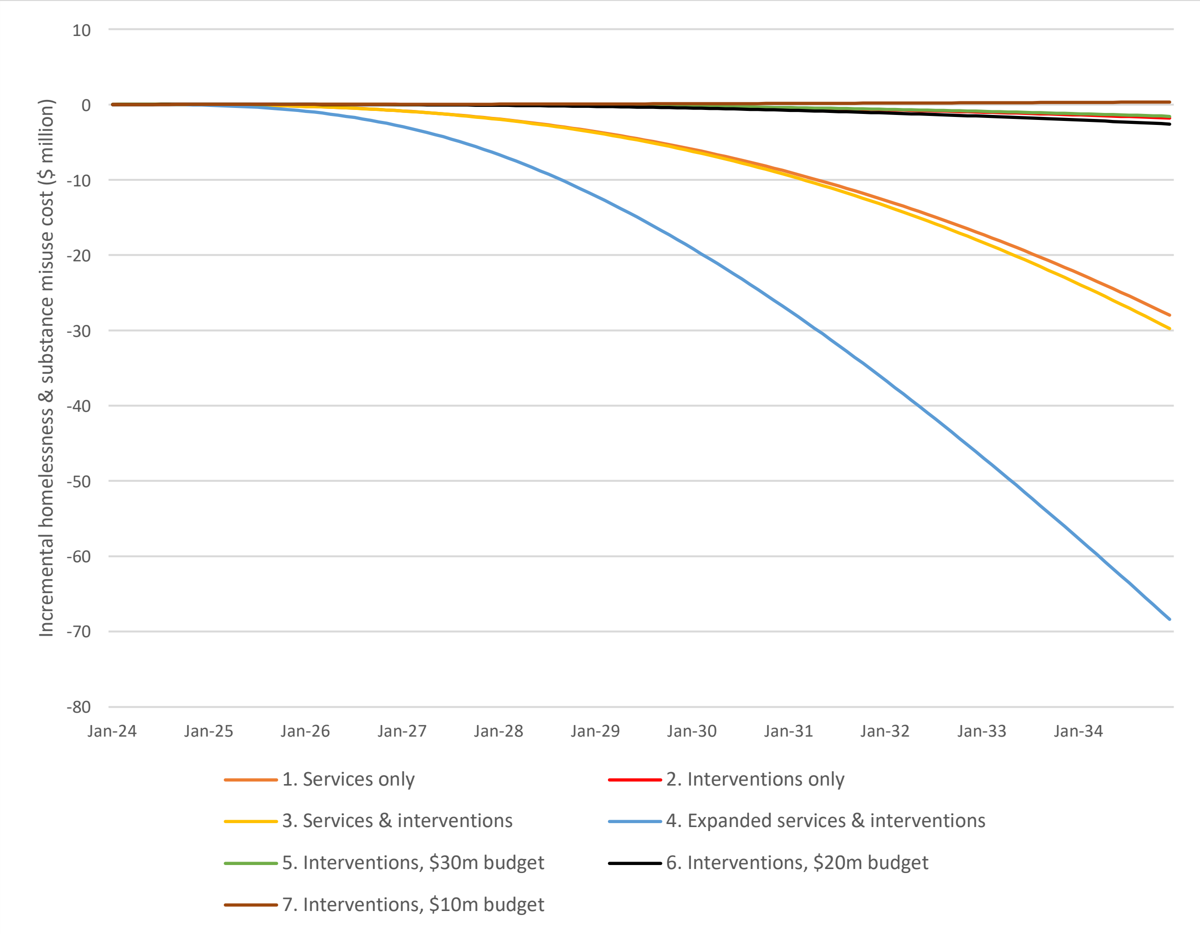


Figure S5: Incremental homelessness and substance misuse costs vs. business as usual, societal perspective (excluding health care and productivity-related components)



Homelessness-related and substance misuse-related health care and productivity costs are allocated to those categories respectively.

Figure S6: Incremental productivity costs vs. business as usual, societal perspective

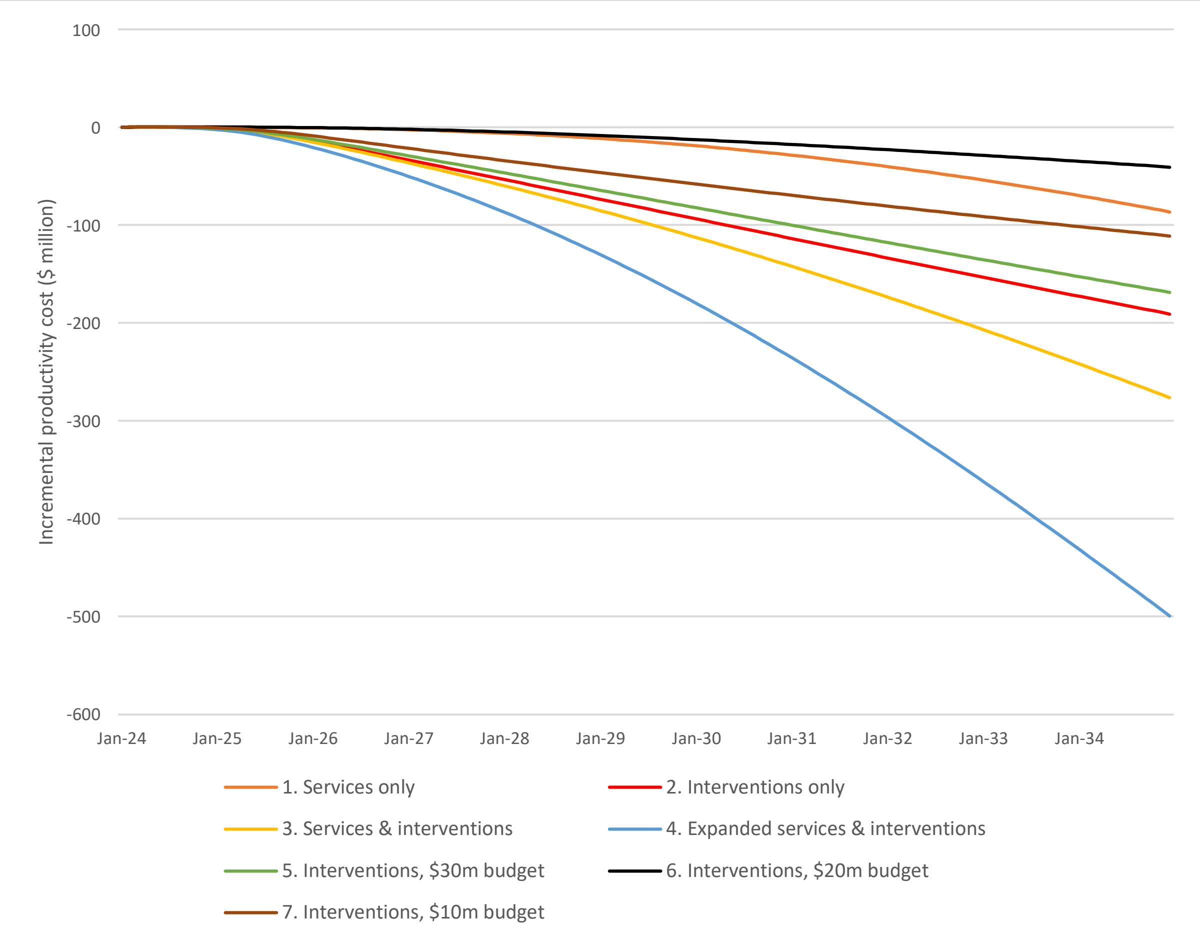


Table S1: Cost-effectiveness analysis results for individual interventions alone

		HEALTH CARE PERSPECTIVE				SOCIETAL PERSPECTIVE			
Intervention	**Incremental QALYs (n)**	**Incremental costs ($)**	**ICER vs. BAU ($/QALY)**	**INMB vs. BAU (Threshold, $M)**	**Rank NMB**	**Incremental costs ($)**	**ICER vs. BAU ($/QALY)**	**INMB vs. BAU (VSLY, $M)**	**Rank NMB**
BAU	-	-	**-**	-	**5**	-	**-**	-	**6**
Tech-enabled integrated care	2,167	-50,704,417	**Dominant**	231	**1**	-91,989,247	**Dominant**	272	**1**
School-based suicide prevention	41	30,735,994	**755,211**	-27	**7**	50,160,632	**1,232,492**	-47	**7**
Post-attempt care	37	3,347,318	**89,797**	-0.25	**6**	-25,413,062	**Dominant**	29	**4**
Youth MH service hubs	122	4,063,613	**33,332**	6	**4**	1,763,885	**14,468**	8	**5**
Safety planning	280	-6,596,529	**Dominant**	30	**2**	-117,554,779	**Dominant**	141	**2**
Acute response team	25	-15,963,486	**Dominant**	18	**3**	-37,767,685	**Dominant**	40	**3**

Table S2: Cost-effectiveness analysis results for individual interventions alone, cost per suicide death avoided

Intervention	Incremental suicides avoided (n)	HEALTH CARE PERSPECTIVE Incremental costs ($)	HEALTH CARE PERSPECTIVE ICER vs. BAU ($/suicide death avoided)	SOCIETAL PERSPECTIVE Incremental costs ($)	SOCIETAL PERSPECTIVE ICER vs. BAU ($/suicide death avoided)
BAU	-	-	**-**	-	**-**
Tech-enabled integrated care	11	-50,704,417	**Dominant**	-91,989,247	**Dominant**
School-based suicide prevention	28	30,735,994	**1,086,242**	50,160,632	**1,772,729**
Post-attempt care	31	3,347,318	**107,248**	-25,413,062	**Dominant**
Youth MH service hubs	0	4,063,613	**9,588,294**	1,763,885	**4,161,973**
Safety planning	181	-6,596,529	**Dominant**	-117,554,779	**Dominant**
Acute response team	24	-15,963,486	**Dominant**	-37,767,685	**Dominant**

Additional methodological overview

Model development process

The participatory model-building process consisted of two main streams of input and advice to the research team: three in-person workshops, and more frequent monthly meetings of an expert advisory committee, also known as the model development group, with youth lived experience advisers integrated in both. The workshops were attended by a range of stakeholders, including psychiatrists, psychologists, allied health workers, general practitioners, and state and federal government health agency representatives. The model development group reviewed and discussed more detailed components of the SDM, including individual stock and flow components, connections between sectors of the model, and identification of the most appropriate sources of input data. Published literature and data from various sources was used to parameterise the model. Evidence on the effectiveness of interventions was obtained through a rapid review process, relying where possible on systematic reviews, but also on single comparative trials or grey literature. Parameter values that could not be derived directly from these sources were estimated via constrained optimisation (parameter optimisation, distinct to outcome optimisation), using historical time series data for a wide range of sociodemographic and health-related outcomes, including labour force participation and unemployment rates, the prevalence of psychological distress, self-harm hospitalisations, emergency department presentations and suicide rates. Powell's method was used to obtain the set of optimal parameter values, minimising the mean of the absolute differences between the observed time series values and corresponding model outputs, where each difference was expressed as a percentage of the observed value [1].

