Identifying clinicians' needs for the acceptance and use of hospital clinical decision support systems over time

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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.

Nicki Newton

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Abstract

Background: As the volume of healthcare data continues to grow, Clinical Decision Support (CDS) systems are becoming necessary for improving the safety, quality, and efficiency of patient care. However, CDS is often underutilised in practice, undermining these potential benefits and resulting in wasted effort and investment. While much prior research has investigated why clinicians do or do not accept and use CDS systems, studies typically take a static perspective that assumes clinicians' needs remain stable over time. This overlooks the dynamic nature of healthcare environments, where users, systems, and organisational contexts are continually changing. A deeper understanding of the temporal nature of CDS acceptance and use is therefore essential to guide the targeted application of strategies that support both early and sustained engagement.

Aims: The overarching aim of this thesis was to investigate how clinicians' needs for the acceptance and use of hospital-based CDS systems change over time, from initial implementation through to sustained use, and how acceptance and use could be improved by applying strategies to address time-sensitive needs.

Methods: A mixed-methods approach was taken, comprising three systematic reviews (Chapters 3a, 3b and 4), two qualitative studies (Chapters 5 and 6), and a mixed-methods study (Chapter 7). Systematic reviews synthesised existing literature on 1) user involvement in CDS design and its impact on acceptance and use (Chapter 3a), 2) methodological approaches used to evaluate CDS acceptance and use over time (Chapter 3b), and 3) the factors reported to influence clinicians' acceptance and use of CDS over time (Chapter 4). Early experiences with two CDS systems implemented in a rural hospital using a pilot approach, were evaluated through semi-structured interviews in Chapter 5. Doctors' experiences with routinely embedded CDS systems were then evaluated using semi-structured interviews in Chapter 6, with a focus on alert fatigue. Chapter 7 used survey and Electronic Health Record (EHR) log data to compare junior doctors' perceptions of alerts and alert fatigue, with their interactions with alerts over time. Data collection and interpretation were informed by Human Factors and Ergonomics perspectives and Implementation Science frameworks, which enabled holistic consideration of the human, technological, and contextual factors influencing acceptance and use and their interactions over time.

Results: Clinicians' needs for CDS acceptance and use were found to shift over time. Early impressions strongly influenced how CDS was accepted and used, or not used, long term.

These impressions were collectively shaped by users' characteristics, past experiences and expectations, which in turn influenced their tolerance for system issues like poor performance, maturity, and fit with the local context, that were common during early implementation. A lack of perceived familiarity, value, and efficiency were also common during early use, but could be mitigated with enhanced system usability, ongoing clinician involvement, and organisational commitment and resources. Factors such as the perceived value of CDS and its fit with workflows were found to emerge early and remain influential over time. Routine use, and disuse, of CDS was influenced by clinicians' self-efficacy, habits, attitudes, and the level of integration of CDS into workflows and organisational culture. However, routine use could be disrupted when CDS systems failed to be adapted as other elements of the work system evolved.

Conclusions: This research provides strong evidence that clinicians' acceptance and use of CDS within hospitals is a dynamic process that must be actively supported throughout the system lifecycle. Drawing on theory and empirical data, this thesis offers practical guidance to assist CDS implementers in addressing user needs that are likely to arise over time. We advocate for the utilisation of strategies such as user involvement, organisational communication, support and leadership, to meet different user needs across all stages of the lifecycle. These findings demonstrate the significant investment required to support clinicians' early and ongoing acceptance and use. Given these demands, hospitals must be highly selective in the CDS systems they choose to implement, focusing resources on systems that provide robust value to clinicians and consequently, improve patient care and outcomes.

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List of acronyms

AI	Artificial Intelligence
BPA	Best Practice Advisory
CBAM	Concerns-Based Adoption Model
CDS	Clinical Decision Support
CDSS	Clinical Decision Support System
CFIR	Consolidated Framework for Implementation Research
CIS	Clinical Information System
CPOE	Computerised Provider Order Entry
DOI	Diffusion of Innovations
ED	Emergency Department
EHR	Electronic Health Record
EMR	Electronic Medical Record
HFE	Human Factors and Ergonomics
IT	Information Technology
JMO	Junior Medical Officer
ML	Machine Learning
MMAT	Mixed Methods Appraisal Tool
NASSS	Non-adoption, Abandonment, Scale-up, Spread and Sustainability
PGY	Postgraduate Year
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SDLC	Systems Development Life Cycle
SEIPS	Systems Engineering Initiative for Patient Safety
SRQR	Standards for Reporting Qualitative Research
UTAUT	Unified Theory of Acceptance and Use of Technology
VTE	Venous Thromboembolism

List of publications

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Chapter 3a "Does involving clinicians in decision support development facilitate system use over time? A systematic review"

NN in consultation with all authors conceived and planned the review. NN searched databases and conducted manual searches. NN, MB, AB and RF screened identified articles for eligibility. NN, MB, AB, RF and AT extracted data. NN drafted the manuscript, with all authors reviewing and providing feedback on the draft.

Chapter 3b "How are clinicians' acceptance and use of clinical decision support systems evaluated over time? A systematic review"

NN in consultation with all authors conceived and planned the review. NN searched databases and conducted manual searches. NN, MB, AB and RF screened identified articles for eligibility. NN, MB, AB, RF and AT extracted data. NN drafted the manuscript, with all authors reviewing and providing feedback on the draft.

Chapter 4 "A systematic review of clinicians' acceptance and use of clinical decision support systems over time"

NN in consultation with all authors conceived and planned the review. NN searched databases and conducted manual searches. NN, MB, AB and RF screened identified articles for eligibility. All authors (NN, MB, AB, RF and AT) extracted data and participated in workshops to synthesise factors. NN (with input from all authors) analysed data and created graphs. The manuscript was drafted by NN, with all authors contributing to subsequent edits and revisions.

Chapter 5 "Opportunities and challenges associated with the pilot implementation of clinical decision support systems in a rural hospital: A qualitative study"

All authors conceived the study. NN, MB, AB, AF and AT designed the study and methods. NN conducted all interviews. NN, AB, and AT analysed interview transcripts. NN drafted the manuscript, with all authors reviewing and providing feedback on the draft.

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All authors conceived the study. NN, MB, AB, AF and AT designed the study and methods. NN collected survey and log data. NN analysed data in consultation with MB and AT. NN drafted the chapter, with MB and AT reviewing and providing feedback on the draft.

Nicki Newton
23 June 2025

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

Professor Melissa Baysari
23 June 2025

CHAPTER 1

General Introduction

OVERVIEW

This thesis explores clinicians' acceptance and use of Clinical Decision Support (CDS) systems integrated with hospital clinical information systems over time. As will be discussed in the following sections, considerable research has been conducted to evaluate clinicians' acceptance and use of CDS systems in practice. However, there is currently limited evidence on how clinicians accept and use CDS systems over time, from initial implementation to ongoing use in routine practice. As will be argued, this is a fundamentally important area of research that can inform the development and application of targeted and timely strategies to improve early and sustained acceptance and use of CDS, and thus help to realise the full scale of benefits CDS systems can offer.

This introductory chapter is organised in six sections. Firstly, existing literature on CDS systems, clinicians' acceptance and use and the factors influencing acceptance and use of CDS, is introduced. Next, theoretical concepts and frameworks describing the dynamic nature of individuals' acceptance and use of technologies are introduced. These theories frame and contextualise the third section of the introduction, that discusses existing research on the factors influencing the acceptance and use of CDS and related systems over time. Fourth, I describe existing evidence on the different patterns of CDS and related system use over time, including disuse and misuse of CDS. Fifth, strategies that are used to improve CDS acceptance and use, and gaps in their application over time, are discussed. Lastly, existing evidence and gaps in evidence that relate specifically to the acceptance and use of CDS integrated with hospital clinical information systems are summarised, proving rationale for the aims of the thesis.

CLINICAL DECISION SUPPORT SYSTEMS

The demand for CDS systems is greater than ever. As patient data, medical literature, and clinical guidelines exponentially grow, clinicians face increasing challenges in efficiently synthesising and applying this information at the point of care.[1] By combining patient specific information with knowledge-bases of diverse evidence and expertise, CDS systems aim to address this issue, presenting clinicians with tailored insights and recommendations to support informed decision-making in practice.[2]

In this thesis, CDS systems are defined broadly in line with Osheroff et al. (2012), as any electronic system that "enhances health-related decisions and actions with pertinent, organized clinical knowledge and patient information to improve health and healthcare delivery" (P15).[2] As such, CDS systems take diverse forms, from simple alerts that prompt clinicians to consider alternative information, to advanced platforms that generate complex diagnostic or treatment recommendations.[3] Figure 1 shows a taxonomy of CDS intervention types as outlined in Osheroff et al. (2012),[2] and Table 1 provides common examples of CDS systems used in hospital settings. CDS systems can leverage clinical guidelines and expert knowledge, employ complex AI-driven algorithms that analyse relationships in medical data, or combine both approaches to provide actionable insights to clinicians at the point of care.[3] While some systems are interruptive, requiring clinicians to interact with the CDS before proceeding, others are passive, providing information only when actively accessed by the user.[4] Applied to support a wide range of decisions in diverse clinical settings, CDS systems have the potential to greatly enhance the quality and consistency of care, reduce medical errors and improve patient safety.[5,6]

A. CDS during data-entry tasks
   1. Smart documentation forms
   2. Order sets, care plans and protocols
   3. Parameter guidance
   4. Critiques and warnings — "immediate alerts"

B. CDS during data-review tasks
   5. Relevant data summaries (single-patient)
   6. Multi-patient monitors
   7. Predictive and retrospective analytics

C. CDS during assessment and understanding tasks
   8. Filtered reference information and knowledge resources
   9. Expert workup and management advisors

D. CDS not triggered by a user task
   10. Event-driven alerts (data-triggered) and reminders (time-triggered)

Figure 1. Taxonomy of CDS Intervention Types, from Osheroff et al. 2012[2]

Table 1. Common examples of CDS systems used in hospital settings

CDS Type	Description	Common uses
Interruptive alerts	Pop-up alerts that interrupt providers while interacting with clinical information systems	Medication alerts such as drug-drug interactions, drug allergies, dosing, and duplicate orders
Passive alerts	Non-interruptive notifications that are displayed in the user interface but do not require immediate acknowledgment or action[7]	Visual flags or icons indicating abnormal lab results, risk scores, or relevant clinical guidelines
Dashboards	Aggregated visual displays providing real-time or near real-time summaries of patient data to support clinical decision making and monitoring[8]	Identify deteriorating patients, monitor lab values and medications, support patient flow
Calculators	Generation of patient-specific scores or recommendations based on clinical rules or risk models	Assist with clinical risk stratification and dosing decisions (e.g. Wells score, creatinine clearance)
Order sets	Predefined groups of clinical orders based on specific diagnoses, procedures, or care pathways	Streamline ordering processes and promote evidence-based practice e.g. pneumonia

		admission order set, sepsis bundle

In hospital settings, where timely and accurate decision-making is critical, CDS systems offer significant value by supporting clinicians to process and apply relevant information under time pressure.[9,10] In this thesis, the term 'hospital' is used to refer to both inpatient and hospital-based outpatient settings. With most hospitals across Australia and globally now adopting clinical information systems, such as Electronic Health Records (EHRs) and Electronic Medical Records (EMRs), greater opportunities for integrating CDS systems into these settings exist.[11] As CDS requires patient-specific data to generate insights, integration with EHRs allows for data to automatically flow to and from the system and be directly incorporated into clinicians' workflows. This makes EHR integrated CDS more practical than standalone systems that require manual data entry or those that function outside the EHR.[12,13] While the terms EHR and EMR represent similar, yet different systems, the term EHR is used to refer to both types of systems for consistency throughout this thesis.

Despite their increasing availability in hospital-based care and potential for success, the anticipated benefits of CDS systems have not always been realised.[14] While some systems demonstrate significant improvements in care processes, efficiency, and clinical outcomes following their implementation, meta-analyses highlight low overall effect sizes and significant variability - some systems perform remarkably well, while the vast majority show little to no impact.[15-17]

A key reason for this variability in impact is that clinicians must use CDS systems in order to produce benefits. As clinicians retain ultimate responsibility for decisions regarding patient care, CDS systems that do not meet clinicians' needs can be, and often are, bypassed, worked around, or simply ignored.[18] In line with this, countless reviews which set out to understand why some CDS systems succeed and others fail, almost exclusively identify factors relating to clinicians' interactions with the system.[3,12,19-22] A recent systematic review and meta-analysis of 55 studies found that CDS systems were only used by clinicians in 34.2% of opportunities to do so.[23] This figure highlights not only missed opportunities to improve patient care, but also wasted investments in time, funding, and effort that is often spent on developing and implementing CDS systems that are rarely, if ever, used.[24] Furthermore, CDS systems that fail to meet clinicians' needs can become burdensome and, rather than

supporting decision-making, may increase workload, introduce inefficiencies and new technology related errors, and exacerbate medical errors.[25,26] Such failures compromise patient safety, care quality, and clinicians' efficiency, undermining the very goals they aim to achieve. Understanding and addressing clinicians' acceptance and use of CDS systems is therefore critical to tackling these challenges and improving CDS systems' ability to improve their targeted clinical and process outcomes (Figure 1).

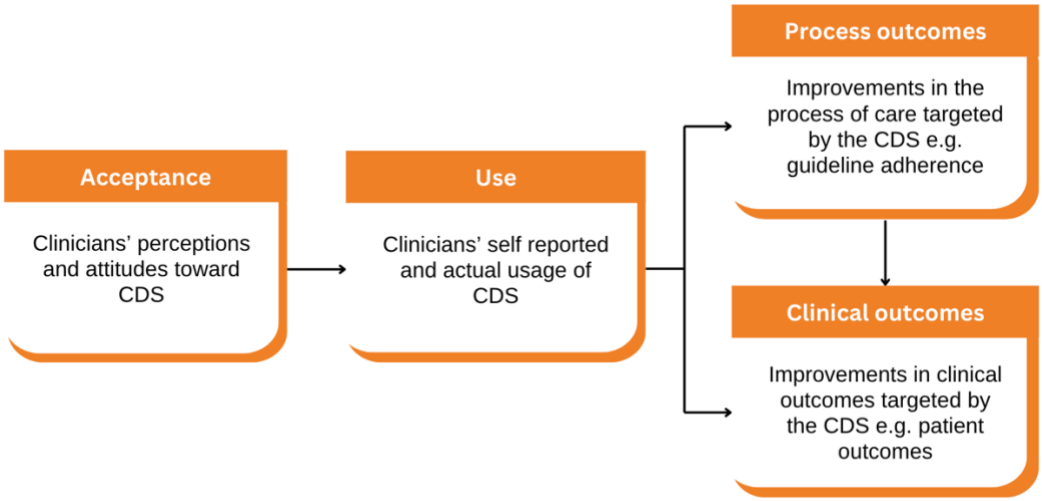

Figure 2. CDS outcomes

The acceptance and use of CDS systems

In this thesis, the terms 'acceptance' and 'use' are defined in accordance with the Unified Theory of Acceptance and Use of Technology (UTAUT).[27] According to the UTAUT, **an individuals' 'use' of a technology (i.e. their perceived or actual interactions with it), is influenced by their behavioural intentions (i.e. 'acceptance'; their perceptions and attitudes toward it) to use the technology** (Figure 1). While similar terms such as 'adoption' and 'uptake' are often used interchangeably to describe the acceptance and use of technology in the literature, these terms appear to be more synonymous with a users' initial decision to use a system rather than their ongoing interactions with it. Thus, the terms 'acceptance' and 'use' are favoured throughout this thesis to refer to perceptions of and interactions with systems, irrespective of a users' stage of use.

It is important to note that while the acceptance and use of technology are closely connected concepts, they are not interchangeable. Although often overlooked in existing studies evaluating clinicians' interactions with CDS, this distinction is critical, given addressing factors that drive acceptance without tackling barriers to use can result in systems that clinicians acknowledge as useful but fail to engage with in practice.[28] For example, in a scoping review of 24 studies evaluating CDS used in Emergency Departments (ED), clinicians' perceptions of CDS were generally positive, but their actual use of these systems was low.[29] Similarly, a study that evaluated a CDS implemented to support the diagnosis of pulmonary embolism in the ED, found that while clinicians perceived pulmonary embolism to be an important issue and the system to be usable, they generally did not use it due to a lack of integration with workflows.[30] These examples align with the UTAUT, which theorises that users can intend to use a system that they see as useful and usable, but may not follow through with using the system if facilitating conditions are lacking.[27] Likewise, a CDS system that clinicians use out of obligation rather than perceived value can lead to inappropriate utilisation, increasing the risk of making incorrect or unnecessary decisions.[31] Despite this, only a handful of studies have explored the relationship between acceptance and actual use of CDS, with none comparing individual users' acceptance with their actual use of CDS in hospital settings, or how this may change over time.

Reviews on the factors influencing clinicians' acceptance and use of CDS

Existing reviews have evaluated the factors that influence clinicians' acceptance and use of CDS systems across diverse contexts (Table 2).[18,20,21,23,28,29,32-36] Identified factors can be categorised as relating to the technology, its users, the organisation and process in which it is embedded, as well as the interactions between these elements. According to a recent review that identified the barriers and facilitators to CDS acceptance and use in hospitals in qualitative, quantitative and mixed methods studies, the most frequently reported factors were the CDS system's integration with clinical workflows, its usefulness and relevance, and technical performance and design.[21] The factors identified in this review align with previous reviews of studies evaluating CDS acceptance, use and implementation (Table 2), as well as reviews identifying features that influence the impact of CDS on its intended outcomes, such as improvements in the process of care delivery[19] and impact on patients.[12,37] Such factors, including fit with workflows, usefulness, and design, are therefore critically important to

address as they are likely to both directly and indirectly (through system acceptance and use) impact effectiveness.

Table 2. Select reviews evaluating factors influencing the acceptance and/or use of CDS

Reference	Focus	Intervention	Key factors identified
Abell et al. (2024)[21]	Barriers and facilitators to successful implementation and adoption	Any CDS in hospital settings	CDS' fit with workflows and users' role or clinical setting, usefulness, technical dependencies and design, trust in CDS input data, evidence base supporting CDS
Ackerhans et al. (2024)[36]	Factors influencing professional identity in the implementation, use and adoption of CDS	Any CDS in any setting	CDS' fit with existing workflows, ability to meet user needs, time pressure, internal communication and involvement of end users
Devaraj et al. (2014)[32]	Barriers and facilitators to CDS adoption	Any CDS in any setting	Time constraints, lack of resources, lack of knowledge or skills, reluctance to use, lack of workflow fit, reliability of information, attitudes toward the system
Hill et al. (2024)[38]	Characteristics of CDS implementations leading to regular use	Any CDS in routine use (i.e. part of a normal workflow) in any setting	Organisational support and prioritisation, shared understanding of value proposition, iterative implementation in response to feedback
Jun et al. (2018)[29]	Factors influencing acceptance and use	Any cognitive support system in ED settings	Perceived usefulness, unfriendly user interface, redundant information, high required user effort, positive perceptions of patient safety, institutional support
Khairat et al. (2018)[18]	Reasons for clinicians not adopting CDS	Any CDS in any setting	Workflow interference, questionable CDS validity, lack of efficiency, alert fatigue, ease of use, time savings, usefulness
Khong et al. (2015)[28]	Theoretical frameworks used to evaluate, and factors influencing, CDS adoption	Any CDS in any setting	CDS usability, performance, process flow, resource availability, education and implementation support, users' efficacy and skills
Kilsdonk et al. (2011)[20]	Factors influencing CDS implementation success	Guideline-based CDS in any setting	Lack of familiarity with CDS, beneficial for inexperienced users, time constraints to use, fit with routine care, CDS relevance, ease of use, lack of efficiency
Kouri et al. (2022)[23]	Reported CDS uptake (use) and	Any CDS in any setting	Formal evaluation of the availability and quality of patient data to inform CDS, identifying

	factors associated with uptake		and addressing other barriers to the behaviour change targeted by CDS
Liu et al. (2021)[39]	Factors influencing CDS adoption and implementation	CDS integrated with an EHR, in inpatient, outpatient and primary care	Effort expectancy, facilitating conditions, performance expectancy with motivational control
Moxey et al. (2010)[34]	Barriers and facilitators to CDS uptake	CDS for prescribing targeting physicians in any setting	Availability of hardware, technical support and training, CDS' fit with workflows, relevance and timeliness, endorsement by colleagues, limited threat to autonomy, did not compromise doctor-patient relationship
Westerbeek et al. (2021)[35]	Barriers and facilitators to CDS acceptance	Medication-related CDS in any setting	Lack of usefulness and relevance, and ease of use and efficiency

A gap in clinicians' acceptance and use of CDS systems: Time

Recent reviews have identified an absence of studies evaluating user acceptance of CDS over time.[21,29,36,40] For instance, within 44 included studies, Abell et al. (2024) did not identify any factors within the domain of embedding and adapting CDS systems over time, citing a lack of longitudinal studies and limited research that evaluated CDS beyond its initial evaluation period.[21] Ackerhans et al. (2024) similarly identified a lack of longitudinal research evaluating CDS' impact on clinicians' professional identity. Another review that documented the point in time included studies evaluated acceptance and use following CDS implementation in ED settings, found a lack of CDS implemented or evaluated over a sustained period.[29] However, this review did not compare the factors influencing acceptance and use at different points in time. A recent review of CDS systems identified common factors associated with routinely used systems, which included the organisational prioritisation of CDS, a shared understanding of the value of CDS, and the ability to adapt and customise the system.[38] However, the review defined 'routine use' as CDS that was used as part of a normal workflow, excluding those only deployed as part of a research study, trial or pilot. As a result, the review may have included studies where CDS had only recently been implemented, provided it was part of standard workflows rather than a trial, which does not necessarily indicate sustained, long-term use by clinicians.

While much existing literature has explored clinicians' acceptance and use of CDS, studies often take a cross-sectional approach, evaluating acceptance, use and their influencing

factors, at a single point in time.[21,36,41] However, acceptance and use of technology are not static, but evolve over time as users gain experience with a system and as it is embedded within an organisation - a concept well documented in theoretical studies and frameworks describing technology acceptance and use.[27,42-44] In the UTAUT for example, a users' level of experience with a system is theorised to influence how certain factors affect their perceptions and behavior.[27] Specifically, experience is reported to moderate the impact of effort expectancy (i.e., perceived ease of use) and social influence on behavioural intentions, as well as the effect of facilitating conditions on actual system use. [27] This indicates that factors like these, which are also frequently identified in CDS literature,[21,45] are likely to be important in predicting acceptance and use at earlier points in a users' journey, but perhaps become less relevant as they gain experience with the system over time.

THEORIES ON TECHNOLOGY ACCEPTANCE AND USE OVER TIME

CDS systems and theories of technology acceptance and use

CDS systems belong to a unique category of technologies implemented in hospitals, as they are, aside from a few exceptions, offered on a voluntary basis. Voluntary systems have been described as those that "provide an alternative to existing work practices and are not expected to replace them" (p96),[46] aligning with the philosophy that CDS systems should support but not replace clinical decision making. The implementation of CDS systems is therefore particularly complex, as it involves navigating organisational challenges such as adapting policies, culture, and workflows, while simultaneously convincing users at individual and collective levels that the CDS is worth using.[46] Theories describing the dynamic nature of technology acceptance and use, both within and outside of organisations, can therefore provide insight into the use of CDS following its implementation over time. In the following section, insights from theories and frameworks in related disciplines, including information systems, implementation science, consumer behaviour and organisational change, are summarised to identify and contextualise the underlying factors that help to understand clinicians' acceptance and use of CDS systems in hospitals over time.

Individuals' acceptance and use of technology over time

Rogers' seminal theory on the diffusion of innovations offers several insights into users' adoption of innovations over time.[43] Originating from the stages of change model in

behavioural psychology,[47] Rogers (2003) describes stages that individuals typically progress through in their 'innovation-decision process'. Individuals' initial decision to adopt an innovation is theorised to first be influenced by their awareness of the innovation, and perceptions of its fit with their needs and existing attitudes. During the decision stage, individuals are then influenced to adopt an innovation based on their appraisals of its relative advantage to them, usually determined by trialling the innovation themselves or receiving insight from peers. The innovation is then put into use during the implementation stage, where individuals may encounter issues and questions in understanding how to use the innovation to best meet their needs. The end of the implementation stage is characterised as the point where the innovation "becomes institutionalised as a regularised part of an adopter's ongoing operations" and loses its separate identity as a new idea (p180).[43] An additional stage, confirmation, is described where users' seek reinforcement of their initial decisions to adopt. Five factors are theorised to influence the rate of innovation adoption into routine use, including the innovations' level of relative advantage, complexity, compatibility, trialability and observability. Additionally, innovations are 're-invented' as they are iteratively adapted to meet users' needs, where a higher level of re-invention is theorised to lead to both quicker and more sustainable adoption. Importantly, Rogers (2003) stresses that the adoption process is influenced by these mutual adaptations of users to the technology, and of the technology to its users over time.[43]

The diffusion of innovations theory also describes several categories of adopters who display unique patterns of innovation adoption, where each group adopts innovations at different speeds and are motivated by differing factors (Figure 3).[43] Innovators and early adopters are theorised to embrace innovations quickly, often driven by curiosity and an innate openness to change, while the early majority adopt more cautiously after observing success among peers. The late majority require social pressure or evidence of widespread use before adopting, and laggards, often sceptical of change, adopt only when it becomes unavoidable or when older alternatives are no longer viable.[43]

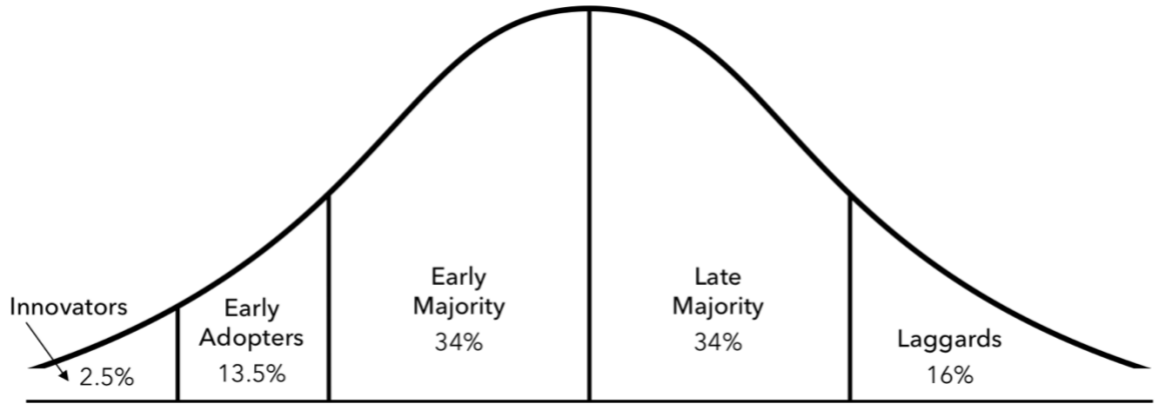

Figure 3. Diffusion of innovations adopter curve from Rogers (2003)[43]

The concerns-based adoption model similarly describes stages that users are theorised to progress through in their use of innovations.[48] Although originally developed for innovations in education settings, it has since been applied in diverse fields including healthcare and other service organisations.[49,50] The model describes differing stages of concerns that are commonly experienced by users as they progress along a continuum of levels of use.[48] In the early stages of an innovations' use, users' concerns are theorised to relate to 'self-concerns', referring to the impact of the innovation on the user (e.g. their ability to use the innovation). With increased use, concerns are theorised to shift to 'task-concerns' (e.g. how they can effectively incorporate the innovation into daily tasks), and lastly to 'impact-concerns' relating to the innovations' impact on others (e.g. the difference using an innovation makes and its value to others). Users' progression through these phases is proposed to be related to the improvement in their skills in using the innovation and consequently gaining control, confidence and responsibility over the innovation over time. Importantly, the model describes how understanding and anticipating these concerns can allow for solutions to be targeted toward the concerns relevant at that time. For example, given self-concerns are believed to be most relevant during early use, training is likely to be an appropriate solution during users' initial interactions.[48] By addressing concerns in a timely manner, it is theorised that the routine use of a system will be achieved more quickly.