Model structure overview

SDM was selected as the modelling framework for this analysis because of its potential for capturing dynamic complexity relevant to mental health planning [2]. The model captures population and demographic dynamics, pathways to mental health care, service interactions, and potentially non-additive effects of intervention and service combinations. The model was validated through face validity among stakeholders and by assessing its ability to reproduce historic trends across observed data in the region from 2011 to 2023. Supplementary Figure 1 in Supplementary Material Part A provides an overview of the model sectors and the causal connections between them. Supplementary Material Part A also contains a detailed description of each sector, including its structure, sources of input data, and calibration graphs.

Optimisation analysis

Optimisation seeks to maximise a system's desirable properties while minimising its undesirable properties [3]. In simulation modelling, this is operationalised through an *objective function* which specifies the problem's objective to be minimised or maximised (the optimisation outcome) through the selection of an appropriate set of system parameters (the *decision variables*) [4]. Detail on optimisation type and settings is available in Table 1 of the main manuscript.

The final cumulative value of incremental net monetary benefit (INMB) for the societal perspective (economic measures are described in detail below) was selected as the optimisation outcome. In other words, the objective of each optimisation analysis was to configure the decision variables related to services and interventions in such a way as to maximise INMB over the course of the 11-year time horizon. INMB was selected as the optimisation outcome because it is a composite measure that includes: the cost of interventions, the cost of services, downstream cost consequences, and health benefits in terms of quality-adjusted life years (QALYs), with QALYs monetised using empirical evidence on the willingness-to-pay for an additional QALY. Other maximands may be of interest to a decision maker, such as suicide deaths avoided, emergency department presentations avoided, or health service cost savings. In the present analysis, they are interrelated 'side benefits' achieved in the pursuit of maximising INMB.

The decision variables were the service capacity growth rates for the eight mental health service types and the six interventions (described above). The interventions are either implemented (on) or not (off) in any combination for the entire 11-year time horizon commencing in January 2024 until December 2034, while multipliers are used to set the rate of growth of services from January 2024 onwards, representing the ratio relative to historical growth rates from 2011 to 2022.

Different constraints were applied to the services and interventions across seven different scenarios. Table 1 of the main manuscript contains full descriptions and the rationale for each scenario and optimisation settings.

'Grid' was the optimisation method used for any scenarios looking for the optimal combination of interventions with services fixed (scenarios 2, 5, 6 & 7). This allows for an exhaustive search of every combination of interventions because the number of simulations is limited by the binary nature of interventions either being on or off. Differential evolution was adopted for the scenarios where services are allowed to vary because of the continuous nature of growth rate multipliers that could be set anywhere between 0 and 1 or 1.5 (scenarios 1, 3 & 4). The number of generations was set so that convergence was achieved by the end of the simulation, with the standard deviation of the population going to zero [1,3]. The objective function was deterministic and unable to capture stochasticity and this is discussed in more detail in the limitations.

Costs

Supplementary Material Part B contains a detailed itemisation of each unit cost, its source, derivation methods and assumptions, including the cost of interventions (Table S5, Table S6, Table S7). The cost of health services was obtained from the Australian Institute of Health and Welfare and the Independent Health and Aged Care Pricing Authority. Costs associated with homelessness and substance misuse were obtained from grey literature reports estimating the associated economic burden. Employee earnings used in the calculation of productivity estimates were obtained from the Australian Bureau of Statistics. Interventions were microcosted in consultation with the model development group, guided by the resources specified in the studies that informed the effectiveness of interventions per references provided below for each intervention description.

Health measures and quality-adjusted life years

The detailed sector descriptions in Supplementary Material Part A describe the calculation methods by which key health outcomes are estimated: suicide deaths, emergency department presentations and self-harm hospitalisations. The QALY is an additional measure that is useful because it includes both changes in survival and quality of life, whilst also reflecting the preference-based utilities linked to distress-related health states. The prevalence of people experiencing distress is a key driver of accumulated QALYs over the timeframe of the model. Because the K10 measure is used to quantify levels of distress in the model, utilities for people aged 12 years and over were derived by using a mapping algorithm to convert low, moderate, high and very high distress levels based on the K10 to the EQ-5D multi-attribute utility instrument [5], with the utility values weighted according to the prevalence of levels of distress from the National Study of Mental Health and Wellbeing [6] and the Young Minds Matter survey [7] to conform to the modelled health states based on distress and disorder combined (Table S8, Supplementary Material Part B). Distressed health states for children aged 11 years and younger were based on the Strengths and Difficulties Questionnaire (SDQ) [8]. A mapping algorithm developed by Sharma et al., with a study population of Australian children, was used to transform SDQ scores to CHU9D utilities (Table S9, Supplementary Material Part B) [9]. The CHU9D has strong psychometric performance in both mental health [10] and general paediatric [11] populations. A recent systematic review confirmed this was the most recent and relevant mapping algorithm with the SDQ as the starting measure [12].

Economic summary measures

Net monetary benefit (NMB) is a conversion of health into financial units to aid the comparability of strategies and presentation of results. NMB is given by multiplying QALYs by the willingness-to-pay for a QALY, AUD$83,004, then subtracting costs. The willingness-to-pay per QALY was obtained from a study by Shiroiwa et al. [13] and indexed to the 2021-22 financial year. We adopted the social value of a QALY (demand for health) approach for valuing the threshold rather than an opportunity cost (supply side) approach [14] because of the intersectoral nature of the interventions and the potential for many costs and benefits to fall outside the health sector. Using a willingness to pay for a QALY value from the literature gives us the benefit of using a threshold based on empirical evidence, rather than an arbitrary threshold (usually AUD$50,000 per QALY in Australia, although this has never been publicly specified by a government agency in Australia). Incremental net monetary benefit (INMB) is the difference in NMB for a scenario of change compared with business as usual (BAU).

Other economic methods

The time horizon was set to 11 years to allow sufficient time for cost and health consequences to be realised after a change to the system. A conventional lifetime time horizon is not relevant due to the dynamic nature of the population, where births and positive net migration ensure the population continues to grow. Costs and health consequences were discounted at 5%, based on the reference discount rate set by the Pharmaceutical Benefits Advisory Committee (PBAC) [15]. Both health care and societal perspectives were adopted due to the diverse stakeholders and decision-makers involved in the participatory model building process, and all results are presented for both perspectives. The societal perspective is broader than, and fully incapsulates, the health care perspective. One of the key differences between the two perspectives is the inclusion of productivity costs in the societal perspective. Costs incurred by non-health sectors are also included in the societal perspective. The costs that apply to each perspective are detailed in Supplementary Material Part B. Neither univariate nor probabilistic sensitivity analyses were carried out due to the computational demands and model run-time across multiple scenarios of the analysis. This limitation is discussed in more detail in the Discussion section.

Assumptions

Assumption	Justification	Implications
Structure, including scope & population		
The model focuses on youth mental health but includes the entire Brisbane South population. Ages below 25 years old are grouped based on advice from the model development group using developmental stages and progression through school. The adult population is represented by a single group of those aged 25 and over.	The whole population was included to capture health and other impacts as young people age, more relevant for longer time horizons, and whole-system representation of mental health service use and other indirect impacts, such as the influence of social determinants.	Economic outcomes are based on all age groups to capture whole-system representation in resource allocation decisions. Stratification of age groups may over or under estimate the impact of interventions in practice that might be targeted at more specific ages. The aggregation of all adults into a single group requires the use of the same average weekly earnings (applied to non-fatal productivity impacts) and the same number of years of productive life lost due to premature mortality for anyone aged 25 and over.
Population is modelled in aggregated stocks rather than individuals	Inherent to system dynamics approach to modelling at the population level and data availability	Individual heterogeneity is not represented at the level of individual trajectories in this system dynamics model
Psychological distress and disorder is represented using 3 categories based on the K10 and proportion of people in distressed health states that had a diagnosable disorder	Adopts categories specified by the Australian Bureau of Statistics and simplifies complexity of a greater number of health states	Fails to account for individual complexity and nuance within distress-based health states, potentially oversimplifying clinical reality
Time horizon and discounting		
Default time horizon set to 11 years	Balances the need for decision-maker and political relevance, capturing some degree of long term effects, and computational feasibility	11 years is shorter than conventional economic evaluation where lifetime time horizon is common. The cost effectiveness of interventions may change beyond this timeframe.
5% discount rate adopted based on guidance issued by Pharmaceutical Benefits Advisory Committee	Common practice in economic evaluation to take account of time preference for money and opportunity cost of capital	Reduces the value of health and cost consequences that occur in future years
Interventions		
Interventions scale up to achieve full effect over 2 years	Account for realistic time lags in implementation that occur in practice	In reality, implementation of some interventions may reach full effect sooner or later than their default values. They may also waver at levels less than full effect over time.
Intervention duration remained over full time horizon of model	Once an intervention is implemented is likely to remain in place for 11 year period	Assumes ongoing funding for program in its implemented state, potentially overestimating the benefits of interventions. In practice intervention are likely to change form over time.
Strength of evidence is treated the same regardless of source. Most are from peer-reviewed literature, usually systematic reviews with meta-analysis, some from single trial studies. Some are from evaluations published in non-peer-reviewed grey literature.	Ensures parameterisation of effects are based on evidence, but this is subject to evidence available at the time of model development.	Effectiveness of interventions may be over or under estimated. The effectiveness of real-world implementation of interventions may differ from modelled outcomes.
Evidence has been generalised from the literature-based interventions to represent the modelled interventions, and the alignment between the modelled intervention and the	Parameterisation of effectiveness is subject to the evidence available at the time of model development. A balance needs to be made between representing the model as closely as	Effectiveness of interventions may be over or under estimated. The effectiveness of real-world implementation of interventions may differ from modelled outcomes.

evidence upon which it is based varies from intervention to intervention.	what would be implemented in the region in practice, and the intervention design as it appears in the literature.	
Uptake rates are based on expert opinion.	Lack of empirical evidence on uptake rates, particularly in the region for which the model was developed, necessitating expert opinion.	Effectiveness of interventions may be over or under estimated. The effectiveness of real-world implementation of interventions may differ from modelled outcomes.
Where interventions have an identical mechanism of effect and they are implemented in combination with each other, the effects are assumed to be multiplicative.	Avoids invalid effect sizes while accounting for some additional effectiveness in the absence of evidence on the combination of interventions.	May over or under estimate the synergistic effectiveness of intervention combinations in practice.
Interventions are not mutually exclusive	Informed by model development group that all interventions could theoretically be implemented given relevant financial resources	Mainly affects calculation of incremental cost-effectiveness ratios. May not fully reflect resource competition and budget constraints at higher levels of intervention cost.
Behavioural assumptions		
Transition rates between distress states depends on socio-economic factors, such as unemployment and homelessness	Reflects evidence on social determinants of mental health	Relationships may be mis-specified or incomplete
Services were assumed to be operating at 100% based on their current activity levels, and service capacity constraints affect waiting times and outcomes	Key system feedback identified in participatory modelling and assumption checked with model development group	Critical driver of unintended consequences
Calibration		
Where data were unavailable, parameters were estimated via calibration to historical trends using Powell's method of optimisation	Ensures internal consistency with observed data	May over or underestimate actual relationships between system components
Quality-adjusted life years		
For people aged 12 and over, utilities were derived by mapping average K10 scores for distressed health states to the EQ-5D using a published mapping algorithm	Necessary for cost-utility analysis	Uncertainty is introduced, both by the underlying mapping algorithm and the representativeness of the resulting K10-EQ-5D QALY changes to actual quality of life changes in practice as a result of some system change
For children aged under 15 years, utilities were derived by mapping average SDQ scores to CHU-9D using a published mapping algorithm	Necessary for cost-utility analysis	Uncertainty is introduced, both by the underlying mapping algorithm and the representativeness of the resulting CHU-9D based QALY changes to actual quality of life changes in practice as a result of some system change
Costs		
Inflation not explicitly accounted for	Costs are indexed to the same financial year, ensuring consistent financial units, but inflation levels in future years is unknown	May under or over estimate actual cash costs that are incurred in any category in future years
Societal perspective includes productivity, selected non-health sector costs	Captures broader economic impact based on judgement of categories most relevant to the decision context	Excludes many cost categories that technically fall within a societal perspective, like environmental impacts. Likely to enhance the cost effectiveness of interventions
Intervention costs informed by stakeholder feedback and model	Reflects most likely resource use and costs if the intervention were implemented in the region	May over or under estimate actual costs incurred by implementing an intervention

development group, informed by resource use mentioned in literature		
Uncertainty		
Only parameter uncertainty was explored, not structural uncertainty	Resource and time constraints	Alternative model structures may yield different results
Effects are assumed to be homogenous for all age groups to which they were applied	Simplifies modelling development given data limitations	May obscure differential impacts experienced by subgroups in practice, such as, socioeconomic group, gender, sexual orientation, race or geography

Limitations – detailed description

There are a number of limitations to this analysis. In some respects, this is a relatively simplistic application of constrained optimisation methods, adopted for strategic-level decision making within the context of an existing dynamic simulation model. Although we have taken advantage of the ability to systematically search for the optimal mix of services and interventions, one of the advantages of optimisation is the ability to move beyond cost-utility analysis to consider non-financial healthcare resource constraints [16]. For example, the model assumed that existing mental health services are already operating at 100% capacity on the basis of long wait times for services. It also assumed that historical growth rates would continue into the future under the BAU scenario, based on historical service contacts. An alternative model with more detailed service specifications could allow a more thorough application of constrained optimisation could take into account actual individual resource constraints, such as number of staff and physical facilities, now and expected into the future, with any changes to service capacity growth and implementation of new interventions operating within these constraints; however, this was outside the scope of the current project.

The second limitation is the extra-welfarist normative judgement to select INMB (societal perspective) based on QALYs as the outcome to be optimised. This does have the advantage of utilising a measure of health that captures changes to both length and quality of life, combined with an empirical valuation based on willingness-to-pay for a QALY to monetise these health benefits. It also has the advantage of using a single, empirical-based measure for the optimisation algorithm to maximise. However, a disadvantage to this approach is overlooking other outcomes that may be relevant to the decision-making context. One example is the INMB for the health care perspective, where the optimal configuration of services and interventions may be different from the INMB for the societal perspective. Another important example is suicide deaths averted, to the extent this is not already captured by life years gained via the QALY. For example, the school-based suicide prevention intervention was excluded from all scenarios, despite it achieving the third-highest number of suicide deaths avoided when modelled individually (Table S2, Supplementary Material Part B). With an incremental cost per suicide death avoided of $1.1 million, this intervention would probably be considered cost effective when compared to the value of a statistical life (VSL) [17]. There are four potential solutions to the choice of INMB as the sole outcome being optimised in such an exercise. The first is to report all relevant outcomes in a transparent manner for the decision maker to consider as we have done here. The second is to set suicide deaths avoided as the outcome being maximised as a form of sensitivity analysis to be compared to the main results; however, this ignores any cost implications. The third solution, which does take account of costs, is deriving INMB based on suicide deaths averted rather than QALYs, with suicide deaths being monetised using an empirical approach, such as the VSL. This approach disregards any non-fatal quality of life effects. The fourth solution is adopting multicriteria outcome optimisation. The limitation of this approach is that weightings tend to be required for each of the outcomes being optimised to help decision makers choose between multiple equally optimal solutions. Solutions 2-4 were outside the scope of the present article.

The third main limitation is the lack of uncertainty analysis in the form of univariate, multivariate or probabilistic sensitivity analysis. This was excluded due to combinatorial load, and prohibitive amount of time it would take to run this type of analysis across all seven scenarios using currently available software. It is plausible that univariate or probabilistic sensitivity analyses could uncover circumstances in which the pertinent configuration of services and interventions and/or outcome estimates would be materially different to the results based on default values reported here. If there is a more concrete, impending decision context with a known budget cap (i.e. a single scenario), uncertainty analysis could be conducted within a reasonable timeframe. Future iterations of the model could take advantage of alternative software and advances in high-performance computing solutions to address this limitation of our analyses.

A fourth limitation is that only the current cost per service-contact is used to inform changes in services capacity growth rates. This is likely to be an accurate representation of the cost of small changes in service volume, but larger changes may be subject to threshold effects, such as the need for more physical space for clinics to operate from and large-scale recruitment programs for more medical staff to provide the services. These costs were excluded from the analysis and could be an important consideration in the context of mental health staff shortages and/or wholesale changes to models of care. These costs were outside the scope of the current model and would need to be balanced against the context of an increasing shift to digital and AI-supported services.

The fifth main limitation is that the effectiveness of services and interventions hinges on the strength of evidence informing each parameter and mechanism of effect, which is variable across interventions and studies. Importantly, this includes evidence on the effectiveness of the numerous combinations of interventions, which is not available from the literature. Here we have assumed that the effect sizes of individual interventions are the same when combined with other interventions. In practice, they could be more or less effective when combined with other interventions depending on the mechanisms of effect and other nuances of implementation. Another aspect of this limitation is that the effectiveness of some interventions was informed by evidence that was generalised from other settings to the present context. More thorough uncertainty analysis, discussed above, is one solution to this, so that known variability is built into the optimisation analysis and uncertainty intervals around outcomes. Another solution is systematically assessing the strength of evidence supporting each mechanism of effect using an established system like Grading of Recommendations Assessment, Development and Evaluation (GRADE) that sits alongside the optimisation analysis for a more complete picture that can be provided to the decision maker [18].

The sixth main limitation is that no differential timing of intervention implementation or changes to service capacity growth rates was applied. Interventions were either implemented or not for the entire 11-year time horizon, as were the multiplier settings for the services capacity growth rates. A more advanced model structure and optimisation analysis would allow the model to invest in, and disinvest from, different combinations of interventions over time, with similar flexibility being applied to service capacity growth rates, which could conceivably ebb and flow with changing population dynamics and intervention implementation over time. This was outside the scope of the current analysis.

Finally, the choice of (a) multiplier constraints set for service capacity growth rates and (b) budget caps applied to intervention costs were essentially arbitrary. The figures in question were chosen here to demonstrate the effect of these parameters on the configuration of intervention combinations and services and the subsequent effects on health and cost consequences. The wide range of options available to a decision-maker when setting these optimisation constraints highlights the importance of modelling exercises like this being supported by participatory model-building processes.

Interventions

Technology-enabled integrated care

In this model, Technology-enabled integrated care involves the use of online technology to facilitate delivery of multidisciplinary team-based, measurement-based care. The modelled intervention has the following combined features:

1. Triage function – this function includes an initial online assessment within the technology to determine who are suitable for different levels of care upon initial presentation (i.e., low intensity versus high intensity) and identifies appropriate service pathways which differ according to care type and urgency. Subgroups with differential service needs can be triaged or stratified based on suicidality, risk of illness progression, and functional impairment.
2. Provision of online materials – this includes access to information and relevant resources/contacts within the technology to prevent disengagement while awaiting care. This facilitates early engagement in online evidence-based treatment sooner, which is likely to provide a more positive experience of care and keeps people engaged with mental health care.
3. Care coordination function – This refers to the use of the technology to assess and identify the care needs of an individual and share information across providers to improve multidisciplinary team-based care approaches. These approaches embrace collaborative care models, which recognize that effective care coordination between service providers, including intensive assessment, personalized treatment plans, targeted referrals, clinical information systems use, and outcome monitoring can improve treatment engagement, satisfaction with care, and mental health outcomes.

Starting year: The year in which this system intervention was introduced (the default is 2024, or January 2024).

Years to reach full effect: The time required for this system intervention to be fully implemented (the default is 2 years).

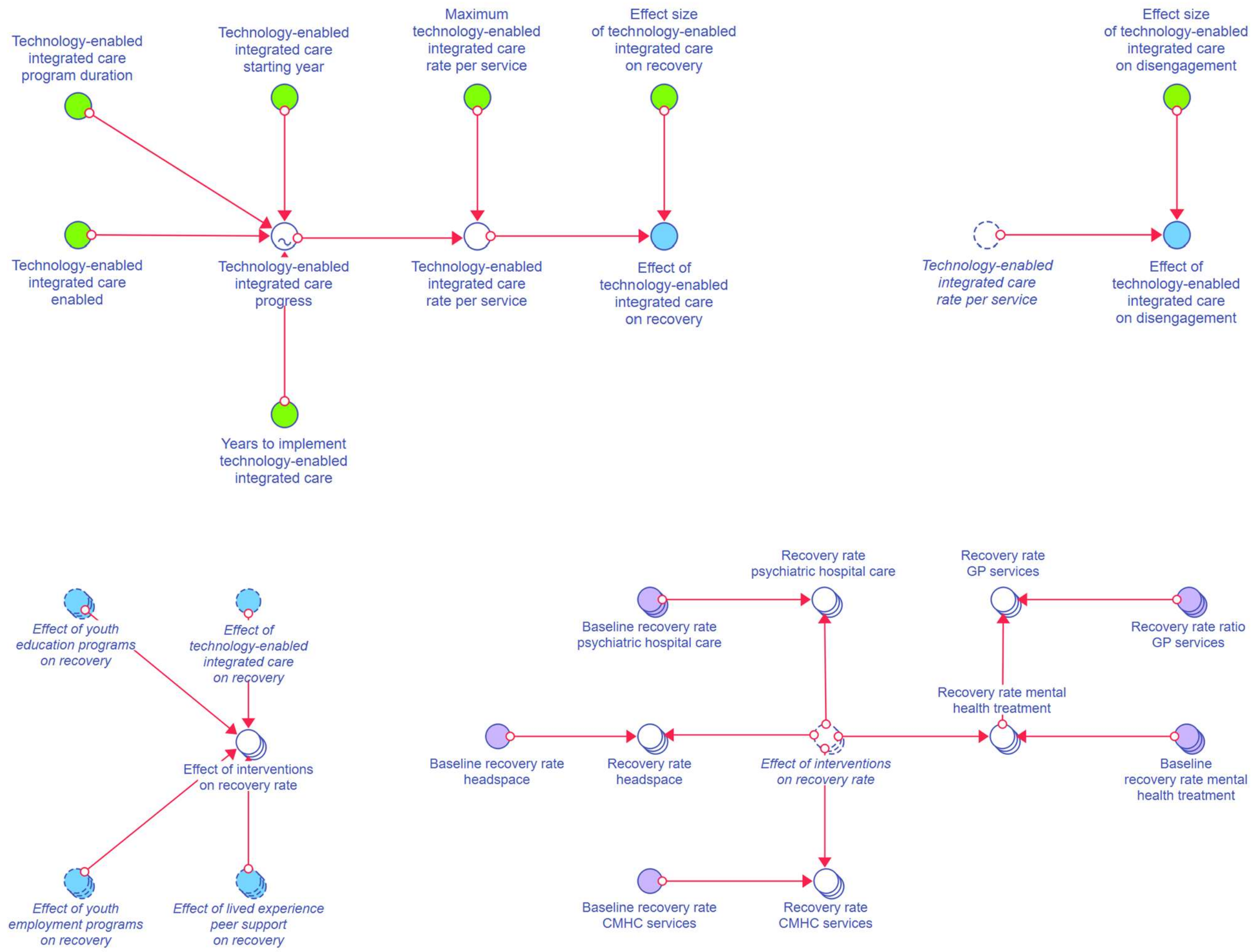
Uptake by clinicians: Proportion of mental health services involving technology-enabled integrated care, which corresponds to the proportion of clinicians using technology-enabled integrated care if service contacts increase at the same rate across clinicians. The program assumes 100% patient consent, based on opt-out consent. The default value of 0.1 means that 10% of clinicians will use technology-enabled integrated care when fully implemented, based on a combination of stakeholder feedback and a recent study of an online mental health platform for young people in Australia which found that 7.7% of people who were referred and onboarded used the platform for at least 24 weeks [19].