Other models expand on the factors that shape individuals' adoption of technologies over time.[51-53] In one model, expectation-confirmation theory was applied to understand users' intentions to *continue using* an information system beyond initial adoption.[51] Users' decisions to continue using a system were found to be most strongly predicted by their satisfaction with

the system. Satisfaction was in turn influenced by users' ongoing process of updating and confirming their expectations of the system, based on their experiences with it.[51] This aligns with self-perception theory, which details how individuals develop attitudes and preferences by observing their own behaviours and experiences, particularly in situations where they lack strong initial opinions.[54] It also supports Rogers' (2003) appraisal that users continue to re-evaluate their decisions to use systems as they acquire updated information based on their experiences over time.[43]

However, technology continuance theory offers a slightly different perspective, suggesting that at a certain point, long-term users stop actively updating their beliefs about a system.[53] When evaluating factors influencing the technology use of users at various stages of use i.e. initial adopters (less than 6 months), short-term users (6-12 months) and long-term users (12+ months), attitudes toward technology emerged as a stable predictor of continued use. In contrast, satisfaction and perceived usefulness were more transient, playing a stronger role in the initial phases of adoption but diminishing over time as users gained increasing experience with the system.[53] Due to the cognitive effort required to continuously update beliefs about a system, it is plausible that users develop mental shortcuts, relying on established attitudes to guide their ongoing use.[55]

The longitudinal model of continued information systems use substantiates and expands on these claims, describing the evolution of individuals' initial use through to continued use of information systems over time.[52] Consistent with previous models, it suggests that users form judgments about a system's usefulness and ease of use based on their initial experiences with it. In systems that are routinely used, this model suggests that judgments become increasingly shaped by heuristic-based appraisals where interactions occur unconsciously. Users are thought to only form conscious evaluations of systems, such as their usefulness and ease of use, when prompted by external factors, such as inquiries by researchers.[54] Another important focus of this model includes the role of past behaviours toward a system on future behaviours toward it. Where technology was used in stable environments, users were reported to consciously and intentionally interact with the system in the early stages of use, but later exhibit automatic interactions with the system (i.e., habits) once routine use was established.[52] Taken together, these theories suggest that users' perceptions *and* actions toward systems evolve over time, until attitudes and habits eventually form and solidify their long-term use.[52,53]

Individuals' rejection of technologies over time

Many of the theories outlined above highlight alternative trajectories of individuals' use of technologies that exist over time (Figure 4).[27,43,48,56] For example, Rogers' innovation-decision process describes how users choose to adopt or reject innovations during the initial decision stage.[43] Various terms, such as rejection, non-use and non-adoption, have been used in these different theories to describe the decision to not adopt innovations. Additionally, even though users may initially choose to adopt an innovation, they may later discontinue their use.[43] This concept is known as discontinuance, adoption abortion, and abandonment. Alternatively, those users who initially decide not to adopt a technology may continue to reject the technology over time, i.e. continued rejection or non-adoption.

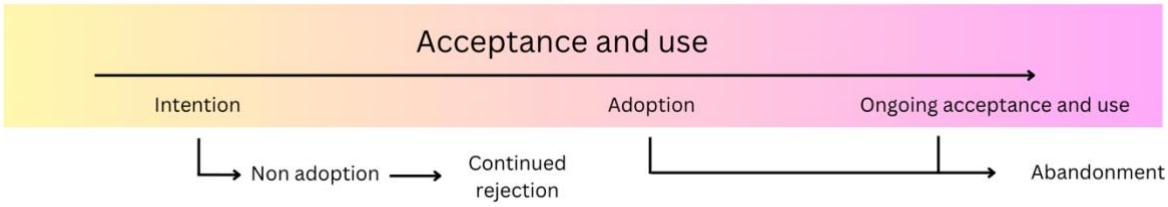

Figure 4. Trajectories of acceptance and use over time, informed by adoption theories and frameworks[27,43,48,56]

These theories offer several insights into rejection trajectories and how to prevent their occurrence. For example, the diffusion of innovations theory highlights two types of rejection, including *active* rejection where individuals consider adopting an innovation but actively decide not to adopt, and *passive* rejection where individuals never consider using an innovation. During the initial decision, an individual may, for example, actively reject an innovation if they don't believe it will meet their needs, or passively reject if they are not made aware of or simply forget about its existence. Later, when confirming their initial decision to adopt, users may reverse their initial decision, actively deciding to discontinue if they are dissatisfied with the innovations' performance (disenchantment), or if a better innovation replaces it (replacement). Interestingly, the reversal of prior decisions is thought to be less likely to occur than initial rejection, as individuals try to avoid cognitive dissonance[57] by maintaining consistency with their initial choices. Consequently, they seek information

that reinforces their existing beliefs (i.e., through confirmation bias[58]) and often adjust their expectations to align with their experiences.

Within organisations, the concerns-based adoption model suggests that the likelihood of an adoption being 'aborted' can be reduced by addressing common concerns in a timely manner.[48] Lastly, the non-adoption, abandonment, sustainability, scale up and spread framework expands on this within healthcare settings, reporting that health information technologies are more likely to be rejected where there is a greater degree of complexity present in the condition, technology, value proposition, adopter system, organisation, wider context, and interactions between these domains that unfold over time.[56]

Socio-technical acceptance and use of technology over time

While these theories are useful in understanding individuals' acceptance and use of technologies and other innovations, they either focus on the use of technologies outside of organisations or take a narrow approach to acceptance and use that largely neglects the technological and organisational aspects of system implementation. Critiques of models such as the concerns-based adoption model, have highlighted its failure to explore use as a collective experience that is shaped not only by individuals but also technical, societal and organisational dynamics.[59] Inherently, the acceptance and use of systems within organisations are increasingly dynamic and complex as they involve ongoing adaptations between the technology, its users, *and* the organisation to achieve long-term benefits.[43,60] Implementing systems in organisational settings results in changes to users' workflows and roles, as well as institutional processes and culture, requiring careful navigation as technology is integrated and assimilated over time.[50] Additionally, within organisations, those making decisions about adopting systems are often not the same individuals who will later need to use the system in their daily work.[43]

A foundational framework for understanding the deployment of technology in organisations is provided in the Systems Development Life Cycle (SDLC).[61] Sequential stages, such as those outlined in the SDLC, provide a structured guide for directing systems development activity, identifying and addressing common challenges, and enabling a more efficient and effective implementation process. Stages outlined in the SDLC include the planning, analysis, design, implementation, and maintenance of software in organisations.[61] During the planning

and analysis stages, the need for a new system is identified and requirements for the system are gathered. In the design and implementation phases, a system is either built, purchased, or a combination of the two, and is tested and implemented into the production environment.[62] The system is then enters a period of maintenance, where the goal is to ensure it continues to operate effectively, addressing new requirements or issues as they arise.

Theories originating in organisational change have expanded on the socio-technical elements of system implementation. These include the diffusion of innovations innovation-process theory,[43] technochange theory[63] and a seminal study describing windows of opportunity[64] for technology adaptation. The innovation-process theory focuses on the organisational perspective of innovation implementation, and like the SDLC, is presented in a series of sequential stages. These include agenda-setting, which includes identifying a problem and seeking solutions; matching, where an innovations' fit with organisational needs are evaluated; redefining/restructuring, where the innovation and workflows are adapted to enhance compatibility; clarifying, where the integration and role of the innovation are refined; and routinising, where the innovation is made part of regular operations.[43] In each stage of the innovation-process, key markers of success are theorised to influence an innovation's progression to a later stages. For example, the better a solution is *matched* to an organisational need or problem during the matching stage, the higher the likelihood the innovation will reach routinisation.

Technochange theory outlines similar stages of a socio-technical systems' lifecycle, including chartering, project, shakedown and benefit capture (Figure 5).[63] Similar to Rogers' redefining/restructuring phase following technology implementation, the shakedown phase emphasises the need to resolve inevitable issues that arise as users start interacting with the technology following its implementation. This phase is characterised by the troubleshooting and addressing of technical problems, addressing user resistance, and adapting workflows to integrate the system effectively. A key contribution of technochange theory is the concept of 'exported problems,' which refers to challenges that arise in one phase of the lifecycle and, if not recognised and addressed, can carry over and impact the success of subsequent phases.[63] Exported problems are described to be particularly problematic because the people who are responsible for addressing issues at one stage of the lifecycle are often no longer involved by the time these problems are recognised in later stages. New stakeholders must then deal with consequences they had little influence over and lack expertise in addressing.

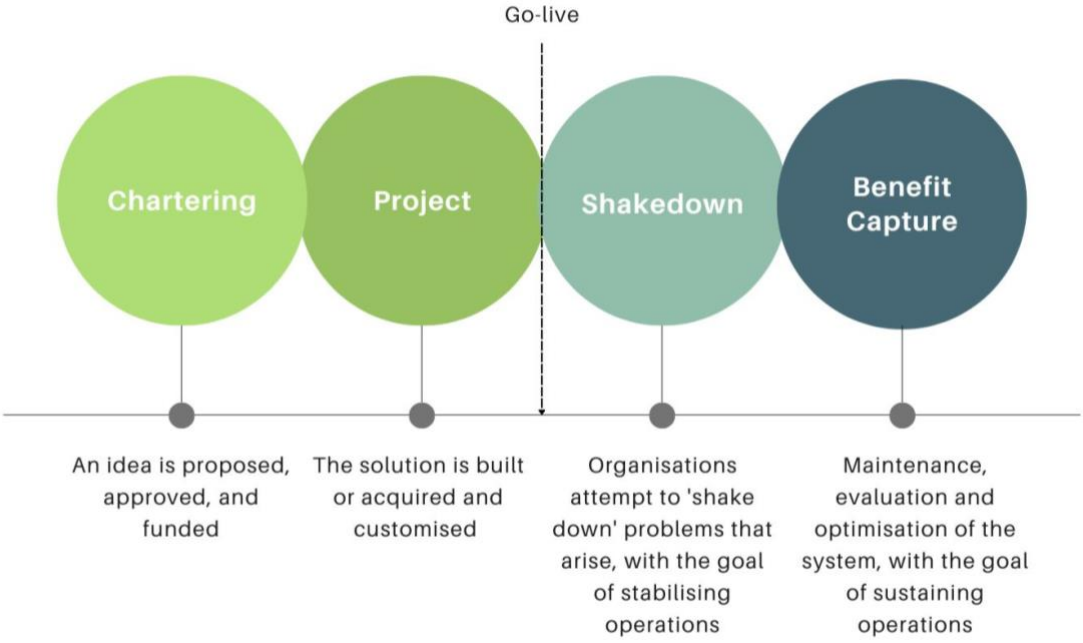

Figure 5. Stages of the technochange lifecycle[63]

One problem that is described to be commonly exported from the shakedown to benefits capture stage is the premature routinisation of system use. In such cases, users may adopt 'workarounds' to combat system limitations rather than utilising the system as intended, often resulting in its intended benefits not being achieved or being minimised.[64,65] In line with Rogers' theory, mutual adaptations between systems, users and organisations are likely to address system limitations and thus promote more effective and sustainable use. Tyre & Orlikowski (1994) provide further insight into the issue of premature routinisation of system use in organisations, following 41 implementations of new technology across diverse settings. They found the immediate period following initial implementation to be a crucial 'window of opportunity' in which adaptations to technologies were made.[64] This window of opportunity was reported to be critical in determining the long-term success of a technology, as it was characterised by a more flexible time; before users, groups, and organisations develop habitual behaviours and processes that embed the technology into their workflows. Changes beyond the shakedown period i.e. during continued use, were found to be much more rare, either comprising brief spurts of activity due to a specific disruptive event, such as changes in legislation and major incidents,[66] or minor system updates spread over longer time periods.[64] Beyond the shakedown period, changes are described to become far more disruptive and costly, as they risk destabilising established routines and procedures. Failing to

act within this window therefore can explain how ineffective system use may become entrenched, limiting the realisation of potential benefits and requiring complex, costly interventions to improve the system and its use.[63]

Normalisation process theory expands on the factors that facilitate the successful integration of systems into routine use, specifically within healthcare organisations.[67] This includes the work undertaken by stakeholders, including their collective sense-making, engagement, actions taken to embed, and reflexive monitoring of an innovations' value, that contribute to its 'normalisation' in routine practice.[67] Key contributions of this theory include its emphasis on the social and collective processes required for sustained system adoption within organisations.

Summary and integration of theories to inform clinicians' acceptance and use of CDS systems over time

The different stages discussed in these theories are presented and compared below. Table 3a relates to stages of individual users' acceptance and use of systems over time, while Table 3b relates to stages of the system lifecycle according to the integration of systems into organisations. These stages have been broadly separated into pre-adoption and post-adoption (Table 3a), and pre-implementation and post-implementation (Table 3b). It is worth noting however, that the stages presented in the two tables do not necessarily align i.e. individual users may still sit within a pre-adoption stage despite the technology sitting at a post-implementation stage, accounting for the tendency of different users within organisations to adopt technologies at different rates.[43]

Table 3a. Theories describing temporal stages of individuals' acceptance and use of innovations

Theory/framework/model	Pre-adoption			Post-adoption		
Innovation-decision (DOI)[43]	Knowledge	Persuasion	Decision	Implementation	Confirmation	
Levels of use (CBAM)[48]	Orientation	Preparation		Mechanical use, routine, refinement	Integration	
Longitudinal model of continued information systems use[52]	-			Initial use	Continued use	
Technology continuance theory[53]	-			Initial use	Short term use	Long term use

Table 3b. Theories describing temporal stages of technology implementation in organisations

Theory/framework/model	Pre-implementation			Post-implementation		
Systems development life cycle[61]	Planning	Analysis	Design	Implementation	Maintenance	
Innovation-process (DOI)[43]	Agenda-setting		Matching	Redefining/ restructuring	Clarifying	Routinising
Technochange[63]	Chartering		Project	Shakedown	Benefits capture	

DOI: diffusion of innovations, CBAM: concerns-based adoption model

Although there exist slight differences in the number of stages, and the activities and actors involved in each stage, these theories collectively emphasise that acceptance and use of technologies **evolve over time**, shaped by individual experiences and broader socio-technical dynamics. These theories highlight the role of individuals' conscious decision-making during initial use of systems, and the role of experiences and satisfaction in confirming these decisions, as well as providing insight into system rejection. Additionally, theories describe the influence of subconscious perceptions and behaviours in terms of attitudes and habits, that drive long-term acceptance and use. Beyond individual adoption, theories relating to organisational technology implementation highlight the complexity of introducing new systems within structured environments. Like individual adoption, theories highlight that actions taken during prior stages of a systems' development are likely to influence its later success. Rogers (2003) and Markus (2004) for example, both highlight that outcomes realised from a system depend on how effectively challenges are addressed during pre and initial implementation.[43,63] Similarly, the importance of early mutual adaptations between users, technologies, and organisations, and collective sense-making and reflection is highlighted in the routinisation of systems over time.[64,67] In summary, both individuals' initial use of technologies, and the initial implementation period of technologies within organisations are likely to be critically important to long-term success.

There is a need to apply these insights to CDS systems utilised in hospital settings, to understand their applicability and any unique acceptance and use challenges faced in this context. For instance, clinical end-users, such as doctors, nurses, and allied health professionals, differ significantly from typical business users in terms of their skills, education, job demands and priorities.[68] Clinicians often possess years of specialised training

and judgment in clinical professions, which can influence how they perceive and interact with clinical information technologies.[36,41] Hospitals similarly operate with complex workflows and hierarchical structures, unique collaboration between multidisciplinary teams, entrenched clinical cultures and setting specific staffing considerations such as rotations, which can disrupt continuity in system use.[69] These settings are further characterised by their high-pressure, high-stakes nature, increasing the likelihood that ineffective or poorly integrated systems are worked around.[10,70] The risks associated with implementing and using technologies in hospitals are also amplified compared to many other industries and settings.[71] For example, errors or inefficiencies in system implementation have the potential to result in severe consequences for patients.[72] In the following sections, existing research that has explored clinicians' acceptance and use of CDS systems over time is outlined, comparing literature to insights from the theories discussed.

FACTORS INFLUENCING THE ACCEPTANCE AND USE OF CDS SYSTEMS OVER TIME

While this thesis is focused on CDS integrated with clinical information systems in hospital settings, there have been limited studies conducted in this context that focus on time and thus insights from studies evaluating similar health information technologies, and/or CDS implemented in differing contexts, are also explored. While these studies still provide valuable insight, as previously described, CDS systems are largely voluntary in nature,[73] separating them from systems such as EHRs and computerised provider order entry (CPOE) systems, which are often tightly aligned to organisational workflows. These larger clinical information systems are typically essential for completing core tasks, such as ordering medications, and therefore, findings relating to these systems may not be entirely translatable to CDS.[27] Similarly, hospital settings differ significantly from general practice and other healthcare settings, for example in terms of patient acuity and familiarity, medical teams involved in care, time pressure, and funding and staffing structures. These differences in context are likely to produce differences in CDS acceptance and use between settings.

Longitudinal studies evaluating clinicians' acceptance of CDS and related systems

Several studies have identified factors influencing acceptance and use of CDS and related systems over time, including longitudinal evaluations of clinicians' perceptions of clinical information systems with embedded CDS and other health information technologies in hospital settings[41,46,74,75] and perceptions of CDS in outpatient and urgent care settings.[76,77] In one study, Baysari et al. (2018) reported factors arising immediately and in the 6 months following the implementation of a CPOE system. Inexperience with the system and reduced patient interactions resulting from system implementation were only raised by clinicians during the initial phases of implementation, whereas new errors, workarounds and patient safety benefits emerged only during later phases.[74] Cresswell et al. (2017) identified the main factor shaping sustained system use over a number of years to be the level of benefit a CPOE system afforded users.[75] In that study, benefits were reported to become increasingly apparent to users over time, and were influenced by the level of engagement of these users in the development and implementation of the system.[75] Such findings align with the concerns-based adoption model, which suggests 'impact-concerns' may be most relevant to users in later stages of use.[48] Expanding on this, Wu et al. (2023) found clinicians' perceptions of benefits from an electronic medication management system were initially influenced by their colleagues' opinions, but one year after implementation, this effect diminished and only the system's usefulness, ease of use and organisational support of the system influenced the benefits clinicians perceived.[78]

Other studies evaluating the impact of CPOE systems have found perceptions of increased job demands[79] and an increase in errors[80] to be present in the immediate period following implementation, that later resolved. A study that evaluated nurses' acceptance of an IV smart pump found nurses were more comfortable with, and had greater acceptance of, the technology at one year compared to 6 weeks following implementation.[81] Negative perceptions about the technical performance and implementation process were reported at 6 weeks post implementation, but appeared to decrease to pre-implementation levels over time. A study evaluating both pre-implementation and sustained acceptance of a robotic dispensing system similarly found that most perceptions of the system remained consistent over time.[82] In line with technochange theory, these studies describe inevitable issues with health information technology performance that occur in the immediate post-implementation

period.[63] While early issues may decrease clinicians' acceptance temporarily, these studies suggest that acceptance is likely to improve and stabilise over time.

While some of the clinical information systems described in these studies contained decision support features, systems were evaluated as a *whole*, which as previously described may not directly translate to CDS. In fact, in some studies, CDS was reported to be frequently ignored despite other elements of the system being used. In another longitudinal study spanning nearly two decades, Elbanna and Linderoth (2015) investigated how and why users chose to engage with telemedicine technology offered on a voluntary basis across general practice and hospital settings.[46] They found that users' perceptions of the technology were formed through mental models, which evolved over time based on changing perceptions about how the technology fit with their professional identity, institutional traditions, and work practices. Notably, the study highlighted the critical role of 'institutional entrepreneurs' in driving the initial adoption of the technology, particularly among users who had initially formed negative mental models. By encouraging engagement, efforts of institutional entrepreneurs enabled users to reassess their perceptions and develop more informed opinions as they gained experience with the technology over time.

Although limited studies have focused on CDS in inpatient hospital settings, some studies have evaluated CDS longitudinally in outpatient and urgent care settings. For example, in a six-year evaluation of clinicians' acceptance of CDS in an outpatient paediatric setting, perceptions were found to be more favourable among those users who were more familiar with CDS and used it more, and as the system itself matured.[76] In urgent care settings, Pope et al. (2013) evaluated the factors needed to implement and sustain the use of a CDS system over a 20 month period.[77] In alignment with normalisation process theory, their findings highlighted the importance of stakeholders developing a shared understanding of the system's value, ongoing buy-in, and the adaptation of the system to align with the unique needs of each organisation, in the sustained use of the system over time. Although employed in different settings, such findings suggest that clinicians' perceptions of CDS are informed by a collective understanding of the system as well as their individual experiences with it, which contribute to the systems' routine integration into practice over time.

Impact of exposure to CDS on clinicians' acceptance and use

Though not specifically studying time following implementation, one study evaluating clinicians' perceptions of CDS systems in hospitals found different clusters of perspectives were associated with different levels of exposure to and familiarity with CDS systems.[41] Clinicians who were less familiar with CDS systems perceived CDS to lack relevance to their work and expressed concerns about its potential to undermine professional autonomy. However, those who were more familiar with CDS and how it could complement their skills were reported to hold more favourable views.[41]

Cross sectional studies evaluating CDS acceptance and use at specific stages following implementation

Other studies have evaluated perceptions of CDS and related technologies at specific stages following implementation. For instance, Faric et al. (2023) explored early experiences associated with a machine learning-based imaging CDS system used in a hospital based radiology setting, and found that clinicians became familiar with the system in a short amount of time due to the ease of integration with existing workflows.[83] They also noted that it took time for clinicians to learn how the system could best be implemented into everyday tasks. A study that evaluated factors influencing clinicians' use of an EHR system during the shakedown phase found users with greater social networks used the system less, potentially due to being able to rely on other colleagues, rather than consulting the system, for information.[84] Other studies focusing on the initial shakedown period of EHR systems have highlighted additional challenges present during this time such as disruptions to operational processes and workflows,[85] and a lack of trust in the information provided by the system while its benefits remain unknown.[86]

There have been limited studies exploring the sustained use and maintenance of CDS, particularly in hospital settings. A study evaluating sustained use of a CDS in a GP setting reported that the only factor found to be quantitatively associated with the CDS' sustained use at 10 months post-implementation was 'general optimism' towards the CDS.[87] However, no other factors evaluated, including usefulness, ease of use or user satisfaction, predicted use. Such findings align with previously discussed theories that suggest attitudes toward systems are an important predictor of continued technology use.[53] Another study applied expectation-confirmation theory to evaluate perceptions influencing the continued use of an EHR system

6 months post-implementation using a survey.[88] It was found that both emotions and habits strongly influenced continued use of these systems. Interestingly, emotions toward the system, such as anger, fear and pleasure, produced a lasting effect on users' satisfaction with the system that influenced their continued use. In contrast, a better perceived fit between the system and user tasks, and facilitating conditions to use the system, led users to develop habits toward using it over time. There was, however, no effect of users' literacy or self-efficacy on continued use.[88] The authors highlighted that factors influencing the continued use of voluntary systems may however be distinct.

PATTERNS OF CDS SYSTEM USE OVER TIME

Longitudinal studies evaluating patterns of CDS and related system use

Existing literature has evaluated patterns in CDS use and factors influencing use over time, but only in primary care settings.[87,89-91] These studies found both overall use of CDS,[89,90] and the use of individual components within CDS,[90] declined over time. The former study reported there were more physicians over the age of 45 in the 'low use' group,[89] and in a follow up study, found those who experienced improvements in patient care as a result of using the system were more likely to use it.[92] In the latter study, only the users' level of clinical experience predicted use of the CDS.[90] In another study, CDS use was analysed over a 10-month period following implementation (corresponding to system use stabilising), with the study finding three patterns of use behaviour over time.[87] One group of users were found to consistently use the system at a low rate, while another group of users had more frequent use initially which gradually declined over time. The remaining group, classified as 'heavy users', used the system moderately initially and increased their use of the system over time. While concerns about the CDS negatively impacting efficiency and the patient-doctor relationship were apparent in the first two user groups, this concern was not reported by heavy users.[91]

A study examining different user profiles of an EHR implemented in a primary care setting, found differing use patterns and barriers and facilitators to use to arise between early-adopters, late-adopters and laggards, as defined by the diffusion of innovations theory.[43,93] More early adopters became advanced and innovative users of the technology, than did late adopters. Interestingly, the study also described the cyclical influence of perceived benefits, where the more benefits that users observed, the more they sought to expand their use of the

system to its more advanced features and consequently saw greater benefit. Laggards on the other hand, lacked sufficient information technology (IT) skills to use the technology, and the one late-adopter who abandoned the system was driven to do so because they perceived negative consequences of using the system i.e. diminished patient-doctor relationship.

Disuse and Misuse of CDS systems over time

'Disuse' and 'misuse' are distinct forms of inappropriate use of technology that have been described in studies evaluating the acceptance and use of CDS systems.[94] Disuse occurs where users underutilise systems, often resulting from negative past experiences with it. Misuse occurs when users overly trust and depend on systems, leading to errors when the system provides inaccurate recommendations or fails to alert the user to important information.[94] Both disuse and misuse of CDS systems have been reported to develop with clinicians' increased experience with and exposure to CDS systems over time. A likely explanation, consistent with the previously discussed theories of technology continuance, is that clinicians initially engage in conscious, goal-directed decision making when using CDS, carefully weighing expected outcomes. As familiarity increases, behaviour tends to shift toward more heuristic and automatic responses. This transition is consistent with dual process models of action control, where behaviours that begin as deliberative and outcome sensitive can, through repetition, become habitual, cue driven, and relatively insensitive to outcomes.[95] Two distinct disuse and misuse behaviours are commonly observed in CDS systems: alert fatigue, and over-reliance or automation bias. As discussed below, both have significant implications for clinicians' ongoing acceptance and use of CDS systems and importantly, for patient safety.

Alert fatigue

Alert fatigue is one of the most frequently identified issues relating to clinicians' acceptance and use of interruptive CDS alerts, the most common CDS system currently used in practice.[3] While alerts aim to enhance patient safety and reduce errors, clinicians are often presented with frequent, irrelevant alerts that undermine their usefulness in practice.[96] Alert fatigue arises as an unintended consequence of this, where clinicians' experience cognitive overload and become desensitised to alerts following their repeated presentation over time.[97] The result is the persistent disuse of alerts, leading clinicians to miss information that may in fact be useful or important.[98]Existing evidence has shown that alert acceptance rates decrease over time as a result of clinicians becoming desensitised to alerts,[99] with several studies exploring

the development of alert fatigue as a habitual behaviour.[100,101] Habits develop when behaviours are repeatedly performed in the presence of consistent cues that reward users or help them to avoid negative outcomes.[102] Over time, the cue itself (e.g. receiving an alert) is sufficient to trigger the behavioural response, with minimal conscious effort or deliberation. The habitual dismissal of alerts is theorised to form and persist as alerts are presented in stable contexts (e.g. when doctors are prescribing medicines) and as overriding the alert provides positive reinforcement of this behaviour (e.g. does not result in an immediate negative outcome).[100] As with all habits, the strength of this behaviour appears to increase as it is consistently reinforced, making it progressively difficult to change as time goes on.[101] Despite being one of the most widely recognised challenges in clinicians' acceptance and use of CDS, there remains a lack of knowledge on the systemic factors that influence clinicians' subjective experiences of alert fatigue, as well as how it develops and influences behavioural responses to alerts over time.[103]

Overreliance on CDS

On the other hand, several studies have found clinicians may misuse CDS by over relying on information generated by the system.[31,104,105] Overreliance on CDS stems from automation bias, which occurs where clinicians become less vigilant in their own information seeking and processing and instead rely on automated systems in place of their own clinical judgement.[106] This can result in clinicians following incorrect advice, consequently contributing to patient harm. Though the factors influencing automation bias have been evidenced in the use of CDS systems, such as medication prescribing alerts and more recently AI-based systems, overreliance is typically studied in simulated rather than real-world healthcare settings.[104,105,107,108] In one study for example, GPs were presented with hypothetical prescribing scenarios along with advice from a system.[104] Those who had less clinical experience and a higher level of trust in the system, demonstrated greater automation bias, more frequently switching their initial decision to be in line with incorrect advice presented by the CDS system.[104]

In aviation settings, where the effects of automation bias on the use of decision support systems have been studied in practice, overreliance has been linked to factors such as users' level of trust and confidence in the system, more frequent system use and greater experience.[31,106,109] In aviation however, decision support systems are often highly accurate,

increasing users' susceptibility to overreliance and differentiating decision support systems used in aviation from many CDS systems currently used in healthcare settings.[31] With the increasing introduction of AI-based CDS systems in healthcare, there is however a growing risk that overreliance will become increasingly prevalent as a result of improvements in CDS accuracy over traditional logic-based systems.[107,110-112] This growing dependence raises concerns about potential skill degradation, as users may increasingly defer to the system rather than actively engaging in independent clinical reasoning.[112] Though previous research has indicated that experience can play a role in overreliance, studies in healthcare contexts are limited to experimental settings and thus provide limited insights on the prevalence of overreliance on CDS in practice. Like alert fatigue, the tendency to over rely on CDS recommendations is likely to be strengthened by habits and attitudes towards the system that may be difficult to adjust once established.[94] Understanding the prevalence of overreliance during early and long-term acceptance and use of CDS systems is therefore necessary to determine how and when strategies to reduce overreliance on these systems should be applied.

STRATEGIES USED TO IMPROVE THE ACCEPTANCE AND USE OF CDS OVER TIME

Several strategies and implementation processes have been reported to improve clinicians' acceptance and use of CDS systems.[23,34,113] For example, Kouri et al. (2022) found studies that formally evaluated the availability and quality of patient data to be used in CDS systems, and those that identified and addressed barriers to the clinical behaviour change targeted by the CDS, significantly influenced system use.[23] In another review that synthesised studies evaluating prescribing related CDS, the availability of technical support and training was found to be associated with acceptance.[34] Other strategies that have been used to improve CDS use include multidisciplinary committees and obtaining targeted feedback to optimise CDS alerting systems in hospitals.[113-115] These strategies are likely to impact clinicians' experiences of CDS by directly targeting important barriers to use, such as the systems' usefulness and usability, and users' self-efficacy to use it. There is, however, a lack of evidence describing when and how these strategies are likely to be effective, given the factors relevant to CDS acceptance and use at different points in time are not yet known.

A systematic review by Gruber et al. (2008) utilised the extended SDLC framework to identify common risks influencing outcomes of clinical information systems at each stage of the system life cycle.[116] They found the highest density of factors influencing success or failure to be during the 'implementation' phase, where training, education and go-live support (or lack thereof), were most frequently reported.[116] More recent case studies[85] and quantitative studies[84] of EHR implementation conducted during the shakedown period corroborate this view, suggesting training beyond go-live can be important to demonstrate the advantages of the system and the necessity of ongoing collaboration between clinical and technical teams. During the maintenance phase, Gruber et al. (2008) found maintaining key resources and the continued adaptation of systems to be most frequently reported.[116]

Wiegel et al. (2020) studied the system optimisation activities occurring at various hospital sites during three time points (prior to implementation, 3-6 months and 18 months-5 years) following the implementation of CPOE with embedded CDS systems.[117] Interestingly, they found the frequency of system optimisation activities reported grew at each timeframe following implementation, with the enhancement and addition of system features (e.g. incorporating new decision support and supporting developments in work practices) being particularly prevalent during the final timeframe. As a result, new training initiatives to support the use of new functionality and those to support users as their proficiency with existing system components increased over time, were observed. The study also reported both reactive and proactive approaches to address user concerns long after implementation. Such research somewhat contrasts research on windows of opportunity previously discussed, suggesting that optimisation activities associated with technologies in healthcare settings may be distinct from other settings.[64] However, while this research provides insights on the strategies used, it does not necessarily define the optimal use of strategies to address user concerns at different stages. Understanding the common issues experienced at each stage can help to inform when and how optimisation activities may be most effective.[9]

Co-design and involvement of clinicians in the CDS system lifecycle

A common strategy that is increasingly being used to improve clinicians' acceptance and use of CDS is co-design, where clinicians are involved in the collaborative development and design of a system alongside technical staff.[118] A recent review that explored clinicians' involvement in machine learning-based CDS systems found that involvement typically

occurred during the 'component development' stage, for example advising on the relevance, performance, or features of models, but was rarely used in earlier or later stages of problem identification or implementation.[119] Studies focusing on the co-design of non-AI based CDS systems similarly mainly report involving clinicians during the system development stage. These studies utilise various approaches, for example, scenario-based design, contextual inquiry and workshops, often reporting improvements in clinicians perceptions of CDS prior to going live.[120-122] However, the few recent studies that have evaluated the impact of co-design on post-implementation use have found low utilisation rates in practice,[123] and identified issues that persisted or arose following implementation.[124] This is likely due to the difficulty in predicting the full extent of issues before a system is used in practice, and the unanticipated issues that therefore inevitably arise once that system is implemented and exposed to real clinical environments.[75,123,125]

Despite commonly being employed during the development stage of CDS systems, involving clinicians at different points of the system lifecycle is likely to important in enhancing both early and routine use. 'Design in use' approaches,[65,126] where clinicians remain involved in the design and improvement of systems beyond their implementation, could help to address these issues but are rarely explored in the implementation of CDS systems. Instead, there is typically little engagement with clinicians and subsequent changes made to CDS systems reported following their implementation.[21] The design in use approach is based on the principle that increased adaptation can improve a technologies' fit with user needs and therefore reduce the emergence of inappropriate workarounds, before user and organisational routines have solidified.[63,64] While no studies were identified to have utilised this method in the implementation of CDS, studies of other health information technology implementations have suggested that the continued involvement of clinicians in the design process can result in systems that are useful and better adapted to local needs.[126]

SUMMARY OF IDENTIFIED GAPS IN EXISTING RESEARCH AND DISCUSSION OF RESEARCH AIMS IN THE CONTEXT OF GAPS

While existing literature provides insight into how clinicians' acceptance and use of CDS systems evolve over time, most longitudinal research has focused on broader health information technology implementations, such as CPOE and EHR systems. Only two studies were identified to have specifically examined the influence of time on CDS acceptance and

use in hospital settings.[41,76] These papers revealed that greater experience and familiarity with the CDS system and increased system maturity, lead to more positive perceptions over time. However, one study was focused on clinicians' general exposure to CDS rather than stages of implementation,[41] and the other utilised surveys which provided insight on general experiences but lacked depth in the understanding of the issues faced over time.[76]

Findings from studies on related systems like EHR and CPOE implementations suggest that early technical challenges, declines in performance, social influence, disruption to clinicians' workflows and a lack of experience can influence acceptance and use during the early stages of system use.[74,78,84,85] Over time however, user acceptance appears to stabilise as users gain increased experience and familiarity with the system and increasingly recognise its benefits.[74,75,78] In line with theories of continued use of information systems, some studies have also identified attitudes and habits that influence continued use of CDS and EMR systems in general practice settings.[87,88] Studies of CDS in these settings however typically report gradual declines in use over time, with differences emerging between different user groups.[87,89-92]

While findings from broader health information technology implementations and CDS used in non-hospital settings provide useful insights, the voluntary nature of CDS and unique context of hospital settings are likely to create differences in patterns of acceptance and use. Thus, there is a need to compare these insights to the evolution of clinicians' perceptions and behaviours toward hospital-based CDS systems, and identify common challenges faced at different points in time. Additionally, although many strategies to improve clinicians' acceptance and use of CDS exist, there is limited understanding of the optimal timing for interventions and the specific challenges that should be addressed by these strategies at different stages of implementation. There is also a lack of clarity on how and when to mitigate issues relating to the misuse and disuse of CDS, such as alert fatigue and over-reliance, which are likely to develop over time. Addressing these gaps is essential to ensure that CDS systems achieve both initial and sustained use, effectively support clinical decision-making, and ultimately improve patient safety and outcomes. The key gaps identified in existing literature regarding CDS systems embedded within hospital clinical information systems are summarised in Table 4.

Table 4. Summary of gaps in existing research CDS systems in hospital settings

#	Overall gap	Specific gaps
1	Limited evidence on the relationship between clinicians' acceptance and actual use of CDS over time	• While acceptance is often assumed to predict use, no existing research has compared individuals' perceptions of CDS with their actual system use over time
2	Limited understanding of how clinicians' acceptance and use of CDS systems evolves over time and the different factors influencing acceptance and use at different points in time	• Studies largely take a cross-sectional approach to evaluate CDS acceptance and use, failing to capture how these factors change over different stages of the system lifecycle and at different stages of clinicians' use • There is a lack of knowledge around the measures and methods used to evaluate CDS acceptance and use, and how these can be applied at different points post-implementation to build a comprehensive understanding • Reviews have highlighted a lack of research beyond the initial implementation period, limiting understanding of what drives sustained use
3	Limited understanding of how misuse and disuse challenges specific to CDS unfold over time, including alert fatigue and overreliance	• Alert fatigue is widely acknowledged as a factor that develops over time as users become desensitised and develop habits toward disuse, but clinicians' subjective experience and how it develops are not well understood • Overreliance appears to be associated with experience with CDS, but its prevalence remains underexplored in real-world settings
4	Lack of clarity on the timing of strategies to improve CDS acceptance and use, and specific challenges that should be targeted at different points in time	• Strategies like co-design are commonly used pre-implementation, but little is known about their impact on CDS acceptance and use post-implementation • 'Design in use' approaches are likely to improve the fit between systems and user and organisational needs, but have not been applied to CDS implementation • Without a longitudinal approach, the most relevant strategies to support acceptance and use at different time points remain unclear

Aims

The overall aim of this program of work was to investigate the influence of time on clinicians' acceptance and use of hospital-based CDS systems, from initial

implementation of CDS to sustained use. Specifically, we aimed to identify factors that were relevant to clinicians at different points in the system lifecycle and at different stages of use, further explore time-dependent factors (e.g. alert fatigue) affecting CDS acceptance and use, and how strategies could be applied to address factors at different points in time. A summary of the aims and associated chapters are described below and presented against the stages of the system lifecycle and users' acceptance in Figure 6.

Specific aims of each chapter included:

1. To systematically review the use of co-design strategies and their impact on clinicians acceptance and use of CDS systems over time (Chapter 3a, addressing Gap 4).
2. To systematically review the methods used to evaluate clinicians' acceptance and use of CDS systems over time and identify gaps (Chapter 3b, addressing Gap 2).
3. To systematically identify factors and the prevalence of factors influencing clinicians' acceptance and use of CDS systems at different points in time following implementation (Chapter 4, addressing Gaps 2, 3 & 4).
4. To evaluate the experiences of clinicians, managers and vendors with two CDS systems used in a rural hospital for differing lengths of time (i.e. 2 weeks-6 months), and identify opportunities and challenges associated with the pilot implementation of CDS, using a design in use approach (Chapter 5, addressing Gaps 2 & 4).
5. To qualitatively explore experiences of alert fatigue in depth associated with routinely used (or disused) alerts, and consequently identify strategies that may help to reduce alert fatigue over time (Chapter 6, addressing Gaps 2, 3 & 4).
6. To compare individuals' acceptance (perceptions) and use (actual use) of CDS systems over time, and their influence on alert fatigue (Chapter 7, addressing Gaps 1 & 3).

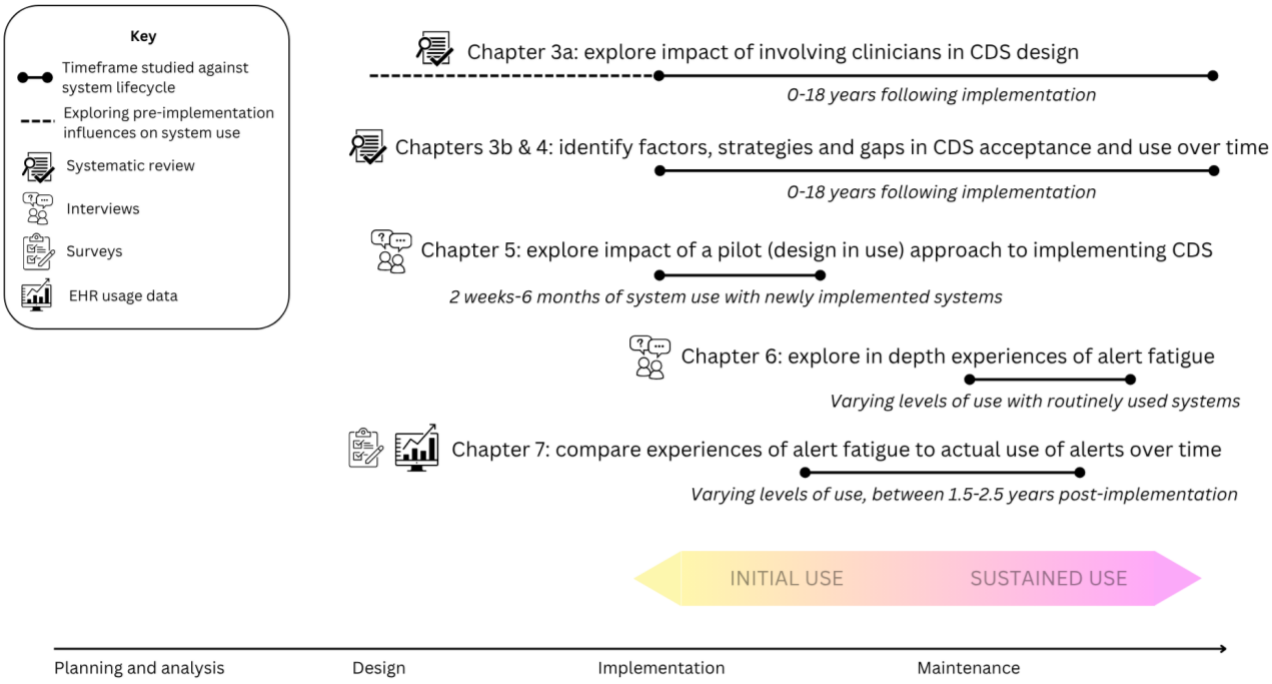

Figure 6. Schematic of thesis chapters and aims aligned to stages of the system lifecycle

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CHAPTER 2

Methods

This thesis adopts a holistic, systems-oriented approach grounded in Human Factors and Ergonomics (HFE) and supported by Implementation Science frameworks to examine clinicians' acceptance and use of clinical decision support (CDS) systems over time. While principles of, and models from, HFE were used to guide the overall approach, Implementation Science frameworks supplemented insights into CDS implementation, uptake, and spread. Mixed methods were employed across the thesis to capture both subjective experiences and objective use of CDS, using systematic reviews (Chapters 3a–4), qualitative interviews (Chapters 5–6), and combined survey and log data analysis (Chapter 7). This chapter discusses the overarching and specific disciplines, approaches, and frameworks applied in each chapter of the thesis.

HUMAN FACTORS AND ERGONOMICS

Human Factors, also known as Ergonomics (HFE), is a "*scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimise human well-being and overall system performance*".[1] HFE uses a systems approach, where the term 'system' is used holistically to refer to the interactions and interconnectedness between *people*, the *tasks* they perform, using *tools and technologies* under certain *organisational conditions* in given *environments*.[2,3] HFE strives for the design of systems that are compatible with human capabilities and needs, rather than requiring humans to adapt to poorly designed systems.[4] The goal is to make it easy for people to perform actions that lead to positive outcomes, while reducing the likelihood of behaviours that could result in harm or inefficiency.

HFE includes three major domains of study, including physical ergonomics, cognitive ergonomics, and organisational ergonomics (also known as 'macroergonomics').[1] Physical

ergonomics focuses on human anatomical, physiological, and biomechanical characteristics, while cognitive ergonomics addresses mental processes such as perception, decision-making, and attention.[5] Macroergonomics considers the broader socio-technical system, including organisational structures, policies, and culture.[6] In healthcare settings, applications of HFE sit across all three domains. For example, physical ergonomics has been applied to improve the design of healthcare facilities, while cognitive ergonomics is frequently applied to optimise the usability of health information technologies.[7-9] Macroergonomics aims to optimise broader components of the 'work system', that is, the interconnected elements that shape how work is done in a given setting, and has been applied to optimise processes and social dynamics, such as clinical workflows, supply chain processes, and team performance.[10,11] HFE in healthcare aims to improve not only worker safety, experiences and organisational outcomes, but also patient safety and the quality of care.[2,7,12]

HFE is well suited to studying the real-world use of CDS systems as it considers decision-making processes and human-computer interactions (cognitive ergonomics),[5] as well as the complexities of integrating technologies into clinical workflows and organisational contexts (macroergonomics).[6,13] HFE principles can and should be applied throughout the CDS system lifecycle, such as the initial scoping, selection and design of CDS systems to support users' capabilities and needs, through to implementation, where alignment with existing workflows is critical.[14-16] Finally, and importantly for the aims of this thesis, the application of HFE to the ongoing evaluation and maintenance of CDS systems used in routine work is critical as it can help to identify emergent and ongoing risks to safety and usability, and inform opportunities for redesign that support continuous improvement.[17] In HFE, healthcare settings are viewed as 'complex adaptive systems', accounting for the inevitable evolution of the work system, that occurs over time.[7]

Guided by the principles and philosophy of HFE, this thesis adopts a holistic systems perspective to examine how CDS systems should be designed, implemented, and iteratively refined to align with users' needs as they, and other elements of the work system, evolve over time.

INTEGRATION WITH IMPLEMENTATION SCIENCE

In addition to a HFE perspective, this thesis integrates frameworks from Implementation Science. Implementation Science is "*the scientific study of methods to promote the systematic uptake of research findings and other evidence-based practices into routine practice, and, hence, to improve the quality and effectiveness of health services and care*".[18] The field has generated numerous frameworks and strategies that can be used to understand and address issues relating to the implementation, adaptation, spread and scale up of interventions, with its scope within a particular organisation ending where interventions are evaluated and assimilated into routine practice.[19,20] In contrast, HFE focuses on the work system, approaching it as a dynamic and continually evolving entity. As such, HFE offers insights into how new interventions should be designed to fit with existing work systems and how the implementation of new interventions reshapes the work system over time. In short, while Implementation Science primarily focuses on facilitating the successful *uptake* of the intervention itself, HFE aims to understand and optimise the broader system in which the intervention is implemented, as an *ongoing*, evolving process.

In this thesis, HFE perspectives and approaches are strengthened with Implementation Science frameworks to facilitate understanding of the acceptance and use of newly implemented CDS systems, the integration of CDS systems into routine practice, and the strategies that can be applied to support these activities.

SPECIFIC METHODS AND FRAMEWORKS USED

Different methods and frameworks were used to collect and analyse data to address each specific aim of the thesis. As numerous methods, theories, models, and frameworks have been previously applied to explore the implementation of CDS systems,[21] we provide rationale for the specific methods and frameworks utilised in each chapter of the thesis below.

Systematic review

The aims of Chapters 3a, 3b and 4 were addressed through mixed-methods systematic reviews. Systematic reviews are a rigorous and transparent method for identifying, appraising, and synthesising evidence to answer predefined questions about a topic, using structured and replicable procedures.[22] By systematically gathering and analysing evidence

across multiple studies, they provide a comprehensive overview of what is known about a particular field, identify areas of consensus and disagreement, and highlight gaps in the literature.[22] Systematic reviews differ from other types of reviews in their methodological rigour. Unlike narrative or scoping reviews, which seek to describe topics of interest or assess the extent of evidence on a broad topic, systematic reviews are focused on answering specific research questions using comprehensive, pre-defined procedures.[23] Though meta-analyses can offer additional benefit, by utilising statistical methods to combine data from existing research into a single quantitative study, meta-analyses were not suitable for the aims of these chapters, given qualitative studies were included in our reviews, in addition to quantitative studies.[23]

Mixed-methods systematic reviews integrate both qualitative and quantitative findings to provide a more complete picture of the phenomenon of interest.[24] This approach is especially important when addressing multi-faceted constructs like CDS acceptance and use, which can be evaluated using both qualitative and quantitative approaches. Mixed-methods systematic reviews can follow either a convergent integrated approach, where data are transformed into a mutually compatible format and synthesised together, or a convergent segregated approach, where data are synthesised separately before integration.[24] As convergent segregated approaches are recommended only to answer combined questions on experiences (qualitative) and effectiveness (quantitative), a convergent integrative approach was selected to align with our aim of understanding experiences across qualitative and quantitative studies.[24] To integrate data sources, the 'qualitizing' of quantitative data is usually recommended, which includes converting quantitative data to textual descriptions for narrative interpretation.[24] This approach was taken in all three chapters.

Chapter 3a aimed to synthesise existing literature that used co-design approaches in the development of CDS systems and evaluated CDS acceptance and use post-implementation. Although co-design is widely recommended and frequently reported during CDS development, it is often assumed to improve user acceptance and use, without rigorous evaluation. As a result, there is limited understanding of whether and how co-design contributes to these intended outcomes in practice.[25] A mixed-methods systematic review was well suited to the aims of this chapter, as it enabled synthesis of a considerable existing body of literature that employed co-design and evaluated acceptance and use using quantitative, qualitative or mixed approaches. This enabled the identification of different co-design

approaches taken, gaps in the reporting of approaches, and commonly reported barriers, facilitators and the outcomes of co-design on early and long-term acceptance and use.

Chapter 3b aimed to identify gaps in the methods used in existing literature to evaluate CDS acceptance and use over time. Many studies have evaluated clinicians' acceptance and use of CDS systems, but there has been little effort to understand differences in the factors influencing acceptance and use over time.[26] As different methods can yield different insights, identifying the methods that are underused at particular time points can help guide the conduct of future research to enable a more nuanced understanding of CDS acceptance and use over time. The mixed-methods systematic review approach allowed for comprehensive analysis of the different quantitative, qualitative and multi-method approaches used, and the identification of gaps in methods used at different time points following CDS implementation.

Chapter 4 aimed to synthesise the factors reported to influence clinicians' acceptance and use of CDS systems in existing literature over time. Again, while many studies have evaluated and reported factors influencing clinicians' acceptance and use of CDS systems, the prevalence of these factors at different points in time was unknown. A mixed-methods systematic review was well suited to address this aim as it allowed for the integration of factors identified in existing qualitative, quantitative and mixed methods research, analysis of patterns in factors reported at the early, mid-term, and later stages post-implementation, and gaps in factors explored at different points in time. Collating factors across studies with varying types of CDS, settings, and users, enabled robust, generalisable insights and recommendations that can be applied to facilitate future CDS implementations and ongoing use.

The Consolidated Framework for Implementation Research (CFIR) was used in Chapter 4 to synthesise factors reported to influence CDS acceptance and use.[27] The CFIR is an Implementation Science framework that consolidates constructs from 19 previous theories and models, such as those for dissemination, innovation, organisational change, and implementation. The CFIR details five domains: the intervention, individuals, inner setting, outer setting, and implementation process, that drive the adaptation and integration of interventions (Figure 1). It was selected for Chapter 4 due to its breadth in capturing holistic system factors, including those relating to the CDS intervention, individual factors of those

using CDS, the contextual factors that influence use within the organisation and broader environment, as well as those relating to the process by which CDS was implemented. Given this chapter focused on the time from implementation of a CDS intervention, the inclusion of implementation process factors in addition to broader system factors was important. Thus, an implementation science framework was determined to be the most appropriate for this objective.

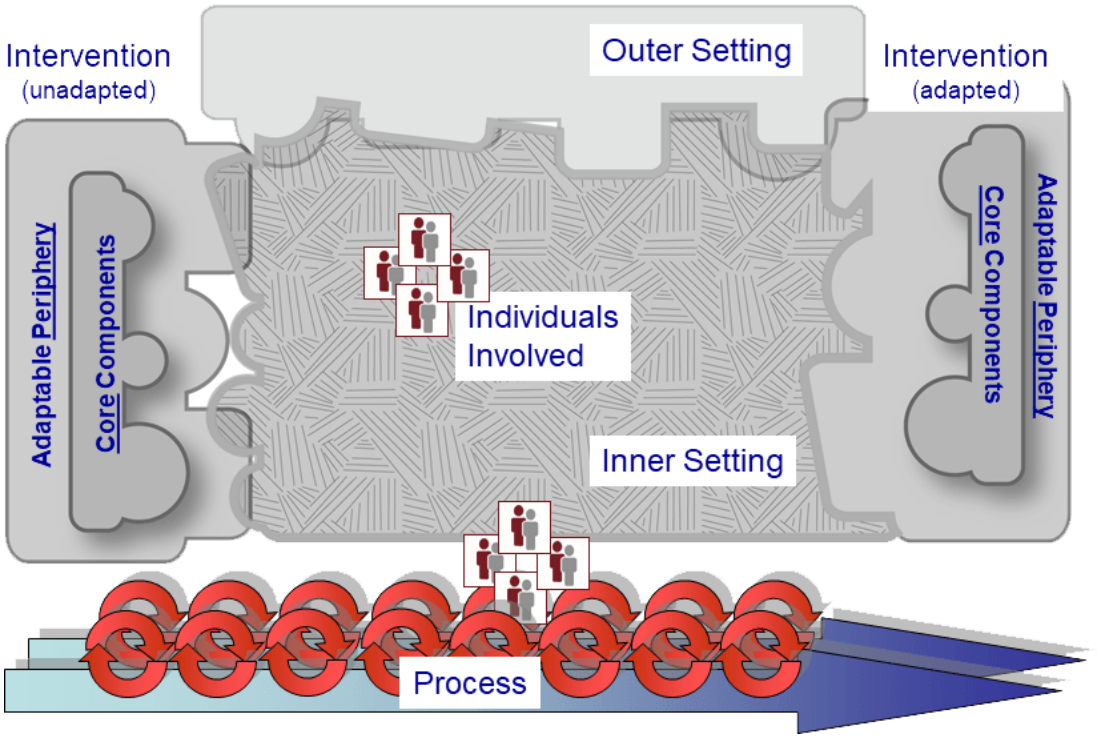


Figure 7. Consolidated Framework for Implementation Research (CFIR)[27]

Qualitative research

The aims of Chapters 5 and 6 were addressed using a qualitative approach. Qualitative research is a form of inquiry that seeks to understand how people make sense of their experiences, social contexts, and the meanings they attach to particular phenomena. Qualitative approaches are valuable for exploring complex or poorly understood issues, generating in-depth insights into participants' perspectives, and examining how meaning is shaped within social and organisational settings.[28] Interviews are a form of qualitative research used to explore participants' perspectives, experiences, and interpretations in depth.[28] Interviews can be structured, semi-structured or unstructured, with the former using an entirely pre-defined set of questions and the latter involving no pre-defined questions,

instead taking a spontaneous approach. Semi-structured interviews fall between the two extremes, using an interview guide with a set of pre-defined questions, combined with questions that are not pre-determined, and instead adapted spontaneously based on participants' responses.[29] We followed a semi-structured approach for Chapters 5 and 6, as this approach permitted flexibility and allowed for the discovery of new and unexpected information, while also ensuring a level of consistency across interviews.

Chapter 5 aimed to evaluate clinicians, managers and vendors' perceptions of two CDS systems implemented using a pilot approach, where clinicians' feedback was iteratively sought and integrated into CDS design post-implementation. While co-design is commonly undertaken during CDS development, less is known about how iterative adaptation following implementation supports clinicians' acceptance and use of CDS over time. Qualitative inquiry through semi-structured interviews provided a comprehensive and in-depth lens by which to explore the interactions between factors that led to the acceptance and use of the CDS systems, disengagement with the systems over time, and experiences with the novel pilot implementation approach.

The Non-adoption, Adoption, Scale-up, Spread, and Sustainability (NASSS) framework was used to synthesise factors in Chapter 5. The NASSS is an Implementation Science framework designed to help implementers anticipate, evaluate, and explain how and why health technologies are adopted, not adopted, sustained, and scaled.[30] It describes seven domains that influence these outcomes, including the clinical condition the technology is designed to support, technical features, its value proposition, its adopters and the organisational and wider systems in which it is implemented (Figure 2). Finally, a seventh domain, embedding and adaptation over time, describes the interactions between all elements of the system that evolve over time, requiring ongoing changes to the technology and organisational responsiveness. As this chapter focused on stakeholders' experiences with newly implemented CDS and the pilot implementation process, an implementation science framework was determined to be most compatible. In particular, the NASSS enabled understanding of experiences and processes that unfolded over time, as well as the system factors that contributed to the failure to scale up, spread and sustain the CDS, and thus was determined to be the most appropriate framework to support data collection and analysis.