Three mechanisms of effectiveness were informed by indirect evidence that was generalised to represent the modelled intervention in the absence of more direct, comparative evidence.

Effect on recovery rate: The multiplicative effect of technology-enabled integrated care on the per-service recovery rate (i.e., the probability that a patient's level of psychological distress will decrease after receiving treatment). The default estimate (1.221) is derived from a systematic review and meta-analysis of measurement feedback systems for the treatment of common mental health disorders published in 2023 by Rognstad et al. [20] and implies that technology-enabled coordinated care increases the per-service probability of a reduction in psychological distress by 22.1%.

Effect on disengagement: The multiplicative effect of technology-enabled integrated care on per capita rates of disengagement from mental health services. The default estimate (0.84) is derived from a meta-analysis of progress feedback, also known as measurement-feedback systems, to improve outcomes and reduce drop-out, treatment duration and deterioration in routine clinical practice for mental health. This study was published in 2021 by de Jong et al. [21].

Figure S7: Technology-enabled integrated care model structure, part a



School-based suicide prevention program

In this model, the school-based suicide prevention program was defined as an educational program delivered universally to all students aged 12-17 years of age within a school setting that aims to prevent suicidal behaviour. It refers to a curriculum-based mental health education and awareness of suicide ideation. It targets all students and focuses on prevention, with young people developing skills to help peers who are experiencing mental health and substance use problems. This component should be co-designed with young people with lived experience.

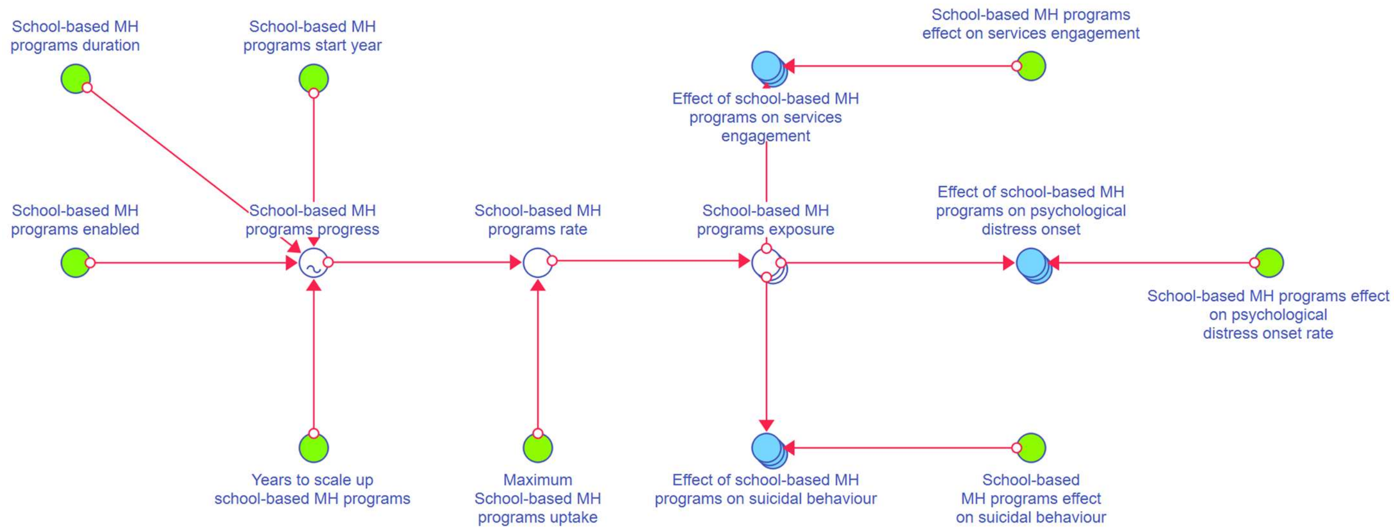
Starting year: The year in which this system intervention is introduced (the default is 2024, or January 2024).

Years to reach full effect: The time required for scaling up this system intervention (the default is 2 years).

Uptake rate: The default is set to 90%, based on offering the intervention to all secondary school students in the region whilst allowing for some opting out and attrition, based on stakeholder feedback.

Effect on suicidal behaviour: The multiplicative effect of school-based mental health programs on the per capita suicide attempt rate. The default value (0.72) was derived from a systematic review and meta-analysis of school-based suicide prevention programs published in 2022 by Walsh et al. [22]. This review included a variety of suicide prevention programs, including those that targeted anti-harassment and anti-bullying. It means that the odds of suicidal behaviour is reduced by 28%.

Figure S8: School-based suicide prevention program model structure



Post-suicide attempt care

In this model, Youth post suicide attempt care refers to an intensive outpatient program, delivered by a multi-disciplinary team, to support adolescents who have recently attempted suicide. The program aims to reduce re-admission to services for those who have recently attempted suicide. The care provided focuses on clinical assessment and evaluation, the establishment of a safety plan, and a 'chain analysis' of the suicidal event. A 'chain analysis' refers to a therapeutic approach of recognising, analysing and challenging the sequence of events leading to suicidal ideation and behaviour.

This program was available for people aged 24 years and under.

Starting year: The year in which this system intervention is introduced (the default is 2024, or January 2024).

Years to reach full effect: The time required for this system intervention to be fully implemented (the default is 2 years).

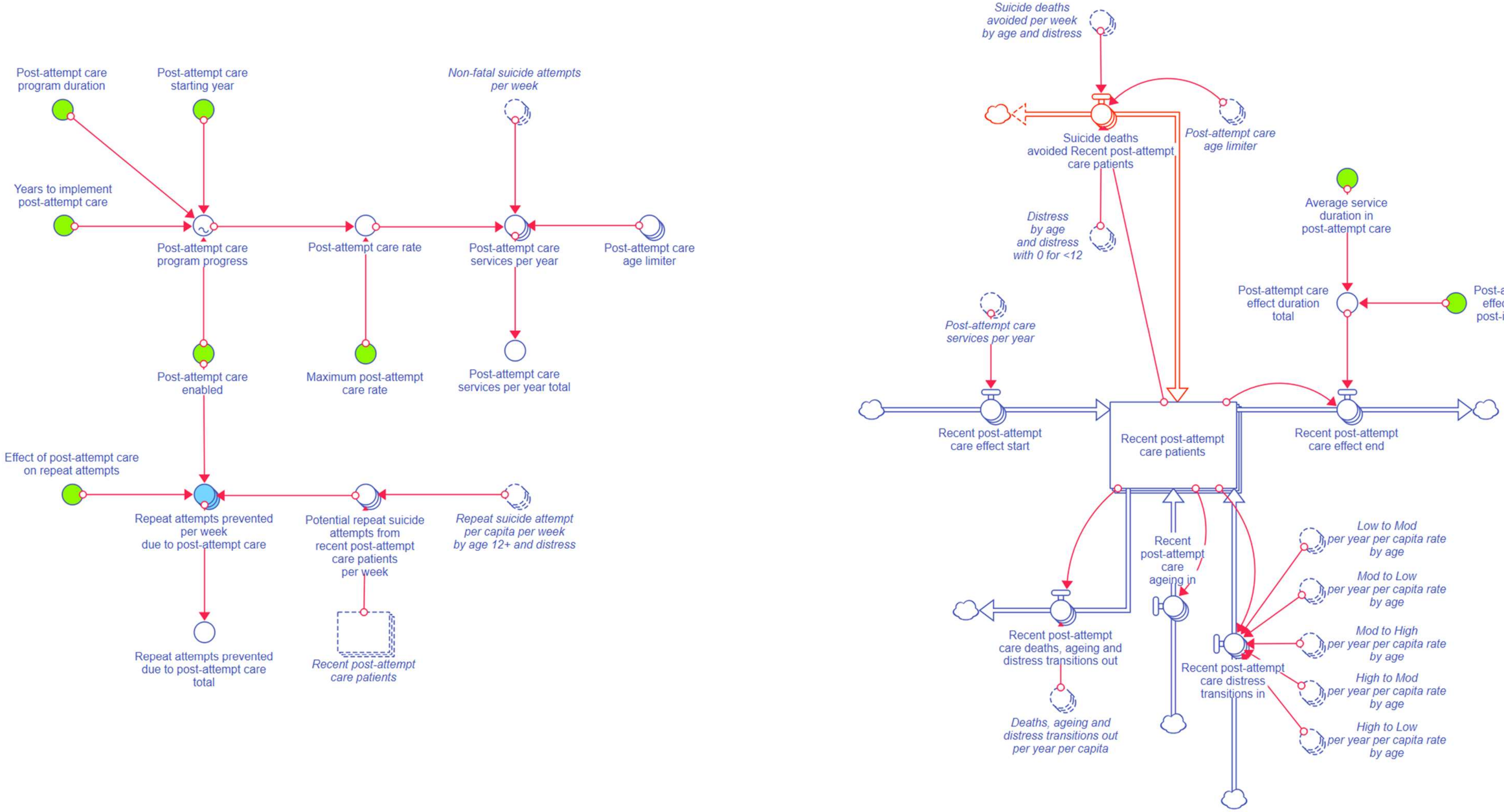
Maximum uptake rate: The maximum proportion of the people aged 12-24 who have recently attempted suicide who would engage with the youth post-suicide attempt care service. The default (0.5) assumes that 50% of these people would enrol.

Effects on repeat suicide attempt: the default value (0.37) applies to the risk of suicide re-attempts and corresponds to a reduction of 63% of suicide re-attempts. This is based on a randomised controlled trial of assertive case management versus enhanced usual care for people with mental health problems who had attempted suicide and were admitted to hospital emergency departments in Japan (the ACTION-J study). This study was published in 2014 by Kawanishi et al. [23].

Duration of care: the outreach program has a duration of 13 weeks.

Duration of effect: duration of the effect on repeat suicide attempts post-intervention. The default value is 26 weeks from the time of recruitment and this was sourced from the same ACTION-J study by Kawanishi et al. [23].