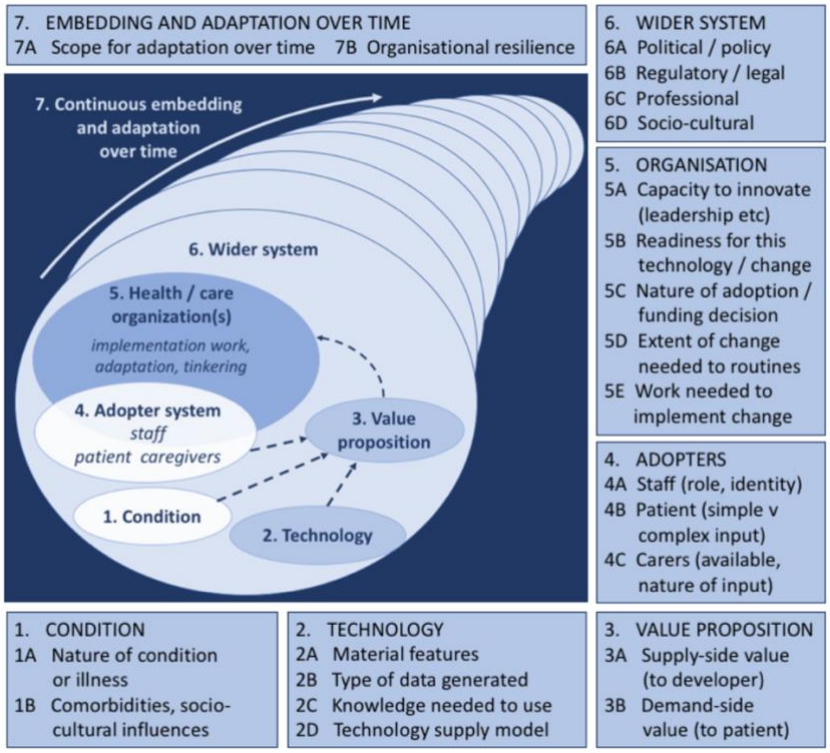


Figure 8. Non-adoption, Adoption, Scale-up, Spread, and Sustainability (NASSS) framework[30]

Chapter 6 aimed to understand junior doctors' experiences of alert fatigue and its development, in depth. Alerts are the most common form of CDS system currently used in practice, with many alerts now routinely embedded within clinical information systems in Australian hospitals.[31] Alert fatigue is defined as a mental state that arises due to clinicians' experiences with alerts that develops over time.[32] However, holistic qualitative inquiries of alert fatigue experiences and how it develops are lacking.[33] Many studies that explore factors influencing alert fatigue use quantitative approaches and focus on the interactions between users, tasks, and technologies, while other elements of the work system are largely ignored.[34] Thus, qualitative methods, using semi-structured interviews, were well suited to exploring in-depth experiences of alert fatigue and the underexplored contextual factors influencing these experiences.

The Systems Engineering Initiative for Patient Safety (SEIPS) model was used to inform data analysis in Chapter 6.[2] The SEIPS is a HFE model developed for healthcare settings to support the analysis of the work system and its impact on patient, and employee and organisational outcomes (Figure 3). The model is often used to evaluate work systems, care

and other processes, and outcomes, with the aim of identifying opportunities for work system redesign that promote safety, wellbeing and performance. The SEIPS was determined to be the most appropriate model for this study given its holistic representation of work systems, including people, tasks, tools and technologies, environment, and organisational contexts, that aligned with the aim of exploring contextual influences on alert fatigue. Additionally, as alert fatigue is often associated with negative impacts on both patient safety and clinician well-being, the SEIPS helped to identify work system elements and interactions that could contribute to these different outcomes. As this chapter focused on alerts that were well established and routinely used as part of doctors' regular work, a HFE model rather than an implementation science framework, was determined to best meet the objectives.

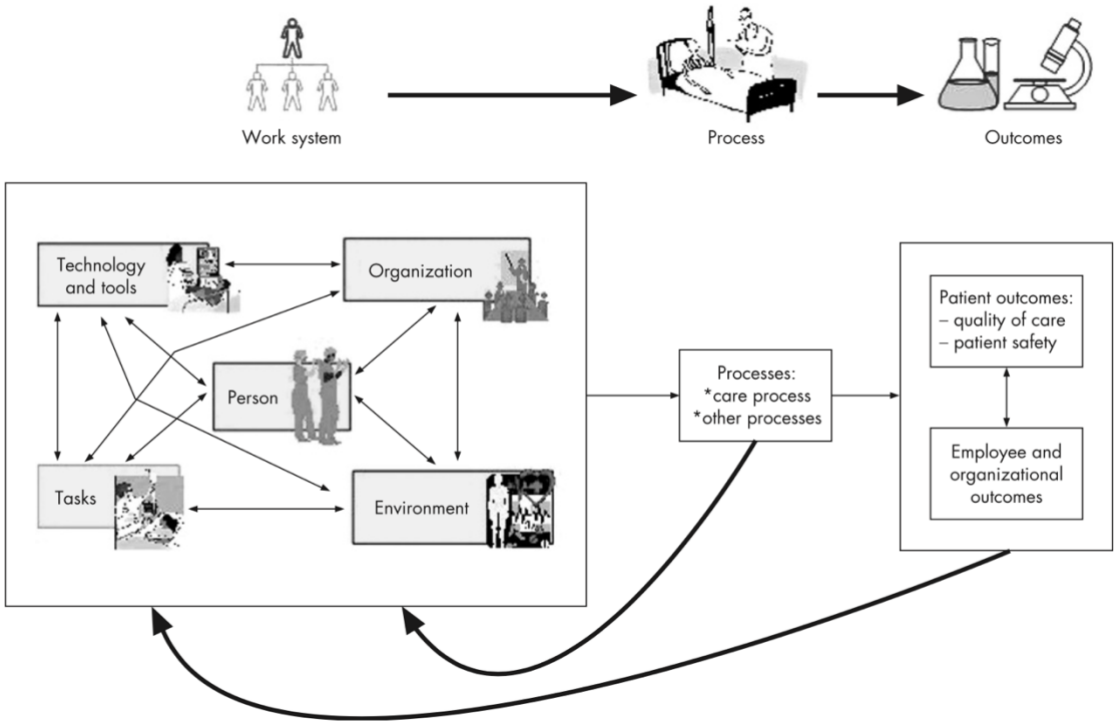


Figure 9. Systems Engineering Initiative for Patient Safety (SEIPS) model[2]

An Information Processing Model was used to further define the process of experiencing alert fatigue in Chapter 6.[35] Originating in cognitive psychology and regularly applied in HFE, information processing models outline how humans receive, interpret, and respond to information in sequential stages, namely, detection, perception, comprehension, and action selection.[35] Applying this model allowed for a more granular understanding of how clinicians attend to alerts, and interact cognitively and behaviourally with them, and where and how alert fatigue occurs within this sequence. Integrating this model alongside the SEIPS enabled

nuanced understanding of the work system factors that influenced different experiences of alert fatigue, and consequently different patient and clinician outcomes.

Mixed methods research

Mixed methods research combines qualitative and quantitative data collection and analysis within a single study or research program to gain a more comprehensive understanding of complex phenomena.[36] By integrating numerical data with narrative or thematic insights, mixed methods enable researchers to explore not only what is happening, but also how and why it is happening. Such insights are particularly valuable for examining constructs that have both objective and subjective components. In healthcare, HFE, and implementation research, mixed methods are often used to capture measurable outcomes and the contextual, experiential, or behavioural factors that influence them. Across this thesis, a mixed-methods approach was necessary to comprehensively explore clinicians' acceptance and use of CDS systems, as qualitative and quantitative methods provide complementary insights into distinct dimensions of these complex outcomes.

Mixed methods research can take different paths, including convergent mixed methods designs, explanatory sequential mixed methods designs, and exploratory sequential mixed methods designs (Figure 4). A convergent mixed methods design involves undertaking and collectively analysing and interpreting quantitative and qualitative study components together, with the aim of developing more comprehensive conclusions.[36] In an explanatory sequential mixed methods design, quantitative components of the research are undertaken prior to qualitative components, which allow for deeper investigation of quantitative findings. In contrast, an exploratory sequential mixed methods design involves undertaking qualitative components of the research prior to quantitative components, enabling the testing of qualitative findings.[36] Chapter 7 incorporates both convergent (testing of qualitative findings from Chapter 6) and exploratory sequential (mix of Likert scale and open-ended survey questions) mixed methods designs.

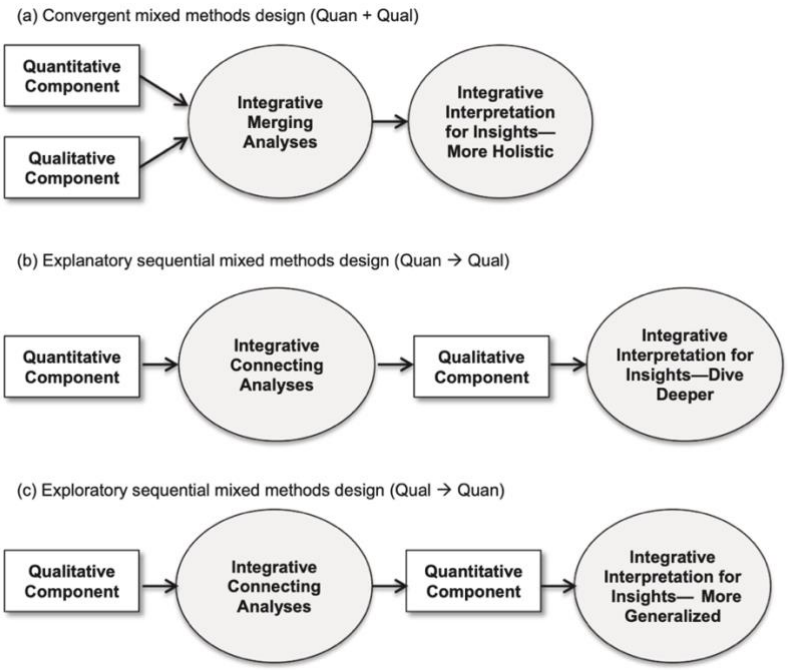


Figure 10. Three approaches to integrating qualitative and quantitative research using mixed methods[36]

System log data is a form of quantitative data, that can be analysed to provide objective, timestamped records of user interactions with digital systems, offering valuable insights into technology use patterns. This type of analysis is commonly used to understand clinicians' use of electronic health records (EHRs), including use and response patterns to alerts.[37,38]

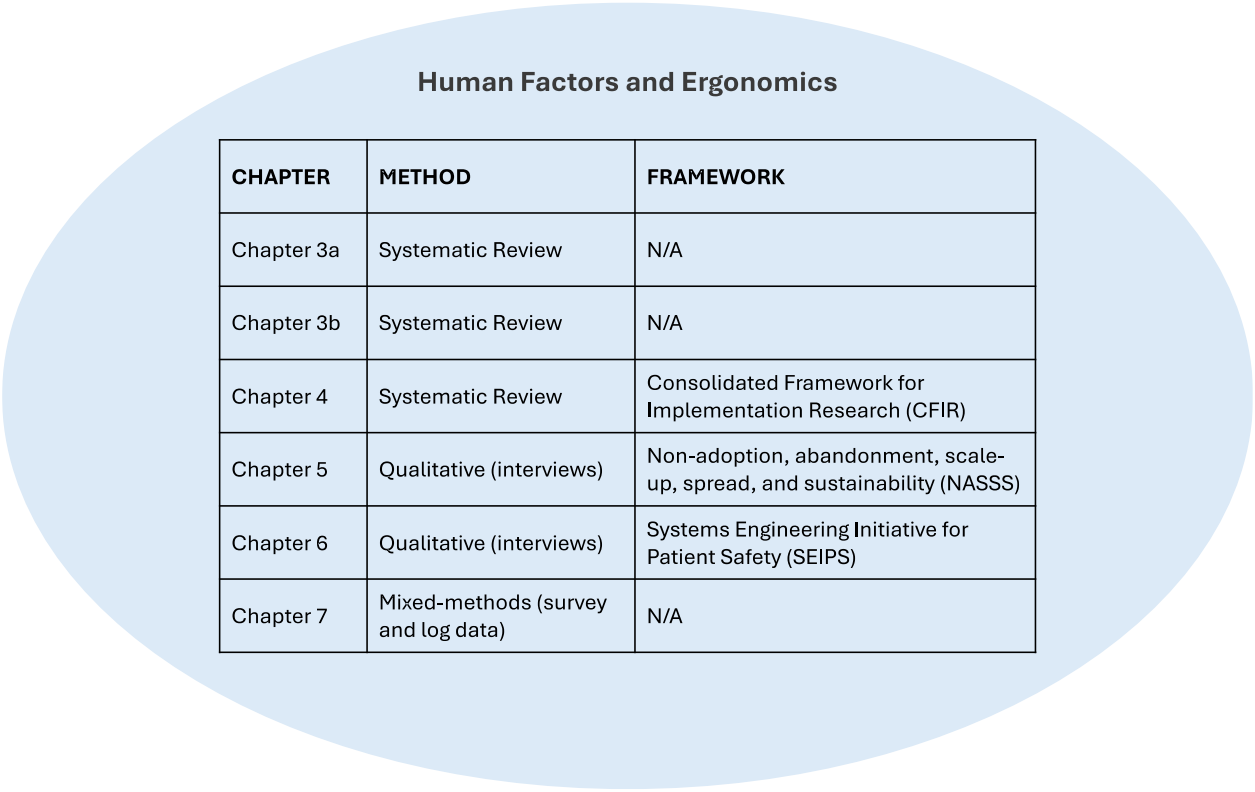
Surveys are a widely used method in health services research for capturing individuals' perceptions, attitudes, and self-reported behaviours. They can be quantitative or qualitative in nature, or a combination of both. Likert-scale (quantitative) items are valuable for quantifying subjective constructs that allow for structured comparisons across individuals or groups.[39] Open-ended (qualitative) items complement structured response formats by allowing participants to elaborate on their experiences in their own words, offering contextual depth and revealing insights that may not be captured through fixed-choice questions.[40] To complement objective quantitative measures of use, surveys can be used to explore perceptions that influence different use behaviours, support the identification of discrepancies between perceived and actual behaviours, and offer a richer, more contextualised understanding of the phenomena.

Chapter 7 aimed to compare junior doctors' experiences of alerts and alert fatigue with their actual use of alerts over time. While alert metrics are commonly used to evaluate alert fatigue, assumptions about the relationship between these metrics and clinicians' subjective experiences of alert fatigue remain untested. Building on findings resulting from the previous (qualitative) chapter, a survey and log data analysis were used to capture clinicians' perceptions of CDS and their actual use patterns, respectively. These methods were chosen as system data offered objective, granular insights into how alerts were used, while the survey enabled structured identification of clinicians' beliefs and attitudes that could be compared to use patterns. This allowed for a more complete understanding of both the cognitive and behavioural dimensions of alert fatigue, their influence on each other, and how this unfolded over time.

As Chapter 7 aimed to answer specific questions relating to perceptions of alert fatigue versus actual use of alerts, no framework was used. However, interview findings from the previous chapter that utilised the SEIPS and information processing models informed analysis. The exploratory sequential mixed methods design enabled the testing of qualitative results from the previous chapter, such as how perceptions of frequency aligned to actual exposure to alerts and experiences of alert fatigue. Similarly, using both Likert-scale items and an open-ended question within the survey (convergent mixed methods design) allowed for comparisons to be made between participants and further contextualise their responses.

SUMMARY

HFE principles and models, and Implementation Science frameworks, enabled the holistic evaluation of clinicians' acceptance and use of CDS over time (Figure 5). Systematic reviews synthesised a large and diverse evidence base on CDS acceptance and use, offering insights into co-design strategies, evaluation methods, and influencing factors, over time. Qualitative interviews provided in-depth perspectives on CDS pilot implementation and barriers to achieving sustained use, as well as alert fatigue. Finally, survey and system log data were used together to triangulate clinicians' perceived and actual experiences of alert fatigue. Collectively, these methods allowed for comprehensive insights into CDS system acceptance and use over time, supporting practical strategies to enhance future design, implementation, and evaluation.



CHAPTER	METHOD	FRAMEWORK
Chapter 3a	Systematic Review	N/A
Chapter 3b	Systematic Review	N/A
Chapter 4	Systematic Review	Consolidated Framework for Implementation Research (CFIR)
Chapter 5	Qualitative (interviews)	Non-adoption, abandonment, scale-up, spread, and sustainability (NASSS)
Chapter 6	Qualitative (interviews)	Systems Engineering Initiative for Patient Safety (SEIPS)
Chapter 7	Mixed-methods (survey and log data)	N/A

Figure 11. Summary of the methods and frameworks used in each chapter of the thesis, guided by an HFE perspective

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CHAPTER 3a

PREFACE

Chapter 1 established that while clinicians' involvement in the design and development of Clinical Decision Support (CDS) systems is widely recommended, there is limited evidence on how such involvement influences clinicians' acceptance and use of CDS post-implementation. Accordingly, existing research has primarily focused on the co-design process itself or on pre-implementation outcomes, rather than how these efforts influence early or long-term use. Given the resource-intensive nature of co-design, further clarity is needed to understand how it meets specific user needs for CDS in practice. A systematic review was therefore undertaken in Chapter 3a to identify studies that evaluated acceptance and use following implementation *and* reported involving clinicians in the design and development of CDS. This review aimed to characterise the strategies used, assess their reported influence on acceptance and use, and inform how co-design should be undertaken and reported in future.

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Does involving clinicians in decision support development facilitate system use over time? A systematic review

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ABSTRACT

Involving clinician users in the design and development of Clinical Decision Support (CDS) systems is touted to improve the fit between system and user needs. However, the impact of clinician involvement on CDS acceptance and use in practice has not been systematically studied. This review aimed to identify the approaches taken to involve clinicians in CDS development and understand the impact of these approaches on barriers and facilitators to acceptance and use in hospital settings over time. Twenty-three studies met full inclusion criteria. Clinician involvement was rarely described in depth and no comparative studies were identified. Despite frequently reporting perceived ease of use, included studies still reported barriers to acceptance and use shortly after CDS implementation and years later. Future studies should report clinician involvement in adequate detail to enable understanding of its impact on CDS acceptance and use over time. Additional recommendations for future research, including conducting comparative studies and maintaining clinician involvement beyond implementation, are described.

Keywords. Clinical decision support, user involvement, clinician involvement, system use, user acceptance

INTRODUCTION

Clinical decision support (CDS) systems aim to assist clinicians in making informed decisions by presenting them with integrated patient-specific information and clinical knowledge at the point of care.[1] CDS has been increasingly implemented in hospital settings to improve patient safety, increase adherence to guidelines and enhance efficiency however, these systems are often implemented with limited consideration of end users' needs.[2] Failure to align CDS with user needs has been demonstrated to hinder acceptance and use in practice and contribute to unintended consequences, such as alert fatigue, disrupted workflows, and new system-related errors, which can pose risks to patient safety.[3]

Involving clinician users in CDS design and development is frequently proposed as a technique that can help to improve the fit between the system and user needs.[2] Approaches to user involvement such as user-centered design, co-design, and participatory design aim to incorporate user requirements into CDS prior to implementation, in turn enhancing system usability, usefulness and fit with existing workflows.[4] The level of users' participation in each of these approaches sits on a continuum, from users being involved as 'subjects' in user-centered design, to users being active decision makers in participatory design.[4] Although user involvement in CDS development is widely reported, it is currently not known how the use of these methods impacts clinicians' acceptance and use once CDS is implemented in live hospital environments. Additionally, while sustained use of CDS is required for implementation success, user involvement is often evaluated in the near-term, with long-term effects ignored.[5] Given the time and resources required to involve clinicians in CDS development,[6] understanding its impact on early and long-term acceptance and use of CDS in practice is critical.

To address this, we conducted a systematic review of studies that involved clinicians in pre-implementation design and development of CDS and evaluated acceptance and use of CDS over time in hospital settings. By doing so, we aimed to understand the approaches taken to involve clinicians in CDS development and the impact of employing these approaches on barriers and facilitators to acceptance and use that arose over time.

METHODS

The protocol for this review is registered in PROSPERO (CRD42022325469).

Search strategy

We systematically searched Ovid MEDLINE, Embase, Web of Science, CINAHL, and PsycINFO databases to identify studies evaluating clinicians' acceptance and use of CDS. To ensure relevance to current CDS implementations, our search was limited to studies published between January 2007 to March 2022. Our search strategy used a combination of MeSH terms and text words related to CDS, acceptance, use, methods, and hospitals.

Inclusion and exclusion criteria

We included CDS targeting any health condition or patient group, implemented and being used in inpatient or outpatient hospital settings. Additionally, CDS had to be integrated with a clinical information system (CIS). Eligible studies reported clinician (e.g. doctors, nurses, pharmacists) end-users' perceptions or attitudes (acceptance), and/or self-reported or actual interactions (use) of CDS, and described involving clinicians in CDS development. Published, peer-reviewed original research and case studies that employed qualitative, quantitative or mixed-methods research were eligible for inclusion. To capture the point in time that factors relating to acceptance and use were observed, eligible studies needed to report the timeframe of data collection following CDS implementation with sufficient granularity.

Study selection, data extraction and analysis

Titles and abstracts of identified studies were screened for inclusion in Covidence by four authors (NN, AB, RF, MB), with two authors performing independent screening of each result. A sample of full texts were independently screened by review pairs and remaining texts were screened by one reviewer each (either NN, AB, RF or MB). Data were extracted by five authors (NN, AB, RF, AT, MB), with two authors performing independent screening of each result. Details extracted included study identifiers, description of CDS, description of user involvement, timeframe of data collection following implementation, and barriers and facilitators to acceptance and use. In the case where a component of a study met inclusion criteria, but another component did not, only the component meeting inclusion criteria was

extracted. Disagreements were resolved through discussion between the review pair and if required, discussion and consensus among four authors.

RESULTS

Twenty-three studies met full inclusion criteria, after excluding 2367 titles and abstracts and 573 full texts, during screening. Different forms of CDS were examined, including passive and interruptive alerts, recommendations, dashboards, and order sets, that targeted activities such as medication prescribing, prevention of adverse events and flagging of high-risk patients, across diverse clinical conditions. Studies described employing user-centered approaches to CDS development such as usability testing, cognitive task analysis and workflow observations, as well as more active methods of clinician involvement such as regular design meetings with multidisciplinary teams (Table 1). Five studies reported employing multiple approaches. Included studies were conducted between 1 month to 5+ years post CDS implementation, however most studies (16/23) were conducted at or before 12 months post implementation.

Table 5. Type and frequency of clinician involvement approaches reported in included studies, according to the timeframe that acceptance and/or use was evaluated following CDS implementation.

Clinician involvement approach used (pre-implementation)	**Number of studies**					
	0-6 months	6-12 months	12-18 months	18-24 months	2-5 years	5+ years
Clinician input (not specified)	3	2	1		2	
Multidisciplinary team	3	2	2	1		
User/usability testing	2	1	1			
User developed (not specified)			2			1
Focus groups	1					
Design walkthrough	1					
Interviews	1					
Expert group			2			
Human factors approach (not specified)		1				
Workflow analysis			1			

Clinician involvement was not reported consistently across studies, with few describing details on the depth and nature of involvement, i.e., who was involved (13/23), how often (4/23), and their role in development (6/23). Those that did, often did not describe post-implementation acceptance or use in detail. Clinicians reported to be involved in CDS development included physicians of various specialties, nurses, and pharmacists. In addition to clinicians, multidisciplinary development teams often included researchers, informaticians and engineers. Clinicians were involved in the design and development of system components, as well as the knowledge base and logic that underlay CDS.

The **impact of clinician involvement** on CDS acceptance and use was only reported in two studies. Pirnejad et al[7] reported that user involvement improved clinicians' collective sense of ownership over the system, whereas Bersani et al[8] described the need for earlier, more intensive and continuous approaches to engagement. No papers evaluated the impact of clinician involvement on acceptance or use of CDS (i.e., compared clinician involvement in CDS development to no involvement, or compared different approaches to involvement).

Perceived ease of system use was frequently cited as a **facilitator** to CDS acceptance and use (10/23), particularly among studies conducted within 12 months post implementation (8/10). Numerous **barriers** were reported across studies of differing timeframes, including challenges relating to system features and display, integration into workflow, and clinical relevance and usefulness of recommendations.

DISCUSSION

We conducted a systematic review of existing literature to understand the approaches taken to involve clinicians in the design and development of CDS, and the impact of clinician involvement on early and long-term acceptance and use. Clinician involvement was generally not described well, with included studies often failing to report the frequency of involvement and the role clinicians played in development. The former being critical to determining the depth of involvement, and the latter being necessary to understand how involvement contributed to acceptance and use.[9] Existing work has reported similar inconsistencies in the reporting of design activities in health research,[5,10] and suggested explanations such as the tendency to split reporting of projects across publications.[9] While reporting guidelines for healthcare design exist,[10] more focused guidance may be necessary where post-

implementation evaluation is the focus of a study. To understand the degree of clinician input into CDS development,[4] and therefore enable comparisons regarding its impact on CDS acceptance and use over time, we recommend that future studies include at a minimum: the approach used to involve clinicians, the type of clinicians involved, the frequency of engagement and the role that clinicians play in design or development.

Studies rarely described findings relating to the impact of clinician involvement on acceptance and use. Further work is therefore needed to understand the benefits and challenges of employing different approaches to clinician involvement on acceptance and use following implementation. This could include comparing user involvement to no user involvement or comparing the use of different approaches.

Despite involving clinicians in CDS development, barriers to system acceptance and use were still observed in studies conducted shortly after implementation and those conducted years later. This emphasises the need for continued user involvement following CDS implementation to ensure the system meets ongoing user needs as they evolve over time. Notably, both studies describing the impact of clinician involvement stressed the need to continue engagement beyond CDS development. Pirnejad et al[7] described how the presence of fast-paced cycles of iteration within the year following implementation contributed to ongoing acceptance, while Bersani et al[8] highlighted that the absence of early and ongoing engagement within the 18 months post implementation hindered acceptance. Existing literature has described strategies to involve users in ongoing CDS optimisation, such as the continued consultation of multidisciplinary teams or committees, ongoing monitoring of CDS use, and creating mechanisms for users to provide quick and easy feedback.[7,11] Thus, it is recommended that future research incorporate such strategies to mitigate barriers to use that arise over time.

CONCLUSION

Due to inconsistencies in the reporting of clinician involvement in CDS design and development, and the lack of evaluation of clinician involvement in included studies, its impact on acceptance and use could not be determined in the current review. We recommend that future research enhance reporting of clinician involvement and examine the impact of different approaches on clinicians' acceptance and use of CDS, for example through

comparative studies, over time. Given the time and resources required for clinician involvement, we need evidence that these approaches meaningfully contribute to early and long-term acceptance and use of CDS in practice.

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CHAPTER 3b

PREFACE

As discussed in Chapter 1, numerous studies have evaluated clinicians' acceptance and use of Clinical Decision Support (CDS) systems. However, most studies have taken a cross-sectional approach that do not account for how experiences and influencing factors change over time. These limitations restrict our ability to comprehensively understand how users' needs for CDS emerge and evolve from early through to sustained use. Chapter 3b therefore presents a systematic review of the methods used in existing research to evaluate clinicians' acceptance and use of CDS systems over time. The review aimed to identify methods used at different points in time post-CDS implementation and highlight gaps where further research is needed.

Published peer-reviewed manuscript

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How are clinicians' acceptance and use of clinical decision support systems evaluated over time? A systematic review

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ABSTRACT

Clinical decision support systems (CDSS) can enhance the safety and quality of patient care, but their benefits are often hampered by low acceptance and use by clinicians in practice. Existing research has explored clinicians' experiences with CDSS in a static nature, with limited consideration of how user needs may change over time. This review aimed to identify the methods used to capture clinicians' acceptance and use of CDSS in hospital settings at different time points following implementation and highlight gaps to inform future work. Seventy-six studies met inclusion criteria, with quantitative methods more frequently employed to examine acceptance and use than qualitative methods. Qualitative methods were rarely used during the early implementation phases, particularly in the first 2 months following implementation. Further work is needed to understand clinicians' experiences immediately following implementation of CDSS and how these insights can be used to support use over time.

Keywords. Clinical decision support, implementation, clinician acceptance, system use

INTRODUCTION

Clinical decision support systems (CDSS) such as alerts, dashboards and order sets, bring together best practice guidance and patient specific information to support clinical decisions at the point of care.[1] CDSS aim to enhance the quality, safety and efficiency of patient care. Despite this potential, implementations of CDSS have demonstrated mixed benefits in hospital settings, with some evidence suggesting minimal improvements in the intended process and patient outcomes.[2] Variability in clinicians' use of CDSS has been identified as a key barrier to achieving positive outcomes. Alarmingly, a recent meta-analysis found the aggregated uptake of CDSS to be just 34.2% across 55 studies, with only 65.6% of clinicians revealed to ever use a system that was implemented in practice.[3]

Clinicians' acceptance of CDSS provides important insight into factors that impede or enhance their intended and actual use of these systems, which can, in turn, inform strategies to support clinicians' needs.[4] While existing research has explored clinicians' acceptance and use of CDSS, there has been limited focus on how acceptance or use may fluctuate as users gain experience and familiarity with the system, and as it is increasingly adapted to their local context over time.[5] Examining system use in a static nature ignores prominent theories in user and implementation research that describe a dynamic process, involving multiple actors working together to incorporate and embed innovations over a prolonged period of time.[6]

As there currently exists limited guidance on how to support the initial and ongoing use of CDSS, we conducted a systematic review to identify the factors that influence clinicians' acceptance and use of CDSS in hospital settings over time. In the current paper, we report on the methods used to evaluate CDSS acceptance and use at different points in time post-implementation. We aimed to highlight emerging trends and gaps in methodologies to guide future research that considers clinician users' priorities as they change over time.