Figure S9: Post-attempt care model structure



Youth mental health service hubs

In this model, Specialised youth mental health service hubs refer to services that cater to the specific mental health needs of young people aged 12 to 17 years. The hubs aim to address the gap that exists between child (younger than 12 years) and adult (18+ years) mental health care, as well as to address the gap in care that exists for the treatment of mild and severe mental health issues. The term 'hub' describes a service that provides multidisciplinary, team-based care, co-located in one service. The team consists of psychiatrists as well as other allied mental health care (e.g. psychologists, social workers, occupational therapists, etc).

Starting year: The year in which this system intervention is introduced (the default is 2024, or January 2024).

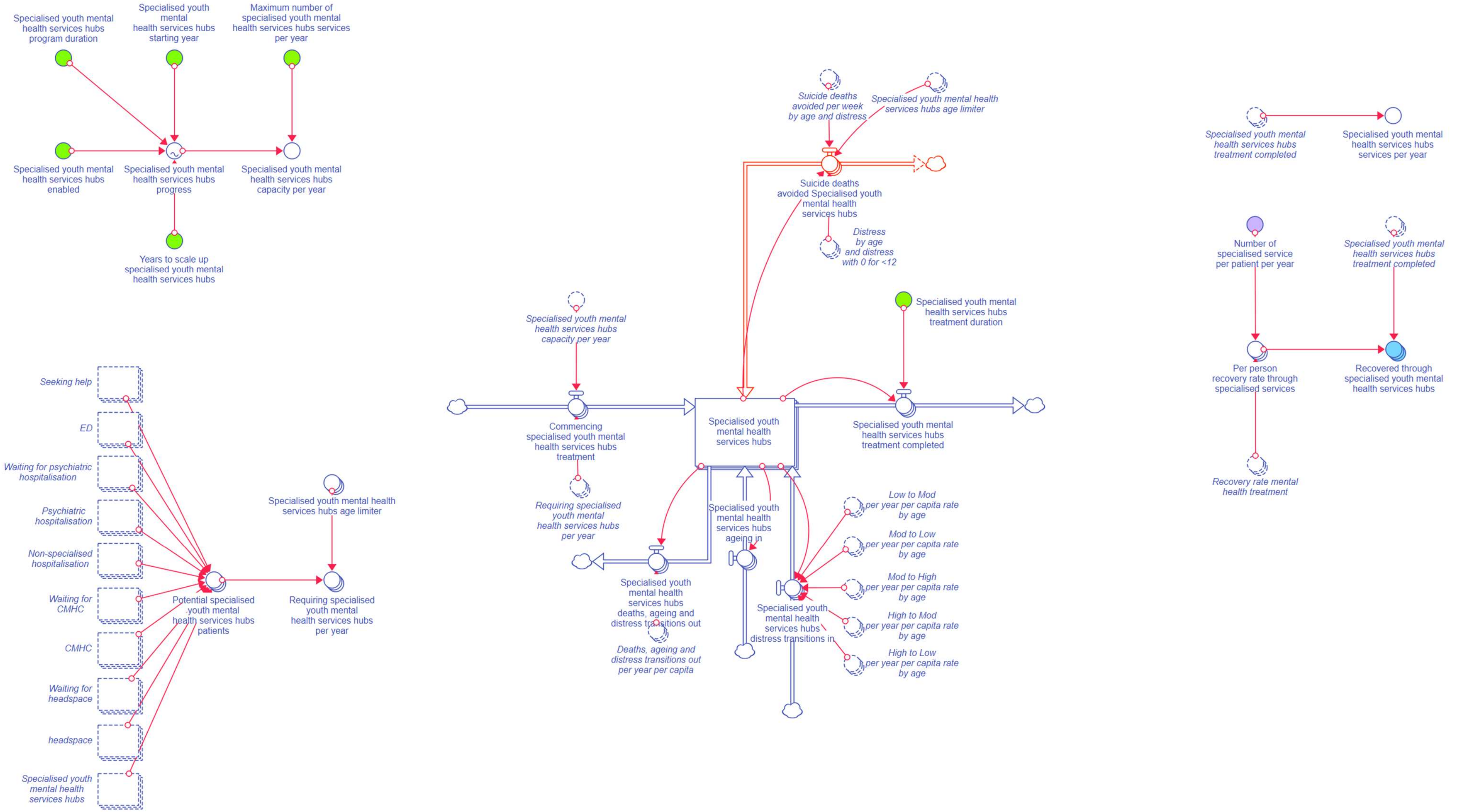
Years to reach full effect: The time required for this system intervention to be fully implemented (the default is 2 years).

Maximum number of clients per year: The maximum number of clients that can be treated at the specialised youth mental health service hubs per year. The default value is 175 and was derived by generalising the rate of recruitment to the Comprehensive Assessment Service for Psychosis and At Risk (CASPAR) study in NSW to the youth population in Brisbane South, combined with expert advice. This study was published in 2021 by Yang et al. [24].

Duration of care: The average duration (weeks) in which the patient is receiving care from specialised youth mental health service hubs. The default value is 22.4 weeks and was obtained from the same study by Yang et al. [24].

Adolescents that engage with the service have a probability of recovering to a lower level of distress that is the same as the baseline rate used for mental health professionals (psychiatrists, psychologists and allied health). The effectiveness of this intervention comes from providing access to care to people that otherwise would have been on waiting lists.

Figure S10: Youth mental health service hubs model structure



Safety planning

In this model, Safety planning for suicide prevention refers to a type of brief intervention for people who are experiencing acute mental health crises, including thoughts or behaviours related to self-harm or suicide. A safety plan is an established set of instructions an individual creates for themselves to utilise when they are experiencing suicidal thoughts or behaviours. It typically includes a list of warning signs, coping strategies, and resources to use to ensure their safety during this time. Safety planning can be supported by a range of health and mental healthcare professionals, including general practitioners, emergency department clinicians, or other mental health professionals such as psychiatrists or psychologists. A safety plan can also be established by the individual without the support of a healthcare professional.

Starting year: The year in which this system intervention is introduced (the default is 2024, or January 2024).

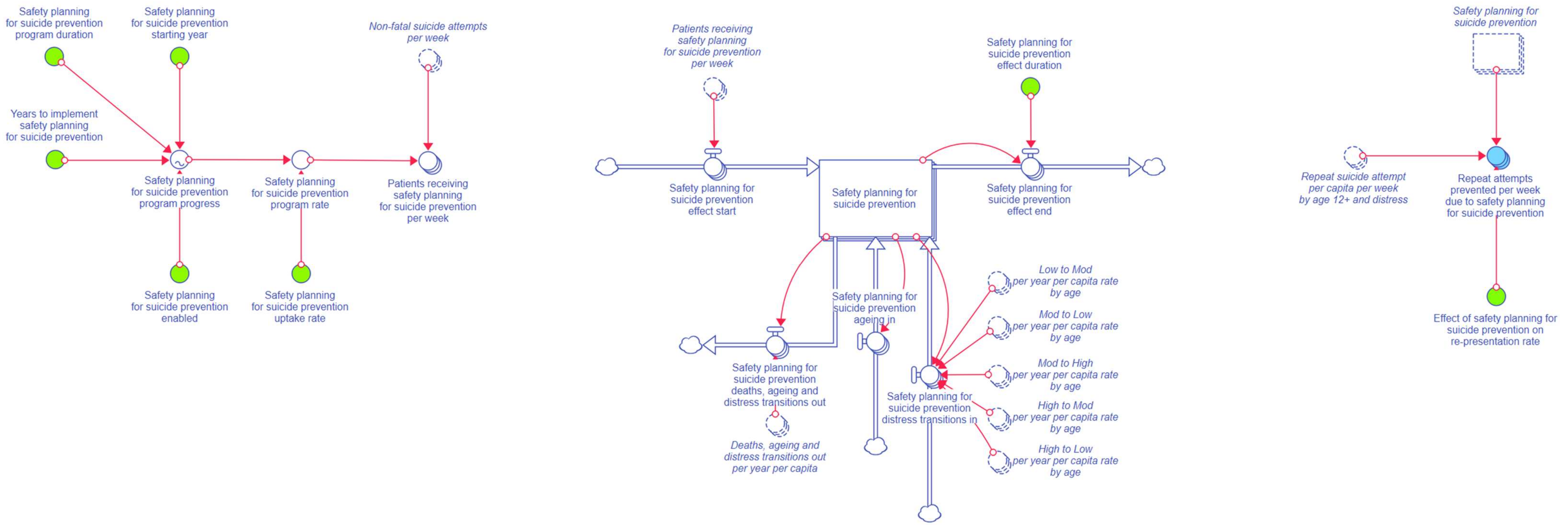
Years to reach full effect: The time required for this system intervention to be fully implemented (the default is 2 years).

Uptake rate: The default value was 100% which assumes that people who had a non-fatal suicide attempt and are aged 12 years and older will receive the intervention. We calibrated non-fatal suicide attempts with intentional self-harm hospitalisations data. We acknowledge that these data do not fully capture the number of non-fatal suicide attempts (for example, those events not resulting in hospitalisation) and that these data may not accurately record the intention of the event.

Duration of effect: The average duration (weeks) in which the patient will have a reduced repeat suicide attempt rate. The default value is 24 weeks and was sourced from the ED-SAFE Study, a multi-site pre-post trial of suicide prevention in adults with a recent suicide attempt or ideation who presented to an emergency department. This study was published in 2017 by Miller et al. [25].

Effect on repeat suicide attempts: The multiplicative effect of safety planning for suicide prevention on the repeat suicide attempts rate. The default value of 0.28 is derived from the same ED-SAFE Study [25] and implies this will reduce the repeat suicide attempts rate by 28% for the duration of effect.

Figure S11: Safety planning model structure



Acute response team

In this model, the child and adolescent acute response team refers to a new clinical team that provides a mobile crisis intervention to children and adolescents in distress, accessed via a dedicated crisis phone line. These response teams are available 24/7 for people who are experiencing a relapse of an existing mental health issue, experiencing a mental health episode for the first time, or experiencing a life crisis with self-harm or suicidal thoughts. The team includes clinicians from various fields (e.g. social work, psychology, psychiatry) to provide a multidisciplinary approach to the young person's care. The care provided includes crisis stabilisation, screening and assessment, suicide assessment and prevention, brief interventions, and referrals to other services for ongoing care. This team is available for people aged 24 years and under.

Starting year: The year in which this system intervention is introduced (the default is 2024, or January 2024).

Years to reach full effect: The time required for this system intervention to be fully implemented (the default is 2 years).