METHODS

The protocol for this review is registered in PROSPERO (CRD42022325469).

Search strategy

Ovid MEDLINE, Embase, Web of Science, CINAHL and PsycINFO were systematically searched from January 2007 to March 2022, to identify studies reporting clinician end users' acceptance and use of CDSS in hospitals following implementation. Our search was restricted to studies published within the past 15 years given the rapid advancement of CDSS implementations. Search terms included combinations of various MeSH terms and text words related to clinical decision support, acceptance, use, methods, and hospitals.

Inclusion and exclusion criteria

We broadly defined CDSS as an electronic system that aims to enhance clinical decisions with targeted clinical knowledge and patient information to support individual patient care.[1] Our population of interest included any hospital-based clinicians (e.g. doctors, nurses, pharmacists) who were end users of a CDSS, targeting any health condition or patient group. Eligible studies reported clinicians' perceptions or attitudes (acceptance), and/or actual interactions (use), of a CDSS that was in use in inpatient or outpatient hospital settings and was integrated within a clinical information system (CIS). We considered published, peer-reviewed original research and case studies that employed qualitative, quantitative or mixed-methods research. To capture the point in time that methods were employed, eligible studies needed to report the timeframe of data collection following CDSS implementation. As the early phases of implementation are often associated with fast-paced changes in perceptions, attitudes, and use, we only included studies that reported results at individual month level within the first 6 months following implementation.[7] Following this, studies reporting findings at a 6 monthly level until 2 years, between 2-5 years, or anytime post 5 years, were included.

Study selection

Titles and abstracts of identified studies were screened for inclusion in Covidence by four authors (NN, AB, RF, MB), with two authors performing independent screening of each result. Full texts of potentially relevant articles were screened against formal inclusion criteria. A sample of full texts were independently screened by review pairs and remaining texts were screened by one reviewer each (either NN, AB, RF or MB). Disagreements were

resolved through discussion between the review pair and if required, discussion and consensus among four authors.

Data extraction and analysis

Data were extracted using a structured data collection form in MS Excel. Details extracted included study identifiers, whether acceptance and/or use was measured, study methodology, and timeframe of data collection following implementation. In the case where a component of a study met inclusion criteria, but another component did not, only the component meeting inclusion criteria was extracted. Further details including CDSS type and target, level of integration with the CIS, acceptance and/or use measurement, overall outcomes and those relating to time, and factors influencing acceptance and/or use, will be extracted from included studies and reported in a separate publication.

RESULTS

Our initial search identified 5127 citations, with 2963 titles and abstracts remaining after removing duplicates. 2367 titles and abstracts, and 520 full texts did not meet full inclusion criteria, resulting in the inclusion of 76 studies in the current review. Inter-rater agreement reached >.81 Cohen's Kappa, representing 'almost perfect' agreement.[8] Of note, 72 studies that would have otherwise met inclusion criteria were excluded due to the time of data collection following CDSS implementation not being reported, and a further 65 studies were excluded as the time following implementation was not reported with sufficient granularity. In 14 of the 76 studies, multiple systems, sites, or methods were evaluated at different points in time.

A variety of methods were used to evaluate the acceptance and use of CDSS, including analysis of system data, questionnaires, interviews, observations, and focus groups (Table 1). Quantitative methods were used more frequently than qualitative. A maximum of 2 methods were used at the same point in time within a single study, with interviews and observations representing 5 out of 11 instances where this occurred. Eleven studies collected system data continuously across timeframes and included a breakdown of usage at different points in time. The data collection timeframe of these 11 studies ranged from 3 months to 3 years and

was broken down into months, weeks, or quarters. These studies were excluded from Figures 1 and 2.

Table 1. Methods used to evaluate clinicians' acceptance and use of CDSS following implementation (n=76)

System Data	Interviews	Focus groups	Observations	Questionnaire
35	19	12	7	34

The use of different methods fluctuated across timeframes (Figure 1). Questionnaires were predominately used in the first 6 months, and focus groups were seldom used beyond 12 months following implementation. The use of observations was limited across timeframes and mostly restricted to collection of quantitative data. Analysis of system data was used more consistently to assess use across all stages post-implementation. There were limited studies, particularly qualitative studies, conducted between 18-24 months post-implementation. Similarly, interviews were rarely conducted between 18 months to 5 years post-implementation.

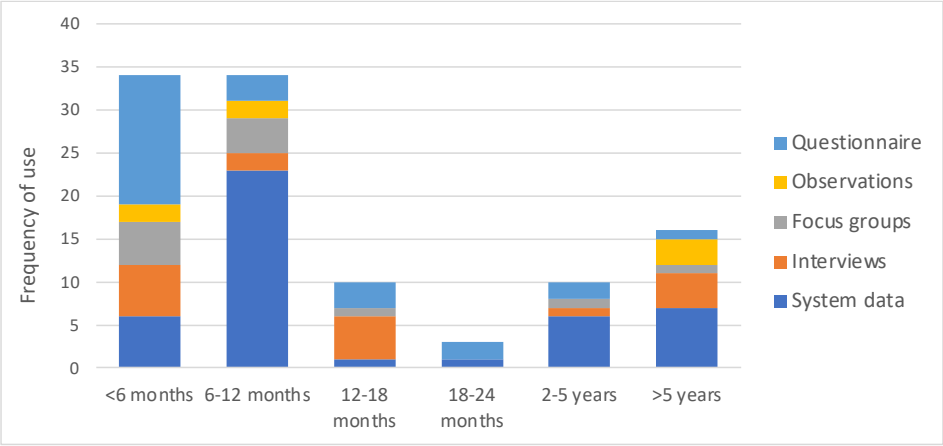

Figure 12. Frequency of methods used to evaluate clinicians' acceptance and use of CDSS over time (n=65), excluding studies that collected system data across timeframes.

While most research appeared to occur within the first 6 months following CDSS implementation, this was largely limited to quantitative methods (Figure 2). This was particularly evident within the first 2 months post-implementation, where no studies used qualitative research methods.

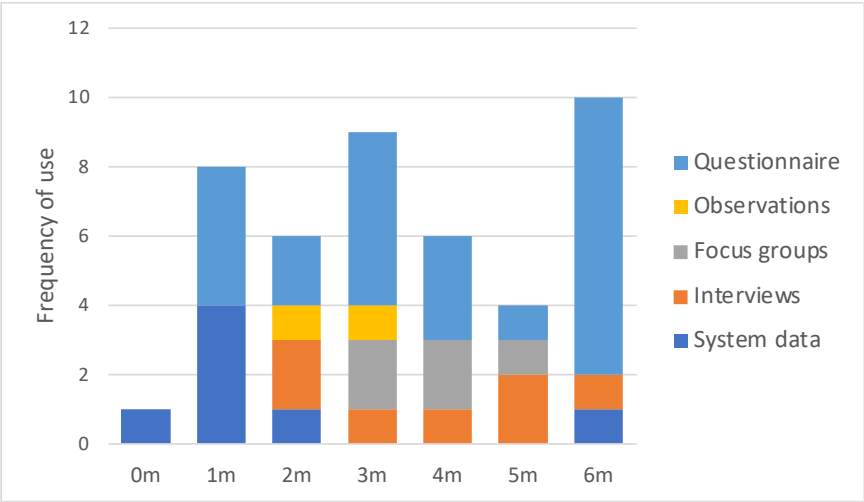

Figure 13. Frequency of methods used to evaluate clinicians' acceptance and use of CDSS across the first 6 months following implementation (n=29).

DISCUSSION

We found quantitative methods to be more frequently employed to evaluate clinicians' acceptance and use of CDSS than qualitative methods across most stages of implementation. This may be partially explained by qualitative studies being less likely to report the time of data collection relative to implementation, which resulted in papers being excluded. Previous research has illuminated the importance of considering time as a critical factor in implementation of digital health technologies, particularly in qualitative research where clinicians' perspectives and needs have been observed to change considerably throughout and beyond implementation.[7]

The lack of qualitative research was particularly notable within the first 2 months of implementation, where no studies were observed to employ qualitative methods. This finding may reflect health services' limited resources to support, or reluctance to support qualitative research during the early phases of system implementation, as well as inherent difficulties in engaging clinicians to participate in in-depth research during this time. However, this timeframe is critically important to understand how to best support users' immediate needs. Often referred to as the 'shakedown' phase, this period of implementation represents an unstable environment where fast-paced adaptations occur to address the problems that inevitably arise.[9] The shakedown phase has been associated with decreases in productivity,

increases in errors, and is touted as a ‘window of opportunity’ to address issues before the systems modification becomes more constrained.[10]

Optimised use of CDSS will require close post-implementation monitoring and evaluation to ensure clinicians’ needs are met as they arise and evolve throughout the implementation process. Our review highlights gaps during the immediate phases following implementation, where further research is needed to understand user experiences and needs relating to CDSS implementation. Additionally, researchers should recognise the importance of reporting when data is collected in relation to CDSS implementation, particularly in qualitative studies, where user perceptions and attitudes toward a system are likely to change rapidly over time.[7]

CONCLUSION

Our review illuminated gaps in current evidence on clinicians’ acceptance of CDSS immediately following implementation. Further qualitative research is needed to understand user needs during this time. Such knowledge can help guide resource allocation for CDSS implementations that anticipates clinicians’ needs as they arise and evolve, supporting their ongoing use of the system over time.

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CHAPTER 4

PREFACE

Chapter 1 outlined the complex interplay of individual, technological, and organisational factors that shape clinicians' acceptance and use of Clinical Decision Support (CDS) systems. It also highlighted that while much prior research has been conducted to identify these factors, studies typically evaluate their influence on acceptance and use as static outcomes, without accounting for how they evolve over time. To address this gap, Chapter 4 presents a systematic review that mapped factors influencing CDS acceptance and use at different points in time post-implementation, using the Consolidated Framework for Implementation Research (CFIR). Through increased transparency around when different needs are likely to arise, strategies to support clinicians can be more efficiently and effectively applied. While Chapters 3a and 3b utilised a similar methodology, they differed in focus, with the former reviewing only studies that reported involving clinicians in CDS development and the latter describing only the methods used to evaluate CDS acceptance and use over time. By consolidating fragmented evidence in existing literature, insights from this and the prior reviews provide a foundation for the subsequent chapters of this thesis, which examine clinicians' experiences with CDS systems at different time points, in depth.

Published peer-reviewed manuscript

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A systematic review of clinicians' acceptance and use of clinical decision support systems over time

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ABSTRACT

Existing reviews have identified factors influencing Clinical Decision Support (CDS) adoption by clinicians in practice but overlook the dynamic and evolving nature of technology and users' needs over time. This review aimed to identify factors that influence early, mid-term, and sustained acceptance and use of CDS in hospital settings. Five databases were searched from 2007 to January 2024 and 67 papers were included. Factors were extracted and synthesised according to the time that data were collected following CDS implementation. Factors relating to the CDS intervention, (e.g. utility), and inner setting (e.g. fit with workflows) were reported across all time periods. Perceived outcomes were more often identified in the first year of use, and individual factors after the first 6 months of use. Strategies to work around CDS limitations were reported 5 years after implementation. Our review provides guidance for developing, implementing, and supporting ongoing use of CDS systems.

Keywords: clinical decision support, acceptance, adoption, uptake, system usage, implementation, sustained use, Consolidated Framework for Implementation Research

INTRODUCTION

Clinical Decision Support (CDS) systems offer many opportunities to improve patient care in hospitals.[1] However, the impact of CDS on workflows and clinical outcomes is generally reported to be low in practice.[2-4] Clinicians' uptake of CDS, an essential step to realising these outcomes, was recently reported to be just 34.2% in a meta-analysis conducted across 60 CDS study arms.[5]

Existing reviews have identified the factors that influence CDS success in depth, providing insight into why some CDS systems are more likely to be used by clinicians than others.[6-10] Factors commonly reported include the systems' usefulness and ease of use, its fit with existing workflows, and the provision of resources to support users.[7,10] However, existing evidence syntheses have conceptualised these factors in a static, cross-sectional nature that assumes they remain equally relevant from clinicians' initial uptake of CDS through to routine, sustained use. This assumption has been challenged in several studies. For example, one study found clinicians' perceptions corresponded to their level of exposure to CDS[11] and another found different issues were relevant to clinicians at different points in time following implementation of a system containing decision support features.[12] Taken together with theories of technology adoption, such as the diffusion of innovations theory[13,14] and normalisation process theory,[15] that describe the temporal nature of embedding complex interventions into routine practice, evidence indicates that CDS use is likely to be a dynamic process where user needs unfold and change over time.

Understanding factors that influence acceptance and use of CDS across the system lifecycle would allow for the deployment of targeted, adaptive, and relevant strategies to anticipate user needs, encouraging both initial uptake and sustained use over time.[5] However, this has not yet been systematically examined. The current study aimed to address this gap by systematically reviewing the literature to identify factors that influence early, mid-term, and sustained acceptance and use of CDS in hospital settings.

METHODS

This systematic review is reported following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.[16] The protocol for this review is registered in PROSPERO (CRD42022325469). Two related reviews, each with minor

variations in study inclusion criteria, have been previously published as conference papers. These papers aimed to review the methods used to evaluate clinicians' acceptance and use of CDS over time,[17] and the use of approaches to involve clinicians in CDS design on post-implementation acceptance and use,[18] which differed from the aims of the current review.

Search strategy

Ovid MEDLINE, Embase, Web of Science, CINAHL and PsycINFO were systematically searched on 17 March 2022, with an additional search conducted on 19 January 2024, to identify studies reporting clinicians' acceptance and use of CDS following implementation in hospital settings. Our search was restricted to studies published within 15 years of the initial search date (i.e. from January 2007) to ensure studies reflected current CDS systems and organisational environments. A professional librarian was consulted in the development of the search strategy (see Supplementary Note 1). A manual search of reference lists of relevant reviews was also conducted.

Inclusion and exclusion criteria

CDS systems were defined as electronic systems that aim to enhance clinical decisions with targeted clinical knowledge and patient information to support individual patient care.[19] All types of CDS systems (e.g., alerts, dashboards) were considered in scope, however eligible CDS must have been integrated with a CIS (e.g., Electronic Medical or Health Records, and Computerised Provider Order Entry systems). Our population of interest included any hospital-based clinicians (e.g. doctors, nurses) who were end users of a CDS system, targeting any health condition or patient group. Eligible studies reported factors influencing clinicians' perceptions of (acceptance), and/or actual interactions (use) with a CDS system to support patient care in inpatient or outpatient hospital settings. Studies that evaluated CDS as part of a broader system were only included if CDS-specific results were reported. We included peer-reviewed original research and case studies that employed qualitative, quantitative or mixed-methods designs, and were available in English. To capture the point-in-time that factors emerged, eligible studies needed to report the specific timing of data collection in relation to CDS implementation.

Study selection

After removing duplicates using EndNote 20 software, [20] titles and abstracts were imported into Covidence (www.covidence.org) and independently screened for inclusion by two authors (NN and AB, RF or MB). Full texts of potentially relevant articles were screened against inclusion criteria. A sample of full texts were independently screened by review pairs (NN and AB, RF or MB), until Cohen's kappa of >.81, representing 'almost perfect' interrater reliability, was achieved.[21] Disagreements were resolved through discussion between the review pair and if required, discussion and consensus among four authors. Remaining texts were screened by one reviewer each (NN, AB, RF or MB).

Data extraction

Data were extracted independently by two authors (NN and AB, RF, AT or MB) using a structured data collection form in Microsoft Excel. The form was developed and iteratively refined following extraction of data from a sample of studies. Data extracted included study details and identifiers (e.g. authors, year), participant role, setting (e.g. department, unit), CDS description (e.g. type, AI vs. non-AI based), acceptance and/or use measurement, factors associated with clinicians' acceptance and/or use of CDS, and the time of data collection following implementation. Missing or unclear information were recorded as not reported (NR). Disagreements were resolved as described above.

Quality Assessment

The methodological quality of included studies was independently appraised by two authors (NN and AB, RF, AT or MB) using the well-established MMAT. [22] Quality was assessed only for study methods and results that met inclusion criteria (see Supplementary Note 3). Disagreements were resolved as described above. As we aimed to comprehensively identify the factors observed to influence CDS acceptance and use over time, quality assessment scores were not used as a basis for exclusion of studies but to guide the interpretation of findings.[23,24]

Data analysis and synthesis of factors over time

We used the CFIR to synthesise findings.[25] The CFIR is an implementation science framework that is widely used in healthcare settings to evaluate individual, technological and

contextual factors influencing the implementation of complex interventions. The CFIR was selected for this review because of its comprehensive structure, ensuring factors were captured via a whole of system approach. Factors were synthesised using a convergent integrative approach,[26] where a word or short phrase that captured the meaning and direction (i.e. positive, negative, no direction) of factors reported in studies was noted under one of five major domains in the CFIR framework: intervention, outer setting, inner setting, individuals, and process.

Following extraction of all data, five reviewers (NN, AB, RF, MB, AT) participated in 7 workshops totalling 11 hours to synthesise factors under CFIR constructs. This included discussion of each original factor documented in the data extraction form and in some cases, merging and/or renaming factors, before allocating to constructs. This created a framework of CFIR domains, constructs and factors that influenced CDS acceptance and use. In cases where factors did not align with any existing CFIR constructs or domains, new constructs or domains were created. All factors were classified as barriers, facilitators or moderators. Moderating factors were those that influenced the level of CDS acceptance and/or use.

The point-in-time that data were collected in each study was grouped into a time category ('timeframe') in line with inclusion criteria detailing time specificity that is described in Supplementary Note 2 and Supplementary Table 1. Graphs were created in Microsoft Excel and Tableau[27] to visualise the occurrence and proportion of overall factors, constructs, barriers, facilitators reported in different domains at each timeframe.

RESULTS

A flowchart of the search strategy, selection process and exclusions is presented in Figure 1. Out of 67 studies included in the review, 23 studies (34%) contained entirely relevant results and all results were extracted from these studies for analysis. Forty four studies (66%) contained partially relevant results, i.e. some results met inclusion criteria and were extracted for analysis, while other results were excluded from analysis. Common reasons for excluding results are detailed in Supplementary Table 2.

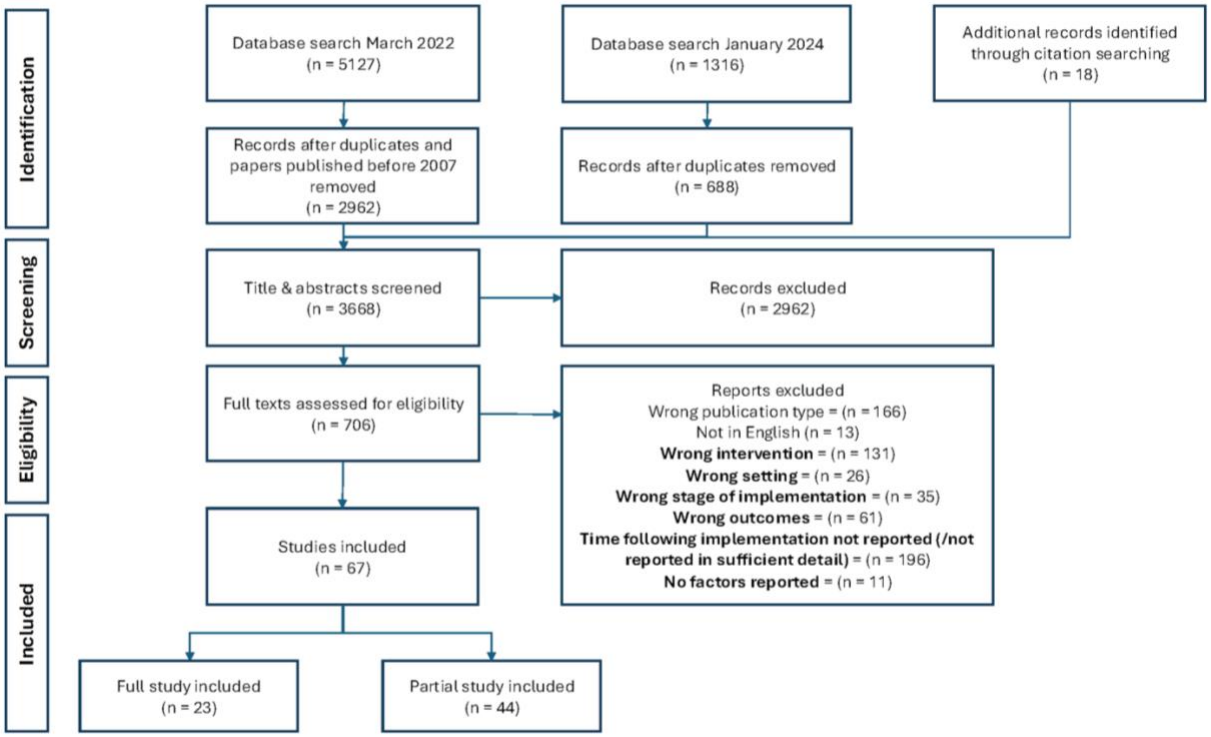

Figure 14. PRISMA flow diagram

Study characteristics and methods

Study characteristics and methods are presented in Supplementary Table 4. Over half of the studies were conducted in the United States (n=38), with remaining studies conducted across 17 other countries (Supplementary Table 4). Methods used to evaluate clinicians' acceptance and use of CDS included surveys and questionnaires (52%), interviews (33%), analysis of system data (19%), focus groups (12%) and observations (7%). Twelve studies used two or more methods at the same point in time, with interviews and observations being the most common pairing (n=5).

Interventions

CDS interventions were heterogeneous, with interruptive alerts targeting medication management being the most common form of CDS evaluated (n=14) (see Table 1). Forty-five studies evaluated knowledge-based CDS systems (i.e. guideline, rule or algorithm based), 13 studied non-knowledge (i.e. AI or ML based systems), 2 evaluated CDS with knowledge and non-knowledge-based components and 7 studies did not report CDS to this level of detail (Table 1).

Table 2. Study interventions

Timeframe	First author	Year	CDS type	Knowledge or non-knowledge based CDS	CDS target	CIS details and level of integration*
0-1 months	Castellanos[28,a]	2018	Passive recommendations	Knowledge	Appropriate procalcitonin testing for sepsis	Off the shelf, unidirectional data exchange, embedded in CIS
	Grauer[29]	2022	Interruptive alerts and indications	Knowledge	Indications for medication orders	Off the shelf, bidirectional, embedded
1-2 months	Castellanos[28,a]	2018	*(as above)*			
	Guidi[30]	2015	Interruptive alerts	Knowledge	Early warning system to detect patients at risk for sudden clinical deterioration and development of severe sepsis	Off the shelf, bidirectional, embedded in CIS
	Sauro[31,a]	2019	Order set	Knowledge	Increase use of low molecular weight heparin for VTE prophylaxis	Off the shelf, bidirectional data exchange, embedded in CIS
	Tsai[32]	2022	Dashboard	Non-knowledge	Monitoring prognostic risk across 8 different diseases	NR, unidirectional, NR
2-3 months	Castellanos[28,a]	2018	*(as above)*			
	DeBie[33]	2021	Dynamic checklist	Non-knowledge	Supporting ICU ward rounds	NR, unidirectional data exchange, NR
	Harrison[34]	2017	Passive alerts	Non-knowledge	Detection of severe sepsis	Developed, bidirectional, embedded in CIS

	Petersen[35]	2020	Report with risk stratification and recommendations	NR	Risk prediction of neonatal hyperbilirubinemia (jaundice) through bilirubin	Off the shelf, unidirectional data exchange, embedded in CIS
	Thayer[36]	2021	Dashboard	Knowledge	Flag high risk asthma patients	Off the shelf, NR (at least unidirectional), embedded in CIS
3-4 months	Berge[37]	2023	Filtered information in clinical documents	Non-knowledge (NLP)	Identifying and classifying patient allergies	NR, unidirectional data exchange, embedded
	Casey[38]	2023	Risk assessment, report and passive alerts	Non-knowledge-based risk assessment, Knowledge report and passive alerts	Prediction of acute heart failure	Off the shelf, NR, embedded
	Chadwick[39]	2017	Interruptive alerts	Knowledge	Prompt to add HIV test to an order	NR, bidirectional data exchange, embedded in CIS
	Huang[40]	2020	Risk assessment and care bundle	Knowledge	Improve nursing care quality for pressure ulcers	NR, NR (some level of data exchange), NR
	Jenssen[41]	2016	Passive alerts	Knowledge	Smoking cessation counselling and treatment for parents who smoke	Off the shelf, bidirectional data exchange, embedded in CIS
	Keim-Malpass[42,a]	2018	Risk assessment visualisation	Knowledge	Predictive monitoring and early detection of acute illness	Off the shelf, unidirectional, not embedded in CIS
	Mahabee-Gittens[43,a]	2018	Passive prompts, interruptive alerts and order set	Knowledge	Tobacco smoke exposure screening and counselling for paediatric caregivers who smoke	Off the shelf, unidirectional data exchange, embedded in CIS

	Rosenthal[44]	2019	Interruptive alerts and order set	Non-knowledge (NLP) triggered alerts and knowledge-based order set	Child physical abuse screening	Off the shelf, unidirectional data exchange, embedded in CIS
	Sauro[31,a]	2019	*(as above)*			
	Yoon[45]	2023	Imaging detection	Non-knowledge	Detection of 8 abnormal findings in chest x-rays	NR, unidirectional, embedded
4-5 months	Feldstein[46]	2023	Interruptive alerts and order set	Knowledge	Identification, evaluation and reporting of potential child abuse	Off the shelf, bidirectional data exchange, embedded
	Keim-Malpass[42,a]	2018	*(as above)*			
	Mahabee-Gittens[43,a]	2018	*(as above)*			
	Suresh[47]	2022	Interruptive alert and screening tool	Knowledge	Child abuse screening to identify child maltreatment	NR, bidirectional, embedded
5-6 months	Ginestra[48]	2019	Interruptive alerts and text message alerts	Non-knowledge	Early warning system to predict severe sepsis or septic shock	NR, unidirectional data exchange, embedded in CIS
	Holroyd-Leduc[49]	2010	Care pathway (strategies; orders; diagnostic tool) embedded in an order set	Knowledge	Delirium prevention among older hip fracture patients	NR, NR, embedded in CIS
	Rabinovich[50]	2022	Imaging detection	Non-knowledge	Detection of pneumothorax, rib fracture, pleural effusion	NR, NR, embedded

					and lung opacities in chest x-rays	
6-7 months	Bellodi[51]	2017	Interruptive alerts (hard and soft stop)	Knowledge	Reduce lab test ordering	NR, bidirectional data exchange, embedded in CIS
	English[52]	2017	Dashboard	NR	Real time surveillance of pharmaceutical therapies	NR, unidirectional data exchange, NR
	Hoekstra[53]	2010	Calculation and recommendations	Knowledge	Potassium regulation, recommendations for pump rate and next administration	NR, unidirectional data exchange, not embedded
	Jones[54]	2019	Interruptive alerts and passive recommendations	Knowledge	ED diagnosis and management of pneumonia	NR, unidirectional data exchange, embedded in CIS
	Uppot[55]	2022	Verbal checklist of targeted electronic health record data	Knowledge	Surgical safety/time-outs performed in ICU	Off the shelf, unidirectional data exchange, not embedded in CIS
7-12 months	Agostini[56]	2008	Interruptive alerts	NR	Educational review and nonpharmacologic alternative recommendation to sedative hypnotic medications for insomnia	NR, unidirectional data exchange, embedded in CIS
	Bell[57]	2019	Interruptive alerts	NR	Antibiotic review, VTE and allergies	Off the shelf, bidirectional data exchange, embedded in CIS
	Cho[58]	2013	Dashboard and data entry form with predictive risk	Non-knowledge (Bayesian Network)	Reducing pressure ulcers	Developed, bidirectional data exchange, embedded in CIS
	Groshaus[59]	2012	Order set	Knowledge	Preventing falls, functional decline and delirium among hospitalized older patients	NR, bidirectional, embedded in CIS