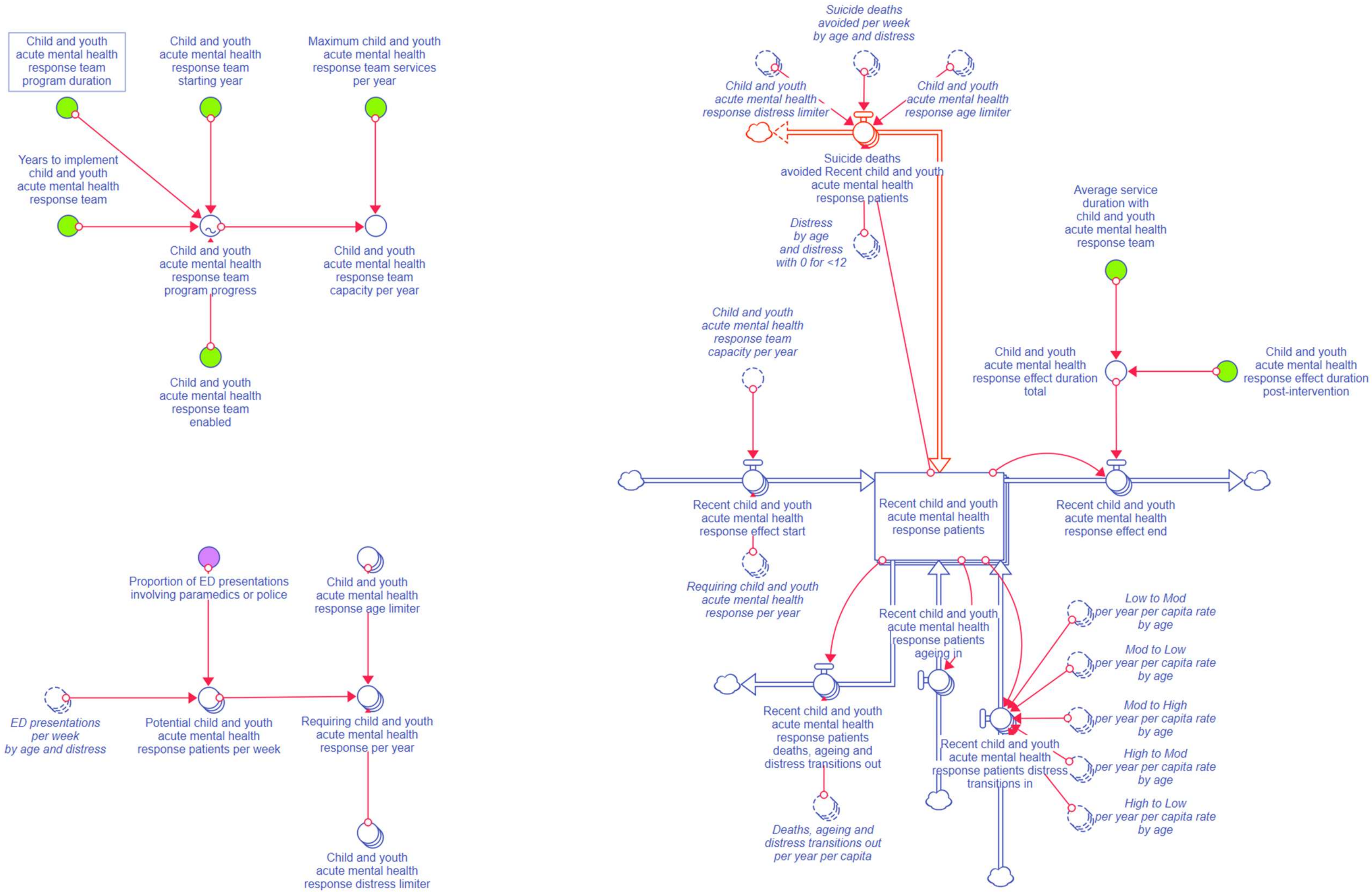
Maximum number of clients per year: The maximum number of clients that can be treated by the child and youth acute mental health response team per year. The default value is 729 and is based on stakeholder feedback.

Duration of care: The average duration (weeks) in which the patient is receiving care from child and youth acute mental health response team. The default value is 2.97 weeks and is derived from a study by Fendrich et al. [26].

Duration of effect post-care: The average duration (weeks) in which the patient will have a reduced mental health related ED presentation rate. The default value is 72 weeks and is derived from a study by Fendrich et al. [26].

Effect on ED re-presentation rate: The multiplicative effect of the child and youth acute mental health response team on mental health related ED presentations rate. The default value of 0.25 is derived from a study by Fendrich et al. [26] and implies that a patient of the child and youth acute mental health response team will have a 25% reduction in their mental health related ED presentation rate for the duration of care plus the duration of this effect post-care.

Figure S12: Acute response team



Costs

Table S3: Individual cost items for health services, homelessness and substance use disorder

Cost group (Level 1)	Cost category (Level 2)	Cost item (Level 3)	Unit of measure 2020-21 AUD	Unit cost (total of all payers)	State	Common wealth	Non-government incl. individuals	Economy	Perspective	Method	Sources	Assumptions
Health care	Specialised mental health services	Mental health-related hospitalisation	per admitted episode	15,624.00	14,775.19	423.80	425.02	0.00	Health Care and Societal	Unit cost provided directly by IHACPA Payer split derived from total funding of MH expenditure	IHACPA, National Benchmarking Portal, https://benchmarking.ihacpa.gov.au Filter: Year 2020-21, Stream: Mental Health, State: QLD, LHN: Metro South (Qld) and Children's Health Queensland combined Funder split: AIHW Mental health services in Australia: Expenditure on mental health services, Table EXP.32 2020-21	
Health care	Specialised mental health services	Community mental health care services (same for CYMHS & CMHS)	per service contact	272.41	257.61	7.39	7.41	0.00	Health Care and Societal	Total cost of CMHS divided by number of service contacts, both for QLD Payer split derived from total funding of MH expenditure	Service contacts: AIHW Mental health services in Australia: State and territory community mental health services, Table CMHC.1 (2020-21) Total expenditure on CMHS: AIHW Mental Health services in Australia: Expenditure on mental health services, Table EXP.1: Recurrent expenditure on state and territory specialised mental health services, states and territories, 2020-21 Funder source split from AIHW Mental Health Expenditure 2020-21, Table EXP.32 https://www.aihw.gov.au/reports/mental-health-services/mental-health-services-in-australia/	

Health care	Medicare-subsidised services	Non-GP mental health professional consultations (psychiatrists, psychologists, allied health)	per service contact	165.14	0.00	118.89	46.25	0.00	Health Care and Societal	Total Australian Government funded cost of Medicare-subsidised non-GP MH services for QLD divided by number of non-GP MH MBS services provided for QLD for Commonwealth split. OOP additional gap payment estimated by calculating the proportion of gap between total fees charged and benefits paid by Medicare for each service type (weighted average for all non-GP MH professionals) based on national data because this is not provided by state. This approach has the advantage of effectively being a weighted average of all relevant MBS item numbers rather than having to pick a specific item/s from the MBS schedule.	Mental health services in Australia: Expenditure on mental health services, Table EXP.18 for total expenditure by service for QLD Mental health services in Australia: Medicare-subsidised mental health-specific services, Table MBS.11 for service counts Mental health services in Australia: Expenditure on mental health services, Table EXP.23 for derived gap proportions https://www.aihw.gov.au/reports/mental-health-services/mental-health-services-in-australia/	% gap payment for Australian national average is generalisable to QLD
Health care	Medicare-subsidised services	General practitioner	per service contact	89.87	0.00	84.54	5.33	0.00	Health Care and Societal	Same as above but for GPs only	Same as non-GP MH professionals but for GPs only	% gap payment for Australian national average is generalisable to QLD
Health care	PBS-subsidised prescriptions	Where the prescriber is a GP	per patient per year	109.32	0.00	96.35	12.97	0.00	Health Care and Societal	Total PBS-subsidised expenditure on any MH-related medication prescribed by GPs divided by number of patients with at least 1 MH-related prescription filled in 2020-21. Proportion of OOP spend derived from general PBS expenditure on all subsidised medicines.	Total expenditure on MH-related medicines by all type of prescribers from AIHW Mental Health Expenditure Table EXP.26 Number of patients with prescription per prescriber from Table PBS.2, where fully subsidised or co-payment involved Proportion of OOP contribution to PBS medicines derived from AIHW general Health Expenditure Table A3	% gap payment for all medicines is generalisable to MH-related prescriptions
Health care	PBS-subsidised prescriptions	Where the prescriber is a	per patient per year	205.19	0.00	180.85	24.34	0.00	Health Care and Societal	As per methods for GPs but for psychiatrists and psychologists	As per sources for GPs but for psychiatrists and psychologists	% gap payment for all medicines is generalisable to

		non-GP mental health professional										MH-related prescriptions
Health care	Emergency care	Ambulance cost weighted average	per attendance	641.00	641.00	0.00	0.00	0.00	Health Care and Societal	Unit cost given	Queensland Ambulance Service https://www.ambulance.qld.gov.au/docs/Public-Performance-Indicators-Fourth-Quarter-2020-21.pdf Cost per incident for Metro South	
Health care	Emergency care	Emergency department presentation	per presentation	662.99	662.99	0.00	0.00	0.00	Health Care and Societal	Unit cost given	IHACPA NHCDC Round 25 2020-21 Appendix Table 8 ED by Jurisdiction, average cost per presentation for QLD, all presentation types https://www.ihacpa.gov.au/resources/national-hospital-cost-data-collection-nhcdc-public-hospitals-report-2020-21	
Health care	Specialised mental health services	Online services currently available	per person per year	0.00	0.00	0.00	0.00	0.00	Health Care and Societal	Various services are currently available at no cost, or accessible at not cost after a referral by a health care professional.		Assume that the cost of maintaining existing online services do not change between interventions and therefore excluded from analysis.
Homelessness	Youth homelessness 15-24yo	Specialised homelessness services	per person	3,695.00	3,695.00	0.00	0.00	0.00	Societal only	Unit cost given	Department of Communites, Housing and Digital Economy, 2020-2021 annual report, Queensland; page 44 https://www.chde.qld.gov.au/__data/assets/pdf_file/0020/18722/annual-report-2010-21.pdf	Assumes all costs borne by State
Homelessness	Youth homelessness 15-24yo	Criminal justice costs	per person per year	10,774.45	10,774.45	0.00	0.00	0.00	Societal only	Unit cost given Indexed from 2011-12 to 2020-21 using GNE IPD	CSI report - MacKenzie 2016 - The cost of youth homelessness - Research Briefing, page 3 https://www.csi.edu.au/media/uploads/CYHA_FINAL_REPORT_18April2016_v0dqGpT.pdf Indexation from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	Assumes all criminal justice costs paid by the state

Homelessness	Youth homelessness 15-24yo	Additional health care costs	per person per year	10,112.96	2,820.24	4,321.19	2,971.53	0.00	Health Care and Societal	Unit cost given Payer split derived from total funding of general health care expenditure Indexed from 2011-12 to 2020-21 using AIHW health price index	CSI report - MacKenzie 2016 - The cost of youth homelessness - Research Briefing, page 2 https://www.csi.edu.au/media/uploads/CYHA_FINAL_REPORT_18April2016_v0dqGpT.pdf Funder splits from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	
Homelessness	Adult homelessness	Specialised homelessness services	per person per year	3,695.00	3,695.00	0.00	0.00	0.00	Societal only	Same as youth homelessness	Same as youth homelessness	Assume same as youth homelessness
Homelessness	Adult homelessness	Additional health care costs	per person per year	17,541.72	4,891.92	7,495.44	5,154.35	0.00	Health Care and Societal	Unit cost given Payer split derived from total funding of general health care expenditure Indexed from 2010-11 to 2020-21 using AIHW health price index	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	
Homelessness	Adult homelessness	Criminal justice costs	per person per year	6,915.69	6,915.69	0.00	0.00	0.00	Societal only	Unit cost given Indexed from 2010-11 to 2020-21 using GNE IPD	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	Assumes all criminal justice costs fall to the state