	Jauk[60]	2021	Risk assessment visualisation	Non-knowledge	Delirium prediction	NR, unidirectional data exchange, embedded in CIS
	Lytle[61]	2015	Interruptive alerts	Knowledge	Fall risk identification and prevention: incomplete assessment and high risk of falls/care plan alerts	Off the shelf, bidirectional data exchange, embedded in CIS
	Neame[62]	2021	Interruptive alerts	Knowledge	Medication alerts: dose range checking	Off the shelf, bidirectional data exchange, embedded in CIS
	Nydert[63]	2017	Interruptive alerts	Knowledge	Medication alerts: dose calculation and dose range checking	NR, NR, embedded in CIS
	Pirnejad[64]	2011	Order sets, calculation and recommendations	Knowledge	Chemotherapy protocols and dosing calculations	Developed, NR, embedded in CIS
	Salwei[65,b]	2021	Passive risk assessment and recommendations	Knowledge	Pulmonary embolism risk assessment and testing	NR, bidirectional data exchange, embedded in CIS
	Salwei[66,b]	2023	Passive risk assessment and recommendations	Knowledge	Pulmonary embolism risk assessment and testing	Off the shelf, bidirectional, embedded
	Stutman[67]	2007	Interruptive alerts	Knowledge	Medication alerts: drug allergy, drug-drug interactions (critical only), duplicate medication checking and pregnancy and lactation	NR, bidirectional data exchange, embedded in CIS
	Henry[68]	2022	Passive alert and risk assessment	Non-knowledge	Early warning system for timely identification and treatment of sepsis	Off the shelf, bidirectional, embedded
1-2 years	Bersani[69]	2020	Dashboard with passive alerts	Knowledge	Patient safety, across 13 patient safety domains	Developed, bidirectional data exchange, embedded in CIS

	Eden[70]	2020	Interruptive alerts	NR	Medication alerts: allergies and drug interactions	NR, bidirectional data exchange, embedded in CIS
	Frymoyer[71]	2020	Dashboard	Non-knowledge	Precision dosing for vancomycin and therapeutic drug monitoring	Off the shelf, unidirectional data exchange, embedded in CIS
	Goldstein[72]	2022	Interruptive alerts	Knowledge	Identify and refer patients with low vision	Off the shelf, bidirectional, embedded
	Hum[73]	2014	Dashboard and passive recommendations	Knowledge	Improving antibiotic prescribing through recommendations for empiric and targeted therapy	Off the shelf, bidirectional data exchange, embedded in CIS
	Salwei[74]	2022	Passive risk assessment and recommendations	Knowledge	Pulmonary embolism risk assessment and testing	Off the shelf, bidirectional, embedded
	Scheepers-Hoeks[75]	2013	Interruptive and passive alerts	Knowledge	Medication and intervention alerts: 13 clinical rules	Off the shelf, unidirectional data exchange, POC alerts embedded in CIS
	Short[76]	2021	Order with calculations	Knowledge	Increase lung protective ventilation adherence for patients with acute respiratory distress syndrome	Off the shelf, bidirectional data exchange, embedded in CIS
	Zhai[77]	2022	Templates and recommendations	Knowledge	Process-based documentation templates, diagnosis and intervention recommendations	NR, bidirectional, embedded
	Chow[78,a]	2016	Advice system and alerts	Knowledge	Antibiotic recommendations: type, dose and duration	NR, bidirectional data exchange, embedded in CIS

2-5 years	Campion[79]	2011	Calculation and recommendation	Knowledge	Intensive insulin therapy dose recommendations to maintain blood glucose control	NR, unidirectional data exchange, embedded in CIS
	Chow[80,b]	2015	Advice system and alerts	Knowledge	Antibiotic recommendations: type, dose and duration	NR, NR, embedded in CIS
	Chow[78,a,b]	2016	*(as above)*			
	Galanter[81]	2010	Interruptive alerts	Knowledge	IV to oral therapy conversion	Off the shelf, bidirectional data exchange, embedded in CIS
	Lichtner[82]	2020	Powerplan (order set), calculations and interruptive alerts	Knowledge	Chemotherapy prescription and administration, including dosing calculations	Off the shelf, NR, embedded in CIS
	Lin[83]	2010	Indications	Knowledge	Platelet transfusions	NR, NR, embedded in CIS
5+ years	Beeler[84]	2016	Interruptive alerts	Knowledge	Medication alerts: medication allergies, DDIs, duplicate drugs, renal recommendations, age-based recommendations, and formulary substitutions	Developed, bidirectional data exchange, embedded in CIS
	Campion[85]	2011	Calculation and recommendation	Knowledge	Intensive insulin therapy dose recommendations to maintain blood glucose control	NR, unidirectional data exchange, embedded in CIS
	Choi[86]	2019	Interruptive alerts	Knowledge	Renal function drug dosing	NR, bidirectional data exchange, embedded in CIS
	Choudhury[87,b]	2022	Calculation and recommendations	Non-knowledge	Blood transfusions	NR, unidirectional, embedded in CIS

	Choudhury[88,b]	2023	Calculation and recommendations	Non-knowledge	Blood transfusions	NR, unidirectional, embedded in CIS
	Luna[89]	2017	Interruptive alerts	NR	Medication alerts: DDIs	Developed, unidirectional data exchange, embedded in CIS
	Ng[90]	2023	Interruptive and passive alerts	Knowledge	Range of best practice advisory alerts	Off the shelf, bidirectional, embedded
	Pontefract[91]	2018	Order sets	NR	Medications (not further reported)	Developed, bidirectional, embedded in CIS
	Van De Sijpe[92]	2022	Passive and interruptive alerts	Knowledge	Screening and alerting module for DDIs	Developed, bidirectional data exchange, embedded in CIS
	Wong[93]	2017	Interruptive alerts	Knowledge	Medication allergy, level 2 DDI alerts, geriatric and renal alerts	Developed, bidirectional data exchange, embedded in CIS
	Wright[94]	2018	Interruptive, passive and hard-stop alerts	Knowledge	DDI alerts	Developed, bidirectional, embedded in CIS

CDS Clinical decision support, *CIS* clinical information system, *AI* artificial intelligence, *NR* not reported, *VTE* venous thromboembolism, *ICU* Intensive care unit, *HIV* human immunodeficiency virus, *NLP* natural language processing, *ED* emergency department, *IV* intravenous, *DDI* drug-drug interaction

*CIS details including commercial or developed CIS, level of data exchange between CIS and CDS, CDS embedded or not embedded within CIS

[a]studies separated for analysis of factors over time

[b]studies combined for analysis of factors over time

Quality assessment

Quality assessment scores for each study are provided in Supplementary Table 5. Using the Mixed Methods Appraisal Tool (MMAT), 32 studies met all 5 quality criteria (48%), 9 met 4 criteria (13%), 10 met 3 criteria (15%), 10 met 2 criteria (15%), 5 met only 1 criterion (7%) and 1 met no criteria (1%). All studies were retained for analysis.

Time following CDS implementation

CDS were evaluated from 0 months (i.e., immediately following CDS implementation), up to 18 years post-implementation (see Supplementary Table 4). In 5 papers, results were reported within multiple timeframes following CDS implementation due to multiple methods being used or methods being repeated at different time-points. These were included in the review as separate "study time-points". There were 3 instances where multiple papers reported findings from the same CDS implementation within the same timeframe following implementation. These 6 papers were consolidated into 3 study time-points. This resulted in 70 separate study time-points included in the review. The timeframe containing the highest number of study time-points was the first 6 months following CDS implementation (n=33, 47%).

Factors influencing acceptance and use over time

A total of 132 unique factors were identified and mapped across six Consolidated Framework for Implementation Research (CFIR) domains (Table 2). Overall, factors within the intervention and inner setting domains were the most frequently reported across studies. Thirty-three unique intervention factors (total n=247; 44% of factors) and 45 unique inner setting factors (total n=164; 29% of factors) were identified. Fewer factors were identified relating to outcomes (n=83, 15%), individuals (n=69, 12%), process (n=21, 4%), and outer setting (n=6, 1%) domains.

Table 3. Factors identified by CFIR domains and constructs

				#study timepoints per construct		
CFIR Domain	**CFIR Construct**	**CFIR Sub-construct**	**Factors**	**Barriers**	**Facilitators**	**Moderators**
Intervention	Intervention source		Ownership Locally developed	-	1	-
	Evidence strength and quality		Evidence based Credibility	3	5	-
	Relative advantage		Relative simplicity Usefulness/utility Relative preference Satisfaction Relative efficiency Alert type System performance System quality	17	36	7
	Adaptability		Ongoing adaptation Adaptation speed Personalisation	3	5	-
	Trialability			-	-	-
	Complexity		Simplicity Time and effort Ease of use Cognitive load Ease of learning	11	22	-
	Design quality and packaging		Level of information System feature Visibility of patient status Interface design Additional navigation Device Automaticity Integration Rule or algorithm design Ease of accessing/locating	31	17	-

	Cost			-	-	-
	Data quality*		Accuracy of data display Recommendation quality Accuracy of data inputs	10	7	-
Outer Setting	Patient needs and resources			-	-	-
	Cosmopolitanism		Site	-	1	4
	Peer pressure			-	-	-
	External policies and incentives		External incentives	-	1	-
Inner Setting	Structural characteristics		Transient workforce Governance	2	-	-
	Networks and communications			-	-	-
	Culture		Value to organisation Trust in leadership	-	2	-
	Implementation climate	Tension for change	Adequacy of previous work system Existing practice quality	3	1	-
		Compatibility	Level of duplication Level of manual data entry New work practices Workarounds Alert fatigue Workflow fit Level of interruption Voluntariness End user appropriateness	28	13	-
		Relative priority	Importance of problem Awareness of problem	2	4	-
		Organisational incentives and rewards	Rewards Incentives Expectations	2	-	-
		Goals and feedback		-	-	-
		Learning climate		-	-	-

	Readiness for implementation		Overall readiness Facilitating conditions	1	1	-
		Leadership engagement	Leadership use Early leadership engagement Leadership recommendation	1	3	-
		Available resources	User manual Training Instructions Combination of resources Signage Staffing Technical support	6	10	-
		Access to information and knowledge	Level of clarity around user roles Access to information	2	-	-
	Task and work context*		Patient factors Role Time pressure Clinical tasks Medication type Department/unit/ward Existing workload Time of day Shift type Time post CDS trigger Stage of patient journey	13	7	23
Individuals	Knowledge and beliefs about the intervention		Autonomy Usefulness of technology Patient care prioritised Attitude to using Intention to use Risky Trust Would recommend	4	10	-

	Self-efficacy		Understanding and skills Used with clinical judgement Confidence to use Level of reliance (over or under) Used with other sources	12	8	-
	Individual stage of change		Habitual use Ongoing use Personalised use Early impressions	2	9	-
	Individual identification with organization			-	-	-
	Other personal attributes		(More or Limited) Clinical experience Resilience Individual user differences	2	4	4
Process	Planning			-	-	-
	Engaging		Codesign User engagement Reminders Peer recommendation/support Supervisor recommendation	5	3	-
		Opinion leaders		-	-	-
		Formally appointed internal implementation leaders		-	-	-
		Champions	Champions	3	-	-
		External change agents		-	-	-
	Executing			-	-	-
	Reflecting and evaluating		Iterative approach User feedback System feedback Communication	1	4	-

Outcomes*	Innovation deliverers	Prompts consideration Staff communication and coordination Workload Clinician confidence Clinical decision making Efficiency Process complexity Awareness of issue Cognitive load Performance	4	21	-
	Innovation receivers	Patient communication Safety Patient care Patient outcomes Timeliness New errors	10	18	-
	Key decision makers	Guideline adherence Standardisation Culture Productivity Professional development Research	1	7	-

CFIR Consolidated Framework for Implementation Research.

Note: Higher-order factors mapped to the relevant CFIR domain and construct/sub-construct. The number of study time-points reporting barriers, facilitators and moderators in each construct/sub-construct of the CFIR are presented, where constructs were counted once per study time-point (see construct count calculation in Supplementary Table 3).

*****Indicates new domains and/or constructs where factors identified did not align with existing CFIR domains/constructs. [25] Constructs within the 'outcomes' domain were informed by the updated CFIR. [95]

As shown in Figure 2, factors relating to the intervention were prominent in studies conducted at all timeframes following implementation, while those within the inner setting were more often reported after 1 year. Though less frequently reported, factors relating to outcomes (a new domain, not previously in CFIR) were predominantly reported in studies conducted in the first year following CDS implementation, whereas factors relating to individuals were more often reported after 6 months post-implementation.

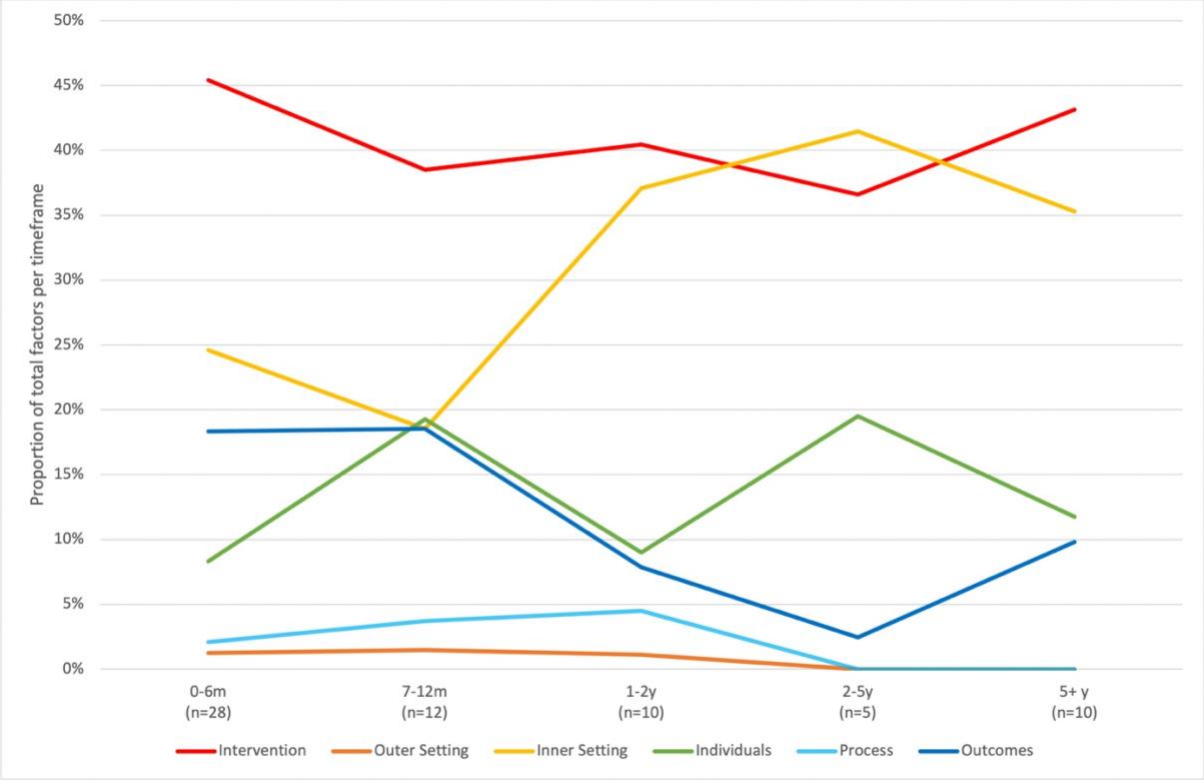

Figure 2. Factors identified in CFIR domains over time

Figure legend: *m* months, *y* years, *n* number of study time-points.
The proportion of factors identified in each CFIR domain are presented relative to the total number of factors identified within each timeframe. Barriers, facilitators, and moderators were counted once per study time-point (see factor count calculation in Supplementary Table 3) and summed across all study time-points within each timeframe.

Figure 3 shows the key constructs reported in each timeframe. Relative advantage (n=60), design quality and packaging (n=48), task and work context (a new construct, not previously in CFIR, n=43) and compatibility (n=41) contained the most barriers, facilitators and moderators reported in study timepoints across timeframes. In Table 3, examples of specific barriers and facilitators identified within these key constructs are presented over time.

Domain	Construct		Time Category				
			0-6 months	7-12 months	1-2 years	2-5 years	5+ years
Intervention	Complexity	B	14% (4)	8% (1)	30% (3)	20% (1)	10% (1)
		F	50% (14)	33% (4)	30% (3)	0% (0)	10% (1)
	Data quality	B	7% (2)	33% (4)	20% (2)	20% (1)	10% (1)
		F	18% (5)	8% (1)	0% (0)	0% (0)	10% (1)
	Design quality and packaging	B	54% (15)	50% (6)	50% (5)	40% (2)	30% (3)
		F	32% (9)	25% (3)	20% (2)	40% (2)	10% (1)
	Evidence strength and quality	B	7% (2)	0% (0)	0% (0)	20% (1)	0% (0)
		F	0% (0)	8% (1)	10% (1)	40% (2)	10% (1)
	Relative advantage	B	25% (7)	25% (3)	30% (3)	20% (1)	20% (2)
		F	75% (21)	58% (7)	60% (6)	40% (2)	0% (0)
		M	7% (2)	8% (1)	0% (0)	0% (0)	40% (4)
Inner Setting	Available resources	B	18% (5)	0% (0)	0% (0)	0% (0)	10% (1)
		F	14% (4)	8% (1)	40% (4)	0% (0)	10% (1)
	Compatibility	B	39% (11)	50% (6)	50% (5)	60% (3)	20% (2)
		F	21% (6)	25% (3)	20% (2)	0% (0)	20% (2)
	Task and work context	B	14% (4)	33% (4)	10% (1)	60% (3)	10% (1)
		F	11% (3)	17% (2)	10% (1)	20% (1)	0% (0)
		M	29% (8)	8% (1)	50% (5)	60% (3)	50% (5)
Individuals	Individual stage of change	B	0% (0)	0% (0)	20% (2)	0% (0)	0% (0)
		F	14% (4)	17% (2)	30% (3)	0% (0)	0% (0)
	Self-efficacy	B	14% (4)	42% (5)	0% (0)	60% (3)	0% (0)
		F	4% (1)	33% (4)	0% (0)	40% (2)	10% (1)
Outcomes	Deliverers	B	11% (3)	0% (0)	10% (1)	0% (0)	0% (0)
		F	39% (11)	42% (5)	20% (2)	0% (0)	10% (1)
	Receivers	B	18% (5)	25% (3)	10% (1)	0% (0)	10% (1)
		F	36% (10)	42% (5)	10% (1)	0% (0)	20% (2)
Total study timepoints in timeframe			28	12	10	5	10

Figure 3. Key constructs identified in CFIR domains over time

Figure legend: Key constructs presented in this figure were identified as barriers, facilitators or moderators in over 25% of study time-points within a given timeframe. The proportion % and number ( ) of study time-points where a construct was identified as a barrier (**B**), facilitator (**F**) or moderators (**M**) to CDS acceptance and use, relative to the total number of study timepoints identified within a given timeframe, are presented. For example, complexity appeared as a barrier in 4 study time-points conducted between 0-6 months, representing 14% of the total 28 study time-points included in this timeframe. Colour saturation was based on the proportion that constructs were reported within each timeframe (i.e. lighter = lower proportion, darker = higher proportion), with red gradients representing barriers, green representing facilitators and blue representing moderating factors. Constructs were counted once per study time-point (see construct count calculation in Supplementary Table 3) and summed across all study time-points within each timeframe.

Table 4. Barriers and facilitators identified in key constructs over time

CFIR Domain	CFIR Construct	Timeframe				
		0-6 months	7-12 months	1-2 years	2-5 years	5+ years
Intervention	Complexity	• Ease of use (-/+) • Time and effort (-/+) • **Ease of learning (+)**	• Time and effort (-/+) • Ease of use (+)	• Ease of use (+/-) • Time and effort (-) • **Cognitive overload (-)**		
	Data Quality	• Recommendation quality (-/+)	• Recommendation quality (-/+) • **Data inputs not trusted** (-)	• Recommendation quality (-)		
	Design Quality and Packaging	• Integration of CDS with other systems e.g. EHR (-/+) • Interface design quality (-/+) • Too much/too little information (-) • Valuable system features (+) • **Limited visibility and transparency (-)** • Design of CDS rules or algorithms (-/+)	• Valuable system features/additional features needed (-/+) • Integration of CDS with other systems (-/+) • Too much information (-)	• Integration of CDS with other systems (+) • **Automaticity of CDS (limited use of passive alerts, negative perceptions of interruptive alerts) (-)**		• Additional needs for system features, rules/algorithms, and interface design identified (-)
	Relative Advantage	• Usefulness and utility (-/+) • System performance (-/+)	• Usefulness and utility (-/+)	• Usefulness and utility (-/+)	• Usefulness and utility (+)	

		• Preferences for alternate systems (barriers where CDS competed with homegrown CDS and CDS available online; facilitators where CDS was previously paper based) (-/+) • Efficiency over previous system (+) • **Satisfied (+)**	• Preferences for alternate systems (-/+) • System performance (-/+)	• Efficiency over previous system (+) • Poor system performance (-)		
	Evidence strength and quality				• **Evidence-based and credible (+)**	
Inner Setting	Available Resources	• Training (-/+) • **Information available (e.g. user manuals, instructions) (-)**		• Training (+)		
	Compatibility	• Workflow fit (-/+) • **Interrupts workflow (-)** • Alert fatigue (-/+)	• Workflow fit (-/+) • Duplication/**less duplication of work** (-/+)	• Workflow fit (-/+)	• Duplication of work (-)	• **Workarounds (-/+)** • Alert fatigue and reductions in alert fatigue following modifications (-/+)

	Task and Work Context	• Time pressure and existing workload (-) • Useful or not useful for specific clinical tasks or patients (-/+)	• Time pressure and existing workload (-) • Useful or not useful for specific clinical tasks (-/+)		• Useful or not useful for specific clinical tasks or patients (e.g. complex patients) (-)	
Individuals	Individual stage of change			• **Early impressions of CDS (-)**		
	Self-Efficacy	• Lack of understanding and skills to use CDS (-)	• Lack of vs **sufficient understanding and skills to use CDS** (-/+) • **Potential for over reliance (-)** • CDS used alongside clinical judgement (-/+)		• CDS used alongside clinical judgement and prior experience (-/+)	
Outcomes	Innovation Deliverers	• Improved staff communication and collaboration (+) • **Improved/impaired clinical decision making (-/+)** • Prompted consideration (+) • **Enhanced confidence (+)**	• **Reduced/did not reduce workload (-/+)** • Prompted consideration (+) • Improved staff communication and collaboration (+) • Increased efficiency (+)			

		• Increased/**reduced efficiency** (-/+)				
	Innovation Receivers	• Improved/**did not change patient care** (-/+) • Improved/reduced patient safety (-/+) • **Increased patient communication (+)** • **Improved/did not change patient outcomes (-/+)** • **More timely care (+)**	• Improved (e.g. reduced errors) /reduced patient safety (incl. **new system-related errors**) (-/+) • **Delays in care (-)** • Improved patient care (+)			

CFIR Consolidated Framework for Implementation Research*, EHR* Electronic Health Record, *CDS* Clinical Decision Support

Note: Key constructs presented in this table were identified as barriers or facilitators in over 25% of study time-points within a given timeframe. Factors reported were identified in 2 or more studies within each timeframe where (+) indicates a facilitator to acceptance and use i.e. positive direction, and (-) indicates a barrier to acceptance and use i.e. negative direction. Factors in **bold** were uniquely reported within a particular timeframe.

0-6 months following CDS implementation

Twenty-eight studies were conducted in the first 6 months following CDS implementation.[28-55] Four of these studies[28,31,42,43] evaluated acceptance and/or use at multiple months post-implementation, yielding 33 study time-points within this timeframe (see Table 1). Factors identified (n=245) most often related to the intervention, followed by the inner setting, outcomes, individuals, process and outer setting, as shown in Figure 2. Supplementary Figures 1A and 1B show the proportion of barriers and facilitators identified in each domain over monthly intervals. Both barriers and facilitators in the intervention domain remained most frequently reported at most monthly intervals, though those relating to outcomes trended upward across this timeframe.

The proportion of barriers and facilitators identified in each domain across all timeframes are presented in Figures 4A and 4B. In the first 6 months post-implementation, barriers (n=80) within the intervention and inner setting domains were more frequent relative to other domains (Supplementary Figure 1A). In contrast, facilitators (n=146) within the intervention and outcomes domains were more often identified (Supplementary Figure 1B). Examples of common barriers and facilitators identified during the first 6 months following CDS implementation are presented in Supplementary Table 6.

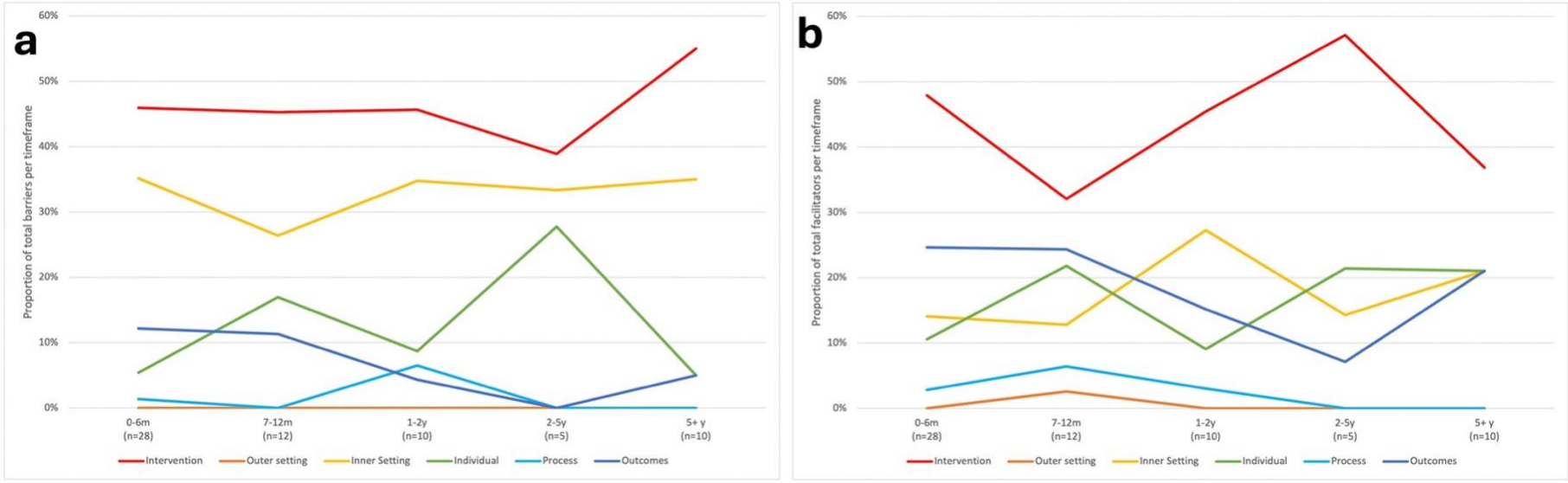

Figure 4. Barriers and facilitators identified in CFIR domains over time

Figure legend: *m* months, *y* years, *n* number of study time-points.

A) The proportion of **barriers** identified in each CFIR domain are presented relative to the total number of barriers identified within each timeframe. Barriers were counted once per study time-point (see factor count calculation in Supplementary Table 3) and summed across all study timepoints within each timeframe.

B) The proportion of **facilitators** identified in each CFIR domain are presented relative to the total number of facilitators identified within each timeframe. Facilitators were counted once per study time-point (see factor count calculation in Supplementary Table 3) and summed across all study timepoints within each timeframe.

7-12 months following CDS implementation

Thirteen studies, evaluating 12 unique systems, were conducted between 7-12 months following implementation, resulting in 12 study time-points (see Table 1).[56-68] Factors (n=137) relating to the intervention remained most prevalent, despite decreasing from the previous timeframe. Those relating to individuals increased, whereas those in the inner setting domain decreased and those in outcomes, process and outer setting domains remained relatively stable (Figure 2).

Barriers (n=55) were most frequently identified within intervention and inner setting domains, though those relating to individuals and outcomes were also prevalent in studies conducted during this time (Figure 4A). Despite decreasing in incidence from 0-6 months post-implementation, facilitators (n=78) in the intervention domain remained the most reported (Figure 4B). Facilitators relating to outcomes and individuals were also frequently reported.

1-2 years following CDS implementation

Ten studies were conducted between 1-2 years following CDS implementation.[69-78] Factors (identified n=90) remained most frequent in the intervention domain, closely followed by the inner setting, increasing from the previous timeframe. Those reported in individuals and outcomes domains decreased, whereas those in process and outer setting domains remained low (Figure 2).

Barriers (n=46) within the intervention and inner setting domains remained the most frequently identified during this timeframe, followed by those in the individuals domain (Figure 4A). Facilitators (n=33) identified in the intervention and inner setting domains were most prevalent, both increasing in incidence from the previous timeframe, while those relating to outcomes and individuals decreased (Figure 4B).

2-5 years following CDS implementation

Six studies were conducted between 2-5 years following CDS implementation, with 5 study time-points identified (see Table 1).[78-84] One study[78] reported factors between 1-2 years, and between 2-5 years. Factors (n=41) within the inner setting domain slightly increased, followed by those within the intervention domain which slightly decreased (Figure 2). Within

the individuals domain, the incidence of factors increased, whereas those within the outcomes domain decreased. There were no factors identified within process or outer setting domains.