Homelessness	Adult homelessness	Welfare and taxation forgone	per person per year	8,395.64	0.00	8,395.64	-8,395.64	0.00	Societal only (transfer payment, expense for Commonwealth but income for non-government)	Unit cost given Indexed from 2010-11 to 2020-21 using wage price inflator derived from ABS	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from Australian Bureau of Statistics Wage Price Index, table 2a https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/wage-price-index-australia/jun-2022#data-downloads	Assumes all welfare and taxation forgone incurred by Commonwealth gov
Homelessness	Adult homelessness	Children placed in care	per person per year	2,742.39	2,742.39	0.00	0.00	0.00	Societal only	Unit cost given Indexed from 2010-11 to 2020-21 using GNE IPD	Zaretzky 2013 AHURI - The cost of homelessness and the net benefit of homelessness programs: a national study - Findings from the Baseline Client Survey, page 4, Table 1, Total case managed column Indexation from AIHW Health Expenditure Database 2020-21 https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	Assumes all childcare protection services funded by state
Substance Misuse	Alcohol dependency	Healthcare cost	per person with alcohol dependence per year	5,562.77	1,551.31	2,376.93	1,634.53	0.00	Health Care and Societal	Total cost of health care due to alcohol addiction from KPMG report divided by estimated prevalence of alcohol use disorder. Payer split derived from total funding of general health care expenditure.	Total cost attributable to aclohol dependence: A KPMG and Rethink Addiction report in 2022 https://www.rethinkaddiction.org.au/understanding-the-cost-of-addiction-in-australia Number of people with alcohol use disorder from ABS National Study of Mental Health and Wellbeing 2020-2022 https://www.abs.gov.au/statistics/health/mental-health/national-study-mental-health-and-wellbeing/2020-2022/Table 2 - 12-month mental disorders and severity by sex.xlsx Payer split for general health care costs: https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data	
Substance Misuse	Alcohol dependency	Justice and law enforcement	per person with alcohol	12,662.34	12,662.34	0.00	0.00	0.00	Societal only	As above but for justice and law enforcement	As above	

			dependence per year								
Substance Misuse	Alcohol dependency	Workplace productivity	per person with alcohol dependence per year	8,020.46	0.00	0.00	0.00	8,020.46	Societal only	As above but for workplace productivity	As above
Substance Misuse	Alcohol dependency	Household productivity	per person with alcohol dependence per year	8,744.59	0.00	0.00	0.00	8,744.59	Societal only	As above but for household productivity	As above
Substance Misuse	Alcohol dependency	Social services	per person with alcohol dependence per year	1,721.76	0.00	1,721.76	-1,721.76	0.00	Societal only	As above but for social services	As above
Substance Misuse	Alcohol dependency	Engaging in harmful consumption	per person with alcohol dependence per year	6,369.54	0.00	0.00	0.00	6,369.54	Societal only	As above but for harmful consumption	As above
Substance Misuse	Illicit drugs dependency	Healthcare cost	per person with illicit drug dependence per year	5,803.52	1,618.45	2,479.80	1,705.27	0.00	Health Care and Societal	Total cost of health care attributable to addiction to other drugs from KPMG report divided by estimated prevalence of dependence on illicit drugs. Payer split derived from total funding of general health care expenditure.	Total cost attributable to illicit drug dependence: A KPMG and Rethink Addiction report in 2022 https://www.rethinkaddiction.org.au/understanding-the-cost-of-addiction-in-australia Prevalence of drug use disorder from ABS National Study of Mental Health and Wellbeing 2020-2022 https://www.abs.gov.au/statistics/health/mental-health/national-study-mental-health-and-wellbeing/2020-2022/Table 2 - 12-month mental disorders and severity by sex.xlsx Payer split for general health care costs: https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2020-21/data
Substance Misuse	Illicit drugs dependency	Justice and law enforcement	per person with illicit drug dependence per year	33,083.48	33,083.48	0.00	0.00	0.00	Societal only	As above	As above

Substance Misuse	Illicit drugs dependency	Workplace productivity	per person with illicit drug dependence per year	13,594.55	0.00	0.00	0.00	13,594.55	Societal only	As above	As above	
Substance Misuse	Illicit drugs dependency	Household productivity	per person with illicit drug dependence per year	8,586.03	0.00	0.00	0.00	8,586.03	Societal only	As above	As above	
Substance Misuse	Illicit drugs dependency	Social services	per person with illicit drug dependence per year	1,130.04	0.00	1,130.04	-1,130.04	0.00	Societal only	As above	As above	
Substance Misuse	Illicit drugs dependency	Engaging in harmful consumption	per person with illicit drug dependence per year	9,716.07	0.00	0.00	0.00	9,716.07	Societal only	As above	As above	
Headspace		Overall headspace services	per occasion of service	234.45	0.00	234.45	0.00	0.00	Health Care and Societal	Unit cost provided directly by KPMG evaluation, indexed to 2020-21 financial year	KPMG 2022 - National headspace evaluation final report June 2022	Assume fully funded by Commonwealth Assume national average applies to BSPHN
Alcohol & other drug treatment services		Overall AOD treatment services	per episode of care	10,122.72	4,960.13	3,138.04	2,024.54	0.00	Health Care and Societal	Total cost of AOD treatment services $1.26 billion divided by 145,226 episodes of care, then indexed to 2020-21	National Drug and Alcohol Research Centre, UNSW - New Horizons: The review of alcohol and other drug treatment services in Australia, Final Report July 2014 https://ndarc.med.unsw.edu.au/sites/default/files/ndarc/resources/New%20Horizons%20Final%20Report%20July%202014.pdf	The total cost of AOD treatment services is incurred by people that actually gain access to those services and have closed episodes of care. Assume national average applies to BSPHN
Child and Youth Mental Health Services		Overall CYMH services	per patient day	2,597.35	2,456.24	70.45	70.66	0.00	0.00	Unit cost provided by AIHW reprot, indexed to 2020-21	AIHW - Expenditure on mental health services 2019-20, page 5 https://www.aihw.gov.au/getmedia/030bb981-9de2-4520-8831-d9ddff1f6c4a/expenditure-on-mental-health-related-services-2019-20.pdf.aspx	Assume national average applies to BSPHN

Table S4: Individual cost items for productivity-related categories

Productivity item	Unit of measure	Amount <25 years	Amount 25+ years	Payer	Perspective	Method	Sources	Assumptions
Absenteeism from paid work due to medium & high distress	per person per year	1,327.23	2,945.42	Economy	Societal only	Days absent for people with MH disorders (11 days) x weighted average weekly earnings for age group (converted to days)	Days off work due to psychological distress for people with MH from Productivity Commission Inquiry, Appendix H https://www.pc.gov.au/inquiries/completed/mental-health/report Median weekly earnings from Australian Bureau of Statistics, Characteristics of employment, August 2021 https://www.abs.gov.au/statistics/labour/earnings-and-working-conditions/employee-earnings/aug-2021#data-downloads	Absenteeism and presenteeism costs are the same for all people with high or medium distress, regardless of whether they are diagnosed with a disorder.
Presenteeism at paid work due to medium & high distress	per person per year	965.26	2,142.12	Economy	Societal only	Days working at reduced activity (8 days) x 50% productivity for those days x weighted average weekly earnings for age group (converted to days)	Days at reduced capacity and 50% productivity for those days from Productivity Commission Inquiry, Appendix H, link as above.	
Absenteeism from paid work due to MH-related hospitalisation	per person per day in hospital	121.00	268.00	Economy	Societal only	weighted average weekly earnings for age group (converted to days)	Average weekly earnings as per absenteeism	
Paid work productivity lost due to premature mortality, human capital approach	per death	31,370.84	69,618.95	Economy	Societal only	Weighted average weekly earnings x 52 weeks x years of productive life lost (67 less age at death) discounted	Average weekly earnings as per absenteeism	Person would have otherwise remained alive and employed to the age of 67
Paid work productivity lost due to high distress, human capital approach	per person per year	31,370.84	69,618.95	Economy	Societal only	Annual cost of lost productivity incurred each year a person remains unemployed due to high distress	As above	
Absenteeism from unpaid work due to medium & high distress	per person per year	688.46	1,104.61	Economy	Societal only	Time spent on unpaid work per day (minutes) / 60 minutes per hour x weighted average hourly earnings for age group x 11 days absent from normal duties Opportunity cost method to value hours of unpaid work using median hourly earnings	Time spent on unpaid work: How Australians Use Their Time (ABS) https://www.abs.gov.au/statistics/people/people-and-communities/how-australians-use-their-time/latest-release#data-downloads Median hourly earnings from Characteristics of Employment (ABS) https://www.abs.gov.au/statistics/labour/earnings-and-working-conditions/employee-earnings/aug-2021#data-downloads	Assume presenteeism does not apply to unpaid work. Assume same unpaid work time lost for all ages. (data not available from time use survey by age AND employment status) Assume days absent from unpaid work is the same as paid work reported by Productivity Commission.

Unpaid work productivity lost due to premature mortality, human capital approach	per death	22,844.37	36,653.00	Economy	Societal only	As above but multiplied by 365 days per year x years of productive life lost (67 less age at death) discounted	As above	Assume unpaid work occurs every day of the year
Absenteeism from unpaid work due to medium & high distress	per person per year	792.81	1,272.04	Economy	Societal only	As above but for unemployed daily time use	As above	
Unpaid work productivity lost due to premature mortality, human capital approach	per death	26,307.03	42,208.73	Economy	Societal only	As above but for unemployed daily time use	As above	
Absenteeism from unpaid work due to medium & high distress	per person per year	860.38	1,380.46	Economy	Societal only	As above but for NILF time use	As above	
Unpaid work productivity lost due to premature mortality, human capital approach	per death	28,549.11	45,806.07	Economy	Societal only	As above but for NILF time use	As above	
Absenteeism for carers (days off due to caring for someone with medium or high distress, with or without disorder)	per person per year	637.07	1,413.80	Economy	Societal only	0.44 x 12 days x average weekly earnings (converted to days)	90% of people with high or very high distress, regardless of diagnosis, have 1 carer. 44% carers experience 1 day absent from work every 30 days Mental health productivity draft report 2019: https://apo.org.au/sites/default/files/resource-files/2019-10/apo-nid265801_5.pdf table page 467	Assumes only absenteeism, no presenteeism for carers because they are not ill. Assumes every person with medium or high distress has 1 carer (but only 44% of those carers experience absenteeism).
Carers payment allowance (to be applied to each person with medium or high distress with diagnosed disorder)	$ per person per year	12,557.15	12,557.15	Commonwealth (income households)	Societal only	Dividing total carer welfare expenditure (allowance, payment and supplement) by carer recipients where main condition is psychological or psychiatric	24% of carer receive a carer's allowance. Productivity Commission Inquiry Report, Mental Health, Volume 3, pages 912 and 913	Assume one carer per person with medium or high distress and a diagnosed disorder