Barriers (n=18) were most frequently identified within the intervention domain and inner setting despite decreasing from the previous timeframe, while the incidence of barriers in the individuals domain tripled (Figure 4A). Facilitators (n=14) within the intervention and individuals domains were most frequently identified, both increasing in incidence during this timeframe (Figure 4B). Those relating to the inner setting and outcomes domains however, decreased.

Over 5 years following CDS implementation

Eleven studies were conducted 5 or more years following CDS implementation, with 10 study time-points identified (see Table 1).[84-94] Factors (n=51) relating to the intervention were most frequently reported, rising from the previous timeframe (Figure 2). This was followed by factors relating to the inner setting, and individuals, which decreased from the previous timeframe, and those relating to outcomes, which increased. Consistent with the previous timeframe, no factors relating to the process or outer setting were identified.

Barriers (n=20) within the intervention domain were most frequently identified during this timeframe, followed by those related to the inner setting. Those relating to individuals and outcomes domains were low (Figure 4A). Facilitators (n=19) were most frequently identified in the intervention domain, decreasing from the previous timeframe. This was followed by the inner setting and individuals, remaining relatively stable compared to the previous timeframe, and outcomes, which increased (Figure 4B).

Moderating factors influencing CDS acceptance and use

Moderating factors (n=55) were more often identified in studies conducted over a year following CDS implementation (between 50-60% of studies conducted during this time) (Figure 3). Moderators were primarily identified in the 'task and work context', including the clinical user role e.g. nurses typically held more favourable views than doctors[30,48] and junior doctors typically held more favourable views than senior doctors.[80] The department, unit or ward, the patient/population and type of shift where CDS was used e.g. whether clinicians were on call, also influenced acceptance and use (Table 2).

DISCUSSION

We conducted a systematic review of studies that reported factors influencing clinicians' acceptance and use of CDS systems following their implementation in hospital settings. Our findings align with previous reviews of studies evaluating clinicians' experiences of CDS, which highlight technological and organisational factors, such as usefulness, usability and fit with workflows, as key issues.[6-10] To our knowledge, this is the first review to collate and synthesise factors according to the point in time they were reported post-implementation. In doing so, we expand on previous work by identifying important themes relating to clinicians' acceptance and use of CDS over time. We discuss these themes in the context of existing research and outline their implications for design, implementation, and evaluation of CDS systems, and reporting of future research.

Firstly, our synthesis suggests that certain barriers can arise early post-implementation and may continue to be experienced if not actively addressed at an early stage.[96] We found barriers relating to the system and inner setting, including poor design quality and packaging, relative advantage, and compatibility between the CDS and existing workflows, were frequently reported across all timeframes (Figures 3 and 4A). Specific barriers within these constructs, such as poor integration and interoperability between CDS and the EMR, fit with workflows, and system performance, were reported in studies conducted early after implementation and up to 2 years post (Table 3). Identifying and addressing these barriers soon after they emerge may improve the likelihood of uptake and sustained use.

Some barriers may be experienced more prominently in the immediate period following CDS implementation and resolve as clinicians become increasingly familiar with the system, as the system is adapted to meet local needs, and as clinicians develop strategies to overcome system limitations over time.[97] We found issues in the intervention, inner setting, and outcomes domains, such as limited transparency of CDS, a lack of resources to support CDS use, and reduced efficiency, to be primary concerns in the first 6 months post-implementation (Table 3). However, in the following timeframe (7-12 months), there was an increase in facilitators, and decrease in barriers, relating to clinicians' skills to use CDS appropriately. Additionally, workarounds to overcome system limitations were rarely identified until later phases of use. These findings align with existing research evaluating computerised provider

order entry (CPOE) systems, where clinicians' inexperience and unfamiliarity contributed to an increase in barriers and errors reported in the immediate post-implementation period.[12,98] Our review, like other studies,[12,99] suggests users develop ways to work around system limitations over time. Though workarounds can be positive, allowing for users to overcome design and workflow inefficiencies, they may also increase the risk of errors occurring.[99] Thus, enhancing CDS design early may minimise workarounds,[100] and providing clinicians with enhanced support, such as ongoing training and information sessions, may be helpful to overcome challenges associated with a lack of familiarity during the early phases of use.[68]

Our review also suggests that clinicians' ability to recognise certain barriers and outcomes increases over time as they become more experienced with CDS. We found concerns about the accuracy of data inputs driving CDS recommendations to be rarely identified until 7-12 months post-implementation, coinciding with an increase in users' understanding of the system. For example, in Lichtner et al[82], clinicians became more 'watchful' of automated behaviour with increased use. Similarly, the prevalence of outcomes identified in our review increased over the first 6 months following implementation (Supplementary Figures 1A and 1B) and up to 1-year post-implementation (Figures 2 and 3). We found some negative outcomes, including delays in care and new system-related errors to be reported only in studies conducted between 7-12 months after implementation. These findings echo existing research evaluating CPOE systems over time.[12,97]

Additionally, changes to the work system and associated context may impact issues experienced over time. In Salwei et al[65] and Campion et al[85], changes made to related clinical information systems (CIS) resulted in the disruption of CDS workflows at 1 year, and over 5 years, following CDS implementation. Building on recommendations from previous reviews, these findings exemplify the importance of engaging clinicians not only during CDS development, but on an ongoing basis to identify and address both expected and unanticipated issues that may arise over time.[6] Furthermore, engaging users prior to changing existing, or deploying new, CIS systems may help to uncover potential workflow impacts to systems already in use. Despite this, no factors related to the implementation process were identified beyond 2 years post-implementation, indicating that strategies such as user feedback and system monitoring to address persistent or late-emerging barriers are rarely utilised long-term.

Staffing changes, such as the rotation of clinicians, and new users of CDS are inevitable and likely to impact how CDS is accepted and used over time.[13] However, only one study reported the impact of the organisations' transitory workforce[65] and no studies investigated how new users adopted existing CDS. The lack of factors relating to available resources identified in later timeframes suggests limited training and education opportunities to support later adopters. Similarly, there were very few studies that reported factors relating to the outer setting environment, with none discussing regulatory or clinical guideline changes that could affect CDS acceptance and use over time. Such topics warrant future research.

Results showed that outcomes may become less visible to clinicians over a prolonged period of time. Interestingly, both positive and negative outcomes were rarely identified in papers beyond 1-year post-implementation (Figure 2). Such findings could reflect the process of 'normalisation', in which a system becomes increasingly integrated into routine practice and consequently 'disappears from view'.[15] Changes to the CDS system however, may spark new benefits realisation. A slight peak in the prevalence of positive outcomes reported in studies conducted beyond 5 years after implementation coincided with intervention factors commonly reported during this time, such as ongoing design needs and modifications (Figure 4B and Table 3). Our findings suggest that those looking to evaluate perceived benefits of CDS systems, should do so within the first year following implementation, before CDS becomes normalised. Future studies should also explicitly explore how perceived outcomes of CDS change over time and whether and how perceived CDS outcomes are sustained, given the lack of outcomes identified in later phases of use may reflect a lack of long-term benefits evaluation in existing studies.

Lastly, clinicians appeared to be able to better understand advantages and limitations of CDS with increased use. Factors relating to clinicians' self-efficacy to use CDS increased over time, with studies conducted between 2-5 years post-implementation often reporting that clinicians combined their clinical judgement, intuition and experience with CDS recommendations, and rejected recommendations where CDS did not align (Figure 3 and Table 3).[79,80,82] This finding is particularly interesting, given increasing concerns of automation bias leading to over-reliance on CDS.[101] While a few studies reported that clinicians were concerned about the 'potential' for over-reliance on CDS,[33,63,68] findings from the review support the theory that clinicians can more accurately consider limitations with increased use of and familiarity with the system over time.[101]

Almost half the studies included in this review were conducted during the first 6 months following implementation (28/67) and fewer factors were identified in studies conducted in later timeframes, particularly >2 years post-implementation (92/556 factors). This indicates a need for further research to comprehensively explore the factors driving sustainable use of CDS systems. Furthermore, there were limited studies that evaluated acceptance and use of CDS at different points in time within a single study. Studies that reported findings at multiple points in time, did so as a consequence of employing multiple methods of evaluation, rather than purposefully exploring changes over time. Though a few studies identified in our search explored clinicians' acceptance of CDS over time, these studies did not provide the point-in-time that CDS systems were evaluated[11] or reported findings on a broader CIS implementation (i.e. did not report findings related specifically to CDS systems),[12,97,102] and thus were excluded from this review.

Though the CFIR provided a useful lens to systematically consider factors related to CDS acceptance and use, we identified additional factors that did not fit within the existing framework. These included the quality of data inputs and outputs of the CDS system in the *intervention* domain, the task and work context in the *inner setting* domain, and perceived outcomes, which should be considered when evaluating acceptance and use of CDS systems. Importantly, while our review suggests that factors influencing clinicians' acceptance and use CDS systems can change over time, 196 papers that would have otherwise been included did not report the time following implementation that evaluation was completed and were excluded from the review. We therefore urge future studies examining acceptance and use of CDS and other digital health interventions to report the time of data collection in relation to implementation. We also recommend that research reporting guidelines be updated to make reporting of time between implementation and evaluation of interventions a requirement.

A key limitation of this review was the between-studies design and heterogeneity of included studies. Thus, factors identified within timeframes may have been influenced by differences in CDS systems, users, settings, methods used, and specific focus of studies conducted at each point in time. Further research employing longitudinal, within studies designs are required to confirm and expand upon the findings laid out in this review. Additionally, as the majority of included studies were conducted in the US and other high-income countries, findings may have limited generalisability to other settings, particularly developing countries.

While we only included studies that specified the time of data collection following implementation, 'implementation' may have been interpreted and reported inconsistently between studies. For example, CDS systems may be implemented in a limited capacity before full implementation whereas others may be implemented using a 'big bang' approach.[103] Likewise, CDS systems are often updated and adapted following their initial 'go-live' date,[102] but this detail is rarely provided in publications. This indicates a need for future research that evaluates what and how changes, such as adaptations to CDS and new users, can impact clinicians' acceptance and use of CDS over time.

Our review provides practical guidance to assist stakeholders in anticipating and identifying issues likely to impact CDS acceptance and use over time. We emphasise the importance of engaging clinicians early after implementation, and on an ongoing basis, to ensure issues that develop over time are promptly and successfully addressed. We must move away from episodic evaluations of clinicians' acceptance and use of CDS systems and towards a framework that considers the complexity of factors, including how they emerge, interact, and change over time. Doing so will allow for more efficient and nuanced approaches that target the issues clinicians experience at different points in time, increasing the likelihood of sustained system success. Reporting the time of data collection post-implementation and employing longitudinal designs in future research is necessary to achieve this goal.

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Competing Interests

All authors declare no financial or non-financial competing interests.

Data availability

The datasets analysed during the current study are available from the corresponding author upon request.

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SUPPLEMENTARY MATERIAL

Supplementary Note 1. Search terms

Searches were conducted on the following dates:

- Initial search: 17 March 2022
- Updated search: 19 January 2024

Databases: Medline, Embase, Web of Science, CINAHL and PsycINFO

Medline
(exp decision support systems, clinical/ or "decision support system*".tw. or "clinical decision support*".tw. or exp clinical decision rules/ or "computeri*ed decision support*".tw.) and (Accept* or adopt* or attitude* or percei* or percep* or barrier* or facilitator* or useful* or usab* or Uptake or perspective* or satisf* or concern* or (observation* or interview* or survey* or questionnaire* or "focus group*")).tw. and (exp hospitals/ or exp hospital units/ or exp hospital departments/ or hospital*.tw. or outpatient*.tw. or inpatient*.tw.)

Embase
(exp "Clinical decision support system"/ or "decision support system*".tw. or "clinical decision support*".tw. or "computeri*ed decision support*".tw. or exp "clinical decision rule"/) and (Accept* or adopt* or attitude* or percei* or percep* or barrier* or facilitator* or useful* or usab* or Uptake or perspective* or satisf* or concern* or usage or "system use" or (observation* or interview* or survey* or questionnaire* or "focus group*" or "log data")).tw. and (exp "hospital"/ or exp "hospital subdivisions and components"/ or exp "hospital department"/ or hospital*.tw. or outpatient*.tw. or inpatient*.tw.)

Web of Science
(TI=("clinical decision support*"
"decision support system*" OR
"computeri*ed decision support*" OR
"clinical decision support*" OR
"clinical decision rule*") OR AB=("clinical decision support*"
"decision support system*" OR
"computeri*ed decision support*" OR
"clinical decision support*" OR
"clinical decision rule*")) AND
(TI=((Accept* OR
adopt* OR
attitude* OR
percei* OR

percep* OR
barrier* OR
facilitat* OR
useful* OR
usab* OR
Uptake OR
perspective* OR
satisf* OR
concern* OR
usage OR
"system use") OR
(observation* OR
interview* OR
survey* OR
questionnaire* OR
"focus group*"OR
"log data")) OR AB=((Accept* OR
adopt* OR
attitude* OR
percei* OR
percep* OR
barrier* OR
facilitat* OR
useful* OR
usab* OR
Uptake OR
perspective* OR
satisf* OR
concern* OR
usage OR
"system use") OR
(observation* OR
interview* OR
survey* OR
questionnaire* OR
"focus group*" OR
"log data"))) AND
(TI=(Hospital* OR
inpatient* OR
outpatient* OR
"hospital department*" OR
"hospital unit*") OR AB=(Hospital* OR
inpatient* OR
outpatient* OR

"hospital department*" OR
"hospital unit*"))

CINAHL

(MH "Decision Support Systems, Clinical+" OR TI "decision support system*" OR AB "decision support system*" OR TI "computeri*ed decision support*" OR AB "computeri*ed decision support*" OR TI "Clinical decision support*" OR AB "Clinical decision support*" OR MH "Clinical prediction rules+") AND ((MH "Attitude of Health Personnel+" or ti Accept* or ab accept* OR ti
adopt* OR ab adopt* or ti
attitude* OR ab attitude* or ti
percei* OR ab percei* or ti
percep* OR ab percep* or ti
barrier* OR ab barrier* or ti
facilitator* OR ab facilitator* or ti
useful* OR ab useful* or ti
usab* OR ab usab* or ti
Uptake OR ab uptake or ti
perspective* OR ab perspective* or ti
satisf* OR ab satisf* or ti concern* or ab concern* OR ti usage or ab usage or ti "system use" or ab "system use") OR (ti
observation* OR ab observation* or ti
interview* OR ab interview* or ti
survey* OR ab survey* or ti
questionnaire* OR ab questionnaire* or ti
"focus group*" or ab "focus group*" or ti
"log data" or ab "log data")) AND (MH Hospitals+ OR TI hospital* or ab hospital* or ti inpatient* or ab inpatient* OR ti
outpatient* OR ab outpatient* or MH
"hospital units+" or ti "hospital department*" or ab "hospital department*")

PsycINFO

(exp decision support systems/ or "decision support system*".tw. or "clinical decision support*".tw. or "computeri*ed decision support*".tw. or clinical decision rule*.tw.) and (exp health personnel attitudes/ or accept*.tw. or adopt*.tw. or attitude*.tw. or percei*.tw. or percep*.tw. or barrier*.tw. or facilitator*.tw. or useful*.tw. or usab*.tw. or Uptake.tw. or perspective*.tw. or satisf*.tw. or concern*.tw. or usage.tw. or "system use".tw. or (observation* or interview* or survey* or questionnaire* or "focus group*" or "log data").tw.) and (exp hospitals/ or "hospital unit*".tw. or "hospital department*".tw. or hospital*.tw. or outpatient*.tw. or inpatient*.tw.)

Supplementary Note 2. Time specificity inclusion criteria and reporting

Time specificity

As the early phases of implementation are often associated with fast-paced changes in perceptions, attitudes, and use,[11] we required time to be reported at a greater level of detail the closer evaluations were conducted to CDS implementation. Supplementary Table 1 shows the level of time specificity that was required for study inclusion, between different timeframes.

In papers that reported results at multiple time points following CDS implementation, factors were extracted on separate rows of the data extraction form and categorised into separate 'study time-points' for the purposes of the review. Similarly, where multiple papers described the same CDS implementation at the same point in time following implementation, factors were combined into a single row and categorised as whole study time-points for the purposes of the review.

Supplementary Table 1. Time specificity criteria description and examples

	Time following implementation			
	0-6 months	**7-24 months**	**2-5 years**	**5+ years**
Reporting required	Monthly level	6-monthly level	Any time between interval	Any time
Description	The month and year of data collection and month and year of CDS implementation reported OR the time (in months) that the study was conducted following CDS implementation was reported	Time of data collection following implementation was reported at 6-month specificity	Time of data collection following implementation was reported anywhere between 2-5 years following implementation	Time of data collection following implementation reported at any time over 5 years
Example	CDS was implemented in June 2015 and data were collected in July 2015	CDS was implemented in June 2015 and data were collected between February 2015 and May 2015	CDS was implemented in 2015 and data were collected in 2018	CDS was implemented over 5 years prior to data collection

Supplementary Table 2. Common examples for excluding study results

Combination	Example issue	Outcome
Multiple data collection methods/timeframe	Time of questionnaire following implementation was reported but timeframe of interviews was not	Questionnaire results included and extracted; interview results excluded
Multiple CDS/timeframe	Time of data collection following implementation of one CDS reported, but another CDS not	CDS with time reported included, CDS without time reported excluded
Multiple sites/timeframe	Time of data collection following implementation of CDS in one site reported, but another site not	Site with time reported included, site without time reported excluded
Multiple CDS/CIS integration	One CDS was integrated with the CIS and another was not	CDS integrated with the CIS included, CDS not integrated with CIS excluded
Multiple implementations/ settings	CDS was implemented in both hospital and primary care settings	CDS implemented in hospital included, primary care excluded
Multiple methods/stage of implementation	Questionnaire conducted pre-implementation and post-implementation	Post implementation findings included, pre implementation findings excluded

Supplementary Table 3. Denominator definitions and working example

Working example In Salwei et al.[52], within the 'design quality and packaging' construct, we identified 1 facilitator and 2 barriers to 'system features', 1 barrier and 1 facilitator to 'integration', and 1 facilitator to 'ease of accessing/locating'		
Denominator	**Definition**	**Example**
Factor count	Factors within a construct were counted per study timepoint, per direction of factor	Factors within the 'design quality and packaging' construct were identified as facilitators 3 times (*1x system features, 1x integration, 1x ease of accessing/locating),* and as barriers 2 times *(1x system features, 1x integration*)
Construct count	Constructs were counted once per study timepoint, per direction of construct	The 'design quality and packaging' construct was identified as a facilitator once (*1x design quality and packaging*) and a barrier once (*1x design quality and packaging*)

Supplementary Table 4. Study methods, timeframe and characteristics

Time	First author	Year	Country	Setting	Participants	Partial or full study	Study design	Data source	Use measurement	Acceptance measurement	Data collection timeframe
0-1 months	Castellanos[28,a]	2018	Germany	Tertiary care university hospital, surgical ICU	Physicians	Partial	Longitudinal	System data	Individual tests for which the CDS was consulted and adherence to recommendations (event level)	-	0-28 days
	Grauer[29]	2022	USA	11 hospitals and 200 clinics, inpatient and outpatient excluding ED and urgent care	Physicians and registered nurses	Partial	Cross sectional	System data	Alert acceptance (event level)	-	0-5 weeks
1-2 months	Castellanos[28,a]	2018	Germany	*(as above)*							28-56 days
	Guidi[30]	2015	USA	Academic health system, hospital wide	Physicians, advanced practice providers and registered nurses	Full	Cross sectional	Survey	-	Utility of alerts	1-2.5 months

	Sauro[31,a]	2019	Canada	Healthcare system, 4 adult medical-surgical ICUs	Physicians, nurse practitioners, medical trainees (residents and clinical fellows), nurses, and pharmacists	Full	Cross sectional	Survey	-	Acceptability, adoption, appropriateness, feasibility, and penetration of CDS	1 month
	Tsai[32]	2022	Taiwan	3 hospitals, EDs	Physicians and nurses	Partial	Cross sectional	Survey	-	TAM survey: Perceived ease of use, perceived usefulness, and perceived acceptance	1 month
2-3 months	Castellanos[28,a]	2018	Germany	*(as above)*				Interviews	-	Qualitative	2-3 months
	DeBie[33]	2021	Netherlands	Tertiary hospital, mixed medical and surgical ICU	Intensivists, residents, ICU physician assistants	Partial	Pre-post	Interviews, questionnaire	-	Usability questionnaire: pragmatic quality, hedonic quality – identity, hedonic quality – stimulation, attractiveness, and user acceptance questionnaire based on TAM	2.5 months
	Harrison[34]	2017	USA	Hospital, medical ICU	Nurse practitioners, physician assistants, physicians	Partial	Cross sectional	Survey, system data	Alert acceptance (event level and clinician level)	User satisfaction	2 months

	Petersen[35]	2020	USA	2 hospitals, newborn nurseries	Neonatal nurse practitioners, paediatric resident physicians, neonatology fellows, paediatric hospitalists, and neonatologists	Partial	Pre post	Survey	Self-reported use	User experience	2 months
	Thayer[36]	2021	USA	Large academic tertiary care children's hospital, emergency department	Physicians	Partial	Cross sectional	Observations, interviews	-	Qualitative	2 months
3-4 months	Berge[37]	2023	Norway	Hospital, anaesthesia and ICU department	Doctors and nurses	Partial	Cross sectional	Survey	-	UTAUT survey: Performance expectancy, effort expectancy, facilitating conditions, social influence, intention to use the system	3 months
	Casey[38]	2023	USA	2 hospitals, EDs	Physicians	Full	Cross sectional	Interviews, survey	Self-reported use	Qualitative and usability testing	3 months
	Chadwick[39]	2017	UK	Urban hospital, hospital wide	Doctors and nurse practitioners	Partial	Cross sectional	Interviews, focus groups	-	Qualitative	3 months
	Huang[40]	2020	Taiwan	Regional hospital, medical unit, surgical unit, medical-surgical unit, and adult intensive care unit	Nurses	Partial	Pre-post	Questionnaire	-	TAM questionnaire: perceived usefulness, perceived ease of use, attitude to use, and	3 months

										behavioural intention	
	Jenssen[41]	2016	USA	Children's hospital, 1 inpatient unit	Residents (on rotation during intervention)	Partial	Cross sectional	Questionnaire	-	Advantages and disadvantages of the CDS, suggested improvements and usability (SUS)	3 months
	Keim-Malpass[42,a]	2018	USA	Academic surgical trauma ICU	Point-of-care clinicians (registered nurses, respiratory therapist, nurse practitioner, attending physician)	Partial	Longitudinal	Focus group	-	Qualitative	3 months
	Mahabee-Gittens[43,a]	2018	USA	Academic paediatric medical center, 5 outpatient urgent care centres	Registered nurses	Partial	Longitudinal	Survey	-	Attitudes and barriers to CDS, CDS usability	3 months
	Rosenthal[44]	2019	USA	Paediatric urban teaching hospitals, 2 general EDs	Physicians and Advanced Practice Providers	Partial	Pre-post	Survey	Self-reported use	Knowledge of CDS, impact on clinical decision making, and education requirements	3 months

	Sauro[31,a]	2019	Canada	(as above)				Interviews	-	Qualitative	3 months
	Yoon[45]	2023	South Korea	Tertiary academic hospital, ED	Emergency physicians	Partial	Cross sectional	Survey	-	User experience and system usability survey: effectiveness, efficiency, safety, satisfaction, and reliability	3 months
4-5 months	Feldstein[46]	2023	USA	6 EDs across 2 hospital systems	ED providers	Partial	Cross sectional	Survey	-	User experience	4 months
	Keim-Malpass[42,a]	2018	USA	*(as above)*						Qualitative	4 months
	Mahabee-Gittens[43,a]	2018	USA	*(as above)*				Interviews		Qualitative	4 months
	Suresh[47]	2022	USA	Tertiary care paediatric hospital, ED	Nurses	Partial	Cross sectional	Survey	-	Feedback survey	4 months

5-6 months	Ginestra[48]	2019	USA	Academic hospital, non-ICU inpatient services	Registered nurses, physicians or advanced practitioners	Full	Longitudinal	Survey	-	Perceptions of CDS regarding: the patient's condition; new information discovered at the time of alert; whether and how the alert changed management; and whether and how the alert was useful and/or improved patient care	5-6.5 months
	Holroyd-Leduc[49]	2010	Canada	2 teaching hospitals, orthopaedic wards	Nurses	Partial	Cross sectional	Focus groups	-	Qualitative	5 months
	Rabinovich[50]	2022	Argentina	University hospital, ED	Emergency physicians and radiology residents	Partial	Cross sectional	Survey, interviews	-	System Usability Scale (SUS): Actual use, perceived usefulness, perceived ease of use, output quality; and qualitative	5 months
6-7 months	Bellodi[51]	2017	Italy	3 hospitals: 2 acute care local hospitals in same network (cardiology and medicine wards), 1 teaching hospital (medicine ward)	Nurses, physicians	Partial	Pre post	Questionnaire	-	User satisfaction survey	6 months

	English[52]	2017	USA	3 hospitals, clinical pharmacies	Clinical pharmacists	Full	Cross sectional	Questionnaire	-	UTAUT questionnaire: performance expectancy, effort expectancy, social influence, facilitating conditions, behavioural intentions and usage behaviour	6 months
	Hoekstra[53]	2010	Netherlands	Tertiary university teaching hospital, surgical ICU and thoracic-surgical ICU	Nurses	Partial	Pre-post	Questionnaire	Compliance with recommended pump rates	-	6 months
	Jones[54]	2019	USA	4 urban hospitals, EDs	ED clinicians	Partial	Cross sectional	Survey	-	Usability	6 months
	Uppot[55]	2022	USA	Urban tertiary care referral facility, 2 ICUs (surgical and medical)	ICU staff (not further specified)	Partial	Cross sectional	Survey	-	User acceptance	6 months
7-12 months	Agostini[56]	2008	USA	Academic medical center, hospital wide	Physicians	Full	Cross sectional	Interviews	-	Qualitative	12 months
	Bell[57]	2019	UK	Teaching hospital, 3 cardiac wards	Medical and nurse prescribers	Full	Cross sectional	Interviews, observations	Observations of alert use: frequency and types of alerts, who received alerts and contextual information, for ward rounds and non-ward round prescribing	Qualitative	1 year

	Cho[58]	2013	South Korea	University teaching hospital, two inpatient surgical ICUs	Nurses	Partial	Pre-post	Questionnaire	-	-	7 months
	Groshaus[59]	2012	Canada	2 hospitals, 4 medical units	Nurses	Partial	Stepped wedge	Interviews	-	Qualitative	9 months
	Jauk[60]	2021	Austria	Regional public hospital, 8 participating departments (5 included in study)	Physicians and nurses	Partial	Cross sectional	Questionnaire	Self-reported use	TAM questionnaire: perceived usefulness, perceived ease of use, attitude to use, and behavioural intention	7 months
	Lytle[61]	2015	USA	University hospital, 16 adult units (2 low performing surgical and medical units pre CDS included in the study)	Registered nurses	Partial	Pre-post	Focus groups	-	Qualitative	11 months
	Neame[62]	2021	UK	Regional specialist children's hospital, inpatient wards excluding paediatric ICU	Trainee doctors, consultants, specialist nurse prescribers, prescribing pharmacists	Partial	Pre-post	Questionnaire	-	Acceptability and usability	9 months
	Nydert[63]	2017	Sweden	NR, 3 paediatric wards	Paediatricians	Full	Cross sectional	Interviews	-	Qualitative	1 year
	Pirnejad[64]	2011	Netherlands	Tertiary academic hospital, hematology and oncology inpatient and	Physicians and nurses	Full	Cross sectional	Interviews	-	Qualitative	1 year

				outpatient departments							
	Salwei[65,b]	2021	USA	Academic hospital, ED	Medical residents and attending physicians	Full	Cross sectional	Interviews	-	Qualitative	9-12 months
	Salwei[66,b]	2023	USA	Academic health system, ED	Emergency physicians	Full	Cross sectional	Interviews	-	Qualitative	9 months
	Stutman[67]	2007	USA	6 community hospitals, hospital wide	Providers and pharmacists	Partial	Longitudinal	System data	Alert acceptance (event level)	-	7-8 months
	Henry[68]	2022	USA	Acute-case non teaching hospital, ED and all medical and surgical units	Physicians and nurses (ED, critical care and general ward)	Full	Cross sectional	Interviews	-	Qualitative	7 months
1-2 years	Bersani[69]	2020	USA	Acute care hospital, 12 units	Nurses, patient care assistance, nursing students, attending physicians, PAs, nurse practitioners, fellows, residents, medical students, unit leadership staff, pharmacists, and other	Partial	Cluster randomised stepped wedge trial	Survey	-	Usability: quality of work life, perceived usefulness, perceived ease of use, and user control	18-21 months
	Eden[70]	2020	Australia	Public tertiary care university hospital, hospital wide	Doctors, nurses, pharmacists and allied health professionals	Partial	Cross sectional	Interviews, focus groups	-	Qualitative	14-16 months