Table S5: Intervention costs

Intervention/ cost item	Unit cost	Unit of measure	Calculation to be performed by model	One-off cost?	Payer	Perspective	Source	Assumptions
Technology-enabled integrated care								
Setup and customisation	$80,000	per clinical governance area per year	$80,000 x 1 clinical governance area	First year only	State	Health & Societal	Innowell, personal communication; model development group for single governance area	There is a single clinical governance area so that care is coordinated and integrated in the same way across BSPHN.
Annual subscription fee	$6,000	per clinician per year	$6,000 x number of clinicians in geographical catchment x % using platform	All years	State	Health & Societal	Innowell, personal communication	Assume the proportion of clinicians in BSPHN using the platform is the same as the proportion of service contacts where the intervention is adopted. Assume there is no cash cost for training clinicians to use the platform because any face to face sessions are provided free of charge by Innowell, combined with existing online resources. Assume there is no time cost for clinicians to undertake training because this is included in their normal ongoing professional development.
School-based suicide prevention programs that target mental illness								
							Microcosted in consultation with model development group.	Assume all cash costs are paid by the state from the health budget. Except for time cost which is state (education department) but in societal perspective rather than health.
Lectures about mental health	$6.54	per student per year	((2 x 1 hour lecture x ($35.35 x 1.12 oncosts per hour for allied health assistant HP1 level 7) / 12.1 student to teaching staff ratio) x uptake-adjusted number of students	All years	State	Health & Societal	The starting point for resources required to deliver program was the Youth Aware of Mental Health Programme (YAM), part of the Saving and Empowering Young Lives in Europe (SEYLE) study by Wasserman et al. [27].	Assume facilitator is allied health assistant employed full time at QH staff wage rates HP1, level 7, 12% oncosts. Assume facilitator delivers lecture per class and the number of students in a class is given by the QLD student to teaching staff ratio. Assume any referrals to mental health services are facilitated by school-employed psychologists or counsellors and assisted by the Ed-LinQ Program at no additional incremental cost. https://www.childrens.health.qld.gov.au/our-work/statewide-ed-linq-program
Role-play sessions	$9.82	per student per year	((1 x 3 hour lecture x ($35.35 x 1.12 oncosts per hour) / 12.1 student to teaching staff ratio) x uptake-adjusted number of students	All years	State	Health & Societal		As above
Educational posters	$2.34	per student per year	(6 posters x $39 per poster) / 100 x uptake-adjusted number of students	All years	State	Health & Societal		Assume 6 posters per 100 students.
32 page booklet to take home	$3.34	per student per year	$3.34 per info booklet per student x uptake-adjusted number of students	All years	State	Health & Societal		
Peer worker support, lectures	$6.51	per student per year	((2 x 1 hour lecture x ($35.14 x 1.12 oncosts per hour) / 12.1 student to teaching staff ratio) x uptake-adjusted number of students	All years	State	Health & Societal		Assume employed under the social and community workers award, usual for peer workers per advice from Jordan

Peer worker support, role-play sessions	$9.76	per student per year	((1 x 3 hour lecture x ($35.14 x 1.12 oncosts per hour) / 12.1 student to teaching staff ratio) x uptake-adjusted number of students	All years	State	Health & Societal		As above
Training, external facilitator	$20.75	per student per year	(((16 hours training x $62.76 x 1.12 oncosts per hour) / 12.1 students per teacher) x 25% of teachers undergo training) x uptake-adjusted number of students	All years	State	Health & Societal		Assume 25% of teachers are trained. Assume person delivering training is employed full time at QH staff wage rates, HP4, Level 1, 12% oncosts, per advice from Jordan and Adam.
Total cash cost per student	**$59.05**							
Time cost for teachers to attend training	$21.20	per student per year	513.08 daily wage teacher incl oncosts x 2 days training / 12.1 students per teacher x 25% teachers undergo training x uptake-adjusted number of students	All years	Economy	Societal		Assume 40 weeks of teaching per year, 5 days work per week, 2 days of training. Assume 12% oncosts
Time cost for teachers to deliver intervention	$62.19	per student per year	$68.41 hourly wage teacher incl oncosts x 11 hours class time / 12.1 students per teacher	All years	Economy	Societal		Assume 7.5 working hours per day Assume any referrals to mental health services are facilitated by school-employed psychologists or counsellors and assisted by the Ed-LinQ Program at no additional incremental cost. https://www.childrens.health.qld.gov.au/our-work/statewide-ed-linq-program
Total time cost per student	**$83.39**							
Post-suicide attempt care								
Clinician [group therapy]	$202.31	per participant per week	($150.53 x 1.12 per hour with oncosts) x 3 hours of group therapy x 2 sessions / 5 participants	All years	State	Health & Societal	Microcosted in consultation with model development group.	Assume clinician is at Queensland Health wage rates Health Practitioners' stream, HP8 Casual Rate at 12% on cost rate (per advice Adam Connell email 18 Oct). Assume 5 participants per group with range 3-7 participants (per advice MDG). Assume intervention is 5 weeks.
Clinician [parent psychoeducation]	$33.72	per participant per week	($150.53 x 1.12 per hour with oncosts) x 1 hour x 1 session / 5 participants	All years	State	Health & Societal	Starting point for resources was from a study by Kennard et al. [28]	Assume one parent participates per participant. Assume intervention is 5 weeks.
Clinician [individual sessions]	$168.59	per participant per week	($150.53 x 1.12 per hour with oncosts) x 1 hour x 1 sessions	All years	State	Health & Societal		Assume duration of session is 1hr. Assume intervention is 5 weeks.
Time Cost for Patients Attending Sessions	$171.99	per participant per week	$24.57 x (3 hours x 2 sessions+1 hour x 1 session)	All years	Economy	Societal		Assume intervention is 5 weeks. Assume time cost for patient rate as same as Economic inputs BSPHN, Weighted houly averages 15 to 24.
Time Cost for Parents Attending Sessions	$32.77	per participant per week	$32.77 x 1 hour x 1 session	All years	Economy	Societal		Assume intervention is 5 weeks. Assume parents are aged 35+ for calculation of time cost rate (weighted average hourly earning source - >63060DO004_202105 Employee Earnings and Hours, Australia, May 2021).

Peer Worker [group therapy & individual sessions]	$84.27	per participant per week	($35.14 x 1.09 oncosts per hour) x 3 hours of group therapy x 2 sessions / 5 participants) + ($35.14 x 1.09 oncosts per hour) x 1 hour x 1 sessions	All years	State	Health & Societal		Assume intervention is 5 weeks. Assume Peer Worker rate, Social and community workers award, level 2, pay point 4 https://calculate.fairwork.gov.au/payguides/fairwork/ma000100/pdf. With 9% oncost rate (per advice Adam and Jordan). Assume duration of session is 1hr.
Specialised youth mental health services hubs								
Clinician Cost	$168.59	per participant per intervention	($150.53 x 1.12 oncost per hour) x 1 hour x 37 sessions	All years	State	Health & Societal	Microcosted in consultation with model development group.	Assume average number of consultations per client per year is 37, using Meadowbrook Headspace Early Psychosis Service as a proxy for CASPAR/YMH service Hub service (Meadowbrook/Southport headspace centre service deliveries per David Hall email 19 Oct). Assume clinician is at Queensland Health wage rates Health Practitioners' stream, HP8 Casual Rate at 12% on cost rate (per advice Adam Connell email 18 Oct).
Peer Worker [individual sessions as therapy assistant]	$191.51	per participant per intervention	($35.14 x 1.09 oncosts per hour) x 1 hour x 5 sessions	All years	State	Health & Societal		Assume Peer Worker rate, Social and community workers award, level 2, pay point 4 https://calculate.fairwork.gov.au/payguides/fairwork/ma000100/pdf. With 9% oncost rate (per advice Adam and Jordan). Assume 5 sessions (per advice Jordan).
Peer Worker [group sessions]	$38.30	per participant per intervention	($35.14 x 1.09 oncosts per hour) x 1 hour x 5 sessions /5 participants	All years	State	Health & Societal		Assume 5 participants per group and 5 sessions (per advice Jordan).
Peer Worker Leader [group sessions]	$52.24	per participant per intervention	($47.93 x 1.09 oncost per hour) x 1 hour x 5 sessions/5 participants	All years	State	Health & Societal		Assume Peer Worker Leader rate, Social and community workers award,level 4, pay point 4. With 9% oncost rate (per advice Adam and Jordan).
Child and youth acute mental health response team								
Peer Worker 3.0 FTE	$196,120.74	Fixed Cost per year	(59975.76 x1.09 oncosts per person) x 3.0FTE	All years	State	Health & Societal	Microcosted in consultation with model development group	Salary oncost rates applied of 12% for medical, 9% for peer workers and 8% for all other workforce types (per advice Adam Connell email 18 Oct). Assume 3FTE peer workers (per advice Jordan). Assume Peer Worker rate, Social and community workers award, level 2, pay point 4, Full-time/Part-time rate.
Psychiatry Registrar 1.0FTE	$135,484.16	Fixed Cost per year	(120968 x 1.12 per person on costs) x 1.0FTE	All years	State	Health & Societal		Staffing as per advice Ryan Queensland Health wage rates, Medical Stream, Resident Medical Officer, L4
Nurse Practitioner 2.0FTE	$300,077.12	Fixed Cost per year	(133963 x 1.12 per person oncosts) x 2.0FTE	All years	State	Health & Societal		Staffing as per advice Ryan Queensland Health wage rates, Nursing Stream, Nurse Practitioner Grade 8, Pay point 2, Per Annum
Allied Health Worker 1.0FTE	$144,201.12	Fixed Cost per year	(191289 x 1.12 per person on costs) x 1.0FTE	All years	State	Health & Societal		Staffing as per advice Ryan Queensland Health wage rates, Health Practitioners' stream, H4 pay point 4, per annum

Administrative Officer Level 3 1.0FTE	$86,293.08	Fixed Cost per year	(79901 x 1.08 per person on costs) x 1.0 FTE	All years	State	Health & Societal		Staffing as per advice Ryan Queensland Health wage rates Administration stream L3
Total	$862,176.22							
Acute Response Team Cost	**$1,360.09**	Cost per service contact		All years	State	Health & Societal		Assume 15% loading to all FTE costs to account for shift work penalty rates. Assume additional service contacts for the 24/7 capacity to be 729.
Safety planning for suicide prevention								
Clinician Cost for CLASP-ED follow up	$295.03	per participant per intervention	($150.53 x 1.12 oncost per hour) x 7calls x 15minutes	All years	state	Health & Societal	Microcosted in consultation with model development group and resources from Miller et al. [25]	Assume 7 brief (10- to 20-minute) telephone calls to the participant from a psychologist/counselor (Miller et al., 2017 [25]).
ED Clinician Cost	$126.44	per participant per intervention	($150.53 x 1.12 oncost per hour) x 45mins	All years	State	Health & Societal		
Time Cost for Patients Attending Sessions	$43.00	per participant per intervention	($24.57 per hour) x 7calls x 15mins	All years	Economy	Societal		Assume time cost for patient rate as same as Economic inputs BSPHN, Weighted houly averages 15 to 24.

Utilities

Table S6: Utilities used to calculate quality-adjusted life years, ages 12 years and greater

	Low distress	Moderate, high, v. high without disorder	Moderate, high, v. high with disorder
12-14	0.9264	0.8880	0.8223
15-17	0.9235	0.8785	0.7983
18-24	0.9185	0.8573	0.8073
25+	0.8772	0.7914	0.7279

Table S7: Utilities used to calculate quality-adjusted life years, ages 11 years and less

Age group	General population without distress	Close to average	Slightly raised	High and very high
0-4 years	0.96	0.8678	0.7602	0.6808
5-11 years	0.96	0.8659	0.7595	0.6750

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