	Frymoyer[71]	2020	USA	Academic quaternary-care children's hospital, NICU and PICU	Clinical pharmacists	Partial	Cross sectional	Questionnaire	-	Satisfaction, perceived usability and overall clinical experience	15 months
	Goldstein[72]	2022	USA	Outpatient practices	Opthamologists	Partial	Cross sectional	Survey	-	User experience survey	17 months
	Hum[73]	2014	USA	2 academically affiliated hospitals, both NICUs	Neonatal attending physicians, pediatric residents, neonatology fellows, house physicians, and nurse practitioners	Partial	Cross sectional	Survey	-	User awareness and acceptance, ease of use, recommendations of additional features	12-14 months
	Salwei[74]	2022	USA	Academic health system, ED	Emergency physicians (residents, fellows and attendings)	-	Cross sectional	Survey	-	Computer system usability questionnaire	12-13 months
	Scheepers-Hoeks[75]	2013	Netherlands	Secondary care teaching hospital, ICU	Intensivists, junior doctors and nurse practitioners	Partial	RCT	Survey	-	Satisfaction and suitability of different types of CDS	17 months
	Short[76]	2021	USA	Quaternary-care hospital, ED and medical, surgical, cardiothoracic, cardiac, and neurological ICUs	Resident physicians, nurse practitioners (NP), and physician assistants (PA)	Partial	Pre post	Focus groups	-	Qualitative	13 months
	Zhai[77]	2022	China	Tertiary hospital, 4 medical-surgical wards	Nurses	Full	Cross sectional	Observations and interviews	Observations of use	Qualitative	13 months - 18 months

	Chow[78,a]	2016	Singapore	Tertiary care academic hospital, hospital wide	Physicians	Partial	Longitudinal	System data	Proportion of CDS completed launches for guidance, launches via autotrigger and acceptance of CDS recommendations (event level)	-	20-24 months
2-5 years	Campion[79]	2011	USA	Academic urban tertiary care hospital, surgical and trauma ICUs	Nurses	Partial	Cross sectional	Interviews, observations	Observations of use	Qualitative	4 years 4 months - 5 years 4 months
	Chow[80,b]	2015	Singapore	Adult tertiary hospital, hospital wide	Junior and senior physicians	Full	Cross sectional	Focus groups, questionnaire	-	Qualitative, and survey on situations for use, the perceived credibility and usefulness, and the desired useful features of CDS	3 years 5-7 months
	Chow[78,a,b]	2016	*(as above)*								2 years - 3 years 8 months

	Galanter[81]	2010	USA	Academic urban tertiary hospital, hospital wide	Medical residents, pharmacists (faculty and residents), registered nurses, attending physicians, and other (student, clinical nurse midwife, unknown)	Full	Cross sectional	System data	Alert acceptance (event level)	-	4-5 years
	Lichtner[82]	2020	Australia	Tertiary paediatric hospital, oncology unit	Clinicians in the oncology unit e.g. oncologists, registered nurses, pharmacists	Partial	Cross sectional	Interviews	-	Qualitative	2 years-2 years 9 months
	Lin[83]	2010	Taiwan	University hospital, hospital wide	Physicians	Full	Cross sectional	System data	Percentage of appropriate indications chosen from CDS (appropriate transfusion order is defined as a blood product ordered with an indication, which satisfies the criteria)	-	3 years 4 months - 4 years 3 months
>5 years	Beeler[84]	2016	USA	2 large tertiary care teaching hospitals, outpatient clinics and ambulatory practices	Prescribers e.g. physicians, nurse practitioners, and physician assistants	Full	Cross sectional	System data	Alert acceptance (event level)	-	9-12 years

	Campion[85]	2011	USA	Academic urban tertiary care hospital, surgical and trauma ICUs	Nurses	Full	Cross sectional	Interviews, observations	Observations of use	Qualitative	5 years
	Choi[86]	2019	Korea	Tertiary teaching hospital, hospital wide	Physicians	Partial	Cross sectional	System data	Alert acceptance (event level)	-	10 years 8 months-10 months
	Choudhury[87,b]	2022	USA	Academic hospital, hospital wide	Attending physicians, resident physicians, registered nurses	Full	Cross sectional	Survey	-	Modified UTAUT survey: Expectancy, perceived risk, trust, use of BUC	5+ years
	Choudhury[88,b]	2023	USA	Academic hospital, hospital wide	Attending physicians, resident physicians, registered nurses	Full	Cross sectional	Survey	-	Modified UTAUT survey: Cognitive workload, perceived risk, trust, intention to use, situation awareness	5+ years
	Luna[89]	2017	Argentina	Academic hospital, hospital wide	Physicians with at least 4 years of experience with CPOE system	Partial	Cross sectional	Interviews	-	Qualitative	5+ years (mid 2000's - April 2013/June 2014)
	Ng[90]	2023	Singapore	2 hospitals and outpatient clinics	Physicians, nurses, pharmacists, allied health	Partial	Pre-post	System data	Alert acceptance (event level)	-	5 years 6 months - 6 years 6 months
	Pontefract[91]	2018	UK	Acute hospital, hospital wide	Pharmacists and physicians	Partial	Cross sectional	Focus groups	-	Qualitative	11-12 years
	Van De Sijpe[92]	2022	Belgium	Teaching hospital, hospital wide	Physicians and pharmacists	Full	Cross sectional	Survey, system data	Alert acceptance (event level)	Satisfaction, usefulness, relevance and reasons for overriding severe alerts	10-12 years

	Wong[93]	2017	USA	Urban tertiary care hospital, adult medical, neurology, and surgical ICUs	Providers, pharmacists, nurses	Partial	Pre-post	System data	Alert acceptance (event and patient level)	-	18 years
	Wright[94]	2018	USA	Hospital, outpatient settings	NR	Partial	Pre-post	System data	Alert acceptance (event level)	-	5+ years

ICU Intensive care unit, *ED* emergency department, *CDS* clinical decision support, *TAM* technology acceptance model, *UTAUT* unified theory of acceptance and use of technology, *NICU* neonatal intensive care unit, *PICU* paediatric intensive care unit, *RCT* randomised controlled trial, *NR* not reported, *CPOE* computerised provider order entry system

[a]studies separated for analysis of factors over time

[b]studies combined for analysis of factors over time

Supplementary Note 3. Detailed quality appraisal results

As data were extracted only from study results that met inclusion criteria, the study design was selected and quality was assessed, based only on the methods and results of the study that were eligible for inclusion in the review. For example, a study evaluating both clinical outcomes using patient data and clinicians' perceptions using interviews, would be assessed as a qualitative study rather than mixed methods, given clinical outcomes were not eligible for inclusion in the review. All studies were assessed using the Mixed Methods Appraisal Tool (MMAT).

Supplementary Table 5. Quality appraisal using the MMAT

Timeframe	First author	Year	*Study design (MMAT)*	SQ1	SQ2	Q1	Q2	Q3	Q4	Q5	*Total yes*	*Total no*	*Total CT*
0-1 months	Castellanos[28,a]	2018	Mixed methods	Yes	Yes	Yes	No	Yes	No	No	**2**	**3**	**0**
	Grauer[29]	2022	Quantitative descriptive	Yes	Yes	Yes	CT	Yes	Yes	Yes	**4**	**0**	**1**
1-2 months	Castellanos[28,a]	2018	*(as above)*										
	Guidi[30]	2015	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Sauro[31,a]	2019	Mixed methods	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Tsai[32]	2022	Quantitative descriptive	Yes	Yes	CT	CT	CT	CT	CT	**0**	**0**	**5**
2-3 months	Castellanos[28,a]	2018	*(as above)*										
	DeBie[33]	2021	Mixed methods	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Harrison[34]	2017	Quantitative descriptive	Yes	Yes	CT	Yes	CT	Yes	Yes	**3**	**0**	**2**
	Petersen[35]	2020	Quantitative descriptive	Yes	Yes	Yes	Yes	CT	Yes	CT	**3**	**0**	**2**
	Thayer[36]	2021	Qualitative	Yes	Yes	Yes	No	No	No	No	**1**	**4**	**0**
3-4 months	Berge[37]	2023	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Casey[38]	2023	Mixed methods	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Chadwick[39]	2017	Qualitative	Yes	Yes	Yes	No	No	No	No	**1**	**4**	**0**
	Huang[40]	2020	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Jenssen[41]	2016	Quantitative descriptive	Yes	Yes	CT	Yes	Yes	Yes	Yes	**4**	**0**	**1**
	Keim-Malpass[42,a]	2018	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	No	**4**	**1**	**0**

	Mahabee-Gittens[43,a]	2018	Mixed methods	Yes	Yes	Yes	Yes	No	No	Yes	**3**	**2**	**0**
	Rosenthal[44]	2019	Quantitative descriptive	Yes	Yes	Yes	CT	CT	No	CT	**1**	**1**	**3**
	Sauro[31,a]	2019	*(as above)*										
	Yoon[45]	2023	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
4-5 months	Feldstein[46]	2023	Quantitative descriptive	Yes	Yes	Yes	Yes	No	Yes	Yes	**4**	**1**	**0**
	Keim-Malpass[42,a]	2018	*(as above)*										
	Mahabee-Gittens[43,a]	2018	*(as above)*										
	Suresh[47]	2022	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
5-6 months	Ginestra[48]	2019	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Holroyd-Leduc[49]	2010	Qualitative	Yes	Yes	Yes	Yes	No	No	No	**2**	**3**	**0**
	Rabinovich[50]	2022	Mixed methods	Yes	Yes	CT	Yes	Yes	Yes	No	**3**	**1**	**1**
6-7 months	Bellodi[51]	2017	Quantitative descriptive	Yes	Yes	CT	CT	Yes	CT	CT	**1**	**0**	**4**
	English[52]	2017	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Hoekstra[53]	2010	Quantitative descriptive	Yes	Yes	No	No	Yes	CT	Yes	**2**	**2**	**1**
	Jones[54]	2019	Quantitative descriptive	Yes	Yes	CT	CT	Yes	Yes	Yes	**3**	**0**	**2**
	Uppot[55]	2022	Quantitative descriptive	Yes	Yes	Yes	CT	Yes	CT	No	**2**	**1**	**2**
7-12 months	Agostini[56]	2008	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Bell[57]	2019	Mixed methods	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Cho[58]	2013	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Groshaus[59]	2012	Qualitative	Yes	Yes	Yes	Yes	No	No	No	**2**	**3**	**0**
	Jauk[60]	2022	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Lytle[61]	2021	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Neame[62]	2015	Mixed methods	Yes	Yes	Yes	No	No	Yes	CT	**2**	**2**	**1**
	Nydert[63]	2021	Quantitative descriptive	Yes	Yes	CT	CT	CT	CT	Yes	**1**	**0**	**4**
	Pirnejad[64]	2017	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**

	Salwei[65,b]	2011	Qualitative	Yes	Yes	Yes	Yes	Yes	No	Yes	**4**	**1**	**0**
	Salwei[66,b]	2021	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Stutman[67]	2023	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Henry[68]	2007	Quantitative descriptive	Yes	Yes	CT	Yes	Yes	Yes	No	**3**	**1**	**1**
1-2 years	Bersani[69]	2020	Mixed methods	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Eden[70]	2020	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Frymoyer[71]	2020	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	No	**4**	**1**	**0**
	Goldstein[72]	2022	Quantitative descriptive	Yes	Yes	Yes	CT	No	CT	Yes	**2**	**1**	**2**
	Hum[73]	2014	Quantitative descriptive	Yes	Yes	Yes	Yes	CT	No	CT	**2**	**1**	**2**
	Salwei[74]	2022	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Scheepers-Hoeks[75]	2013	Quantitative descriptive	Yes	Yes	Yes	Yes	CT	Yes	CT	**3**	**0**	**2**
	Short[76]	2021	Qualitative	Yes	Yes	Yes	Yes	No	Yes	No	**3**	**2**	**0**
	Zhai[77]	2022	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Chow[78,a]	2016	Quantitative non randomised	Yes	Yes	Yes	Yes	No	Yes	Yes	**4**	**1**	**0**
2-5 years	Campion[79]	2011	Qualitative	Yes	Yes	Yes	Yes	No	No	No	**2**	**3**	**0**
	Chow[80,b]	2015	Mixed methods	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Chow[78,a,b]	2016	*(as above)*										
	Galanter[81]	2010	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Lichtner[82]	2020	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Lin[83]	2010	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	CT	**4**	**0**	**1**
>5 years	Beeler[84]	2016	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Campion[85]	2011	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Choi[86]	2019	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Choudhury[87,b]	2023	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Choudhury[88,b]	2022	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Luna[89]	2017	Qualitative	Yes	Yes	Yes	CT	CT	Yes	No	**2**	**1**	**2**
	Ng[90]	2023	Quantitative descriptive	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**

	Pontefract[91]	2018	Qualitative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	**5**	**0**	**0**
	Van De Sijpe[92]	2022	Quantitative descriptive	Yes	Yes	Yes	CT	Yes	No	Yes	**3**	**1**	**1**
	Wong[93]	2017	Quantitative descriptive	Yes	Yes	Yes	Yes	No	Yes	Yes	**4**	**1**	**0**
	Wright[94]	2018	Quantitative non randomised	Yes	Yes	CT	Yes	Yes	No	Yes	**3**	**1**	**1**

MMAT Mixed Methods appraisal tool, *SQ* MMAT screening question, *Q* MMAT question, *CT* can't tell

[a]studies separated for analysis of factors over time

[b]studies combined for analysis of factors over time

Supplementary Figure 1. Barriers and facilitators identified in CFIR domains 1-6 months following CDS implementation

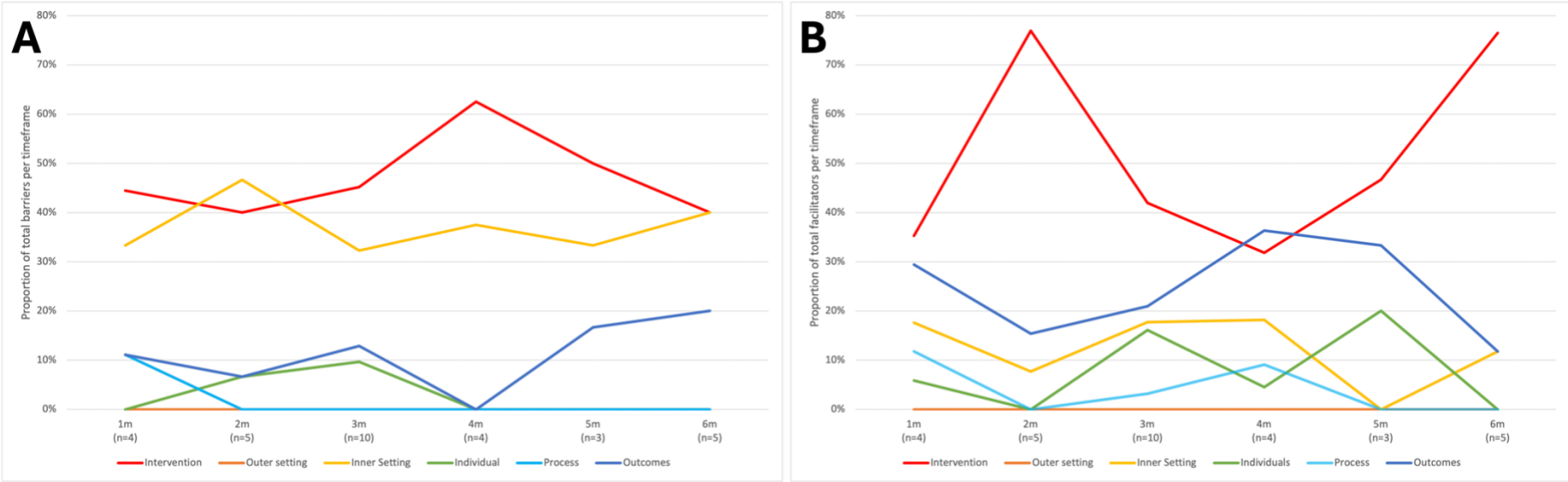

Figure legend: *m* months, *n* number of study time-points.

A) The proportion of **barriers** identified in each CFIR domain are presented relative to the total number of barriers identified at monthly intervals in the first 6 months following CDS implementation. Barriers were counted once per study time-point (see factor count calculation in Supplementary Table 3) and summed across all study time-points within each monthly interval. Studies conducted between 0-1 month (n=2) were excluded from this figure as no barriers were reported during this time.

B) The proportion of **facilitators** identified in each CFIR domain are presented relative to the total number of facilitators identified at monthly intervals in the first 6 months following CDS implementation. Facilitators were counted once per study time-point (see factor count calculation in Supplementary Table 3) and summed across all study time-points within each monthly interval. Studies conducted between 0-1 month (n=2) were excluded from this figure as only one facilitator was reported during this time.

Supplementary Table 6. Barriers and facilitators identified in key constructs in studies that evaluated CDS between 1-6 months post-implementation

CFIR Domain	CFIR Construct	Timeframe					
		1 month	2 months	3 months	4 months	5 months	6 months
Intervention	Complexity			• Easy to use (+) • **Easy to learn (+)**	• Easy to use (+) • Time and effort to complete (+)	• Ease of use (+/-)	• Easy to use (+) • Time and effort (-/+)
	Data Quality			• Recommendation quality (+)			
	Design Quality and Packaging		• Integration with other CIS (-)	• **Rule or algorithm design (-)** • **Interface design (-/+)** • **Visibility of patient status (-)**	• Integration with other CIS (-)		
	Relative Advantage	• Usefulness (+/-)	• **Efficiency (+/-)** • **Valued system features (+)**	• Usefulness (+/-) • **System performance (+)** • **Satisfied (+)**		• Usefulness/utility (-/+)	• Usefulness (+/-) • **Preferred (+/-)**
	Evidence strength and quality						
Inner Setting	Available Resources			• **Resources to support system use (-/+)**			

	Compatibility			• Workflow fit (+/-)	• Workflow fit (+/-)	• Workflow fit (-)	
	Task and Work Context						
Individuals	Individual stage of change						
	Self-Efficacy			• **Poor understanding and skills (-)**			
	Knowledge and beliefs about the intervention			• **Attitude to using (+)** • **Intention to use (+)**			
	Individual stage of change			• **Ongoing use (+)**			
Outcomes	Innovation Deliverers			• **Improved confidence (+)** • **Improved clinical decision making (+)** • **Improved/reduced efficiency (+/-)**	• **Prompts consideration (+)**		
	Innovation Receivers	• **Timeliness (+)** • Improved patient care (+)		• Improved patient care (+) • **Improved patient communication (+)** • **Improved or reduced safety (+/-)**		• Improved patient care (+)	

CFIR Consolidated Framework for Implementation Research, *CIS* Clinical Information System.

Note: Key constructs presented in this table were identified as barriers or facilitators in over 25% of study time-points within a given timeframe. Factors reported were identified in 2 or more studies within each timeframe where (+) indicates a facilitator to acceptance and use i.e. positive

direction, and (-) indicates a barrier to acceptance and use i.e. negative direction. Factors in **bold** were uniquely reported within a particular timeframe.

Supplementary Table 7. Completed PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	P1
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	P1
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	P1-2
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	P2
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	P11-12
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	P11
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	P11 & Supplementary Materials
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	P12
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	P12
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	P12
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	P12
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	P12
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	P13

Section and Topic	Item #	Checklist item	Location where item is reported
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	P13
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	P12-13
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	P13
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	P12-13
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	N/A
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	N/A
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	N/A
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	N/A
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	P2
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	P10
Study characteristics	17	Cite each included study and present its characteristics.	P3 & Supplementary Materials
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	P3 & Supplementary Materials
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	P3-8
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Supplementary Materials
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision	P3-8

Section and Topic	Item #	Checklist item	Location where item is reported
		(e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	N/A
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	N/A
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	N/A
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	N/A
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	P8-10
	23b	Discuss any limitations of the evidence included in the review.	P11
	23c	Discuss any limitations of the review processes used.	P11
	23d	Discuss implications of the results for practice, policy, and future research.	P8-11
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	P11
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	P11
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	N/A
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	P13
Competing interests	26	Declare any competing interests of review authors.	P13
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	P13

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CHAPTER 5

PREFACE

In Chapter 3b, the need for in-depth qualitative research examining the early stages of CDS implementation was highlighted, while Chapters 3a and 4 reinforced the importance of involving users beyond initial system development to address needs that arose over time. Chapter 3a additionally highlighted the lack of evidence that evaluated different approaches to user involvement within a single study. Chapter 5 addressed these gaps, by qualitatively evaluating clinicians' early experiences of two CDS systems implemented in a hospital using a pilot approach, where the aim was to iteratively adapt CDS based on clinicians' feedback in practice. Due to differences in the departmental context, one CDS system was implemented with limited user involvement, while the other was implemented with stronger early and ongoing user involvement (including post-implementation design-in-use). Comparing clinicians', managers and vendors experiences of these systems provided insight into how different approaches influenced clinicians' early acceptance and use, perceptions of system relevance and utility, and trust in the CDS and its implementers. Furthermore, it provided evidence around how the novel design-in-use strategy could improve acceptance and use of CDS over time, where challenges arose and how they could be overcome in future.

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Opportunities and challenges associated with the pilot implementation of clinical decision support systems in a rural hospital: A qualitative study

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ABSTRACT

Background: Despite their potential, Clinical Decision Support (CDS) systems often lack alignment with clinicians' needs and are underutilised in practice. Pilot implementations can help to improve the fit between systems and local needs by engaging users in real-world testing and refinement. Although pilot implementations of CDS have been reported, limited evidence has explored the factors contributing to pilot success.

Objectives: This study aimed to explore the opportunities and challenges associated with the pilot implementation of a CDS system that ultimately did not progress to full-scale implementation.

Methods: We conducted interviews with clinicians, health service managers, and vendors involved in the pilot implementation and use of a mobile application-based CDS and a dashboard-based CDS in two departments (Emergency and Patient Flow) of a rural Australian hospital. A semi-structured interview guide was developed using the Non-adoption, Abandonment, Sustainability, Scale-up, and Spread (NASSS) framework. Interviews were audio-recorded, transcribed, and thematically analysed.

Results: Analysis revealed four major themes: system performance and design, implementation processes, organisational support and resources, and perceived benefits of the CDS. The pilot implementation allowed for greater user input into the iterative design of CDS in practice, particularly in the Emergency Department, where clinicians had both the capacity and willingness to engage. However, technical issues encountered early in the pilot deterred many users who did not re-engage even after issues were resolved. Although some users remained engaged, they became frustrated as organisational resource constraints meant that critical issues impacting the CDS's clinical utility went unresolved.

Conclusions: Successful CDS pilots depend on the readiness of organisations, departments, and users to engage in pilot activities. Pilot implementations should be pursued in settings where users have both the capacity and willingness to participate in iterative feedback processes and where organisations have sufficient resources to address emerging needs.

Keywords: Decision Support Systems, Clinical; Pilot Projects; Hospitals; Attitude of Health Personnel; Human Centered Design

BACKGROUND AND SIGNIFICANCE

Clinical Decision Support (CDS) systems provide clinicians with targeted information to assist decision-making at the point of care.[1] Although several studies have demonstrated that CDS can improve patient outcomes, practitioner performance and care efficiency, many systems fail to achieve these outcomes and are underutilised once implemented in practice.[2-5] Co-designing CDS with its intended users can result in systems that are useful and easy to use.[6-10] However, not all issues can be predicted or "designed-out", and unanticipated issues will arise once the system is implemented and exposed to real clinical environments.[11-14]

Pilot implementations offer a practical method to determine how a CDS system will fit with existing systems and workflows when used in practice, and to engage users in ongoing system improvement. Piloting a system allows for the early detection and resolution of design and workflow issues, provides useful insight into a systems' utility, and informs whether and how the system could be implemented at a larger scale.[15-17] Though pilot implementations of CDS are common, studies typically focus on CDS performance and outcomes,[18,19] rather than outcomes of the pilot itself (i.e. whether or not to continue to full-scale implementation). Understanding the opportunities and challenges associated with employing pilot implementations of CDS is critical to inform when and how pilots can best be utilised to improve CDS uptake in future. To fill this gap, we conducted a study after the cessation of a pilot implementation of a CDS system in a rural hospital that did not continue to full-scale implementation.

OBJECTIVES

To explore the opportunities and challenges associated with pilot implementations of CDS and develop recommendations for future CDS pilots.

METHODS

Study design and reporting

We employed a qualitative design, using the Non-adoption, Abandonment, Sustainability, Scale-up and Spread (NASSS) framework to collect and analyse data.[20] The study is reported in line with the Standards for Reporting Qualitative Research (SRQR).[21]

CDS intervention and context

The study was conducted following a proof-of-concept pilot project, funded as part of a broader innovation initiative with the state health departments' digital centre of excellence. The initiative aimed to address key challenges in healthcare delivery through collaborations between health services and industry partners. While limited in-kind implementation support was provided by the vendor and organisation, no formal implementation support was scoped or provided in the project.

The pilot leveraged and tested a commercial CDS platform in a rural hospital in New South Wales, Australia. The Emergency Department (ED) was first selected for the pilot due to the willingness of clinical stakeholders within the department to engage. A patient flow-based CDS, while not originally scoped, was quickly deployed to support an urgent emerging need: the COVID-19 pandemic. Doctors were formally engaged in the design of the CDS in the ED, but limited engagement occurred with patient flow nurses. Specific CDS use cases for the pilot were developed iteratively and resulted in different applications being deployed in two departments within the hospital (see Supplementary Material for further detail). These included:

1) A mobile application (app) used by doctors in the ED to enhance visibility of patient information, view patient imaging and test results, and support clinical coding.
2) A dashboard with alerts used by nurses in the Patient Flow Department to virtually monitor a small cohort of COVID-19 patients in inpatient and home care settings.

Setting and sample

Stakeholders, including clinical users, hospital managers and vendor staff, involved in the pilot implementation of the CDS system, were eligible to participate. Participants were purposefully sampled to ensure a diverse range of perspectives were captured and to increase information power.[22,23] First, hospital and vendor staff known to the research team were contacted via email and invited to participate. Additional participants were then recruited through snowballing techniques,[24] where participants recommended other staff involved in the pilot implementation of the CDS.

Data collection

A semi-structured interview guide was developed using the 7 domains of the NASSS framework: the condition, technology, value proposition, adopter system, organisation, wider system and embedding and adapting over time (see Supplementary Material).[20] Questions prompted participants about their experiences with the CDS, the pilot implementation and the removal of the CDS system post-pilot. Interviews were conducted from April to September 2023 by one author (NN), a PhD candidate experienced in qualitative health services research. All interviews were conducted online via video conference, audio-recorded and transcribed verbatim.

Data analysis

All de-identified transcripts underwent independent thematic analysis[25] by two authors (NN and AB or AT). Transcripts were uploaded to NVivo 14.23.1 and inductively coded by developing short phrases (codes) that summarised quotes. Codes were deductively mapped to the 7 domains of the NASSS framework as they were identified. A coding structure was developed by two authors (NN and AB) following analysis of the first transcript, which was discussed and iteratively updated as analysis progressed. We later grouped codes into themes, according to the core issues that emerged. Interviews continued until thematic saturation was reached, i.e. no new overarching themes were identified in transcripts and sufficient conceptual depth to explain these themes was reached.[26] We compared the perspectives of different participants, across the different use cases.

RESULTS

Twelve participants took part in the study, including 6 clinicians, 3 hospital managers and executives, and 3 vendor staff members (Table 1). Of the 6 clinicians, 4 used the ED-based CDS and 2 used the patient flow-based CDS. Hospital managers and vendor staff were involved in both pilots, however two managers mainly provided insight into the patient flow deployment and one vendor participant mainly provided insight on the ED deployment. Interviews lasted an average of 45 minutes.

Table 5. Participant characteristics

Characteristics	Participant ID	n (%)
Role		

Nurse	*P07, P09*	2 (17%)
Doctor	*P02, P03, P06, P11*	4 (33%)
Hospital manager/executive	*P01, P04, P08*	3 (25%)
Vendor	*P05, P10, P12*	3 (25%)
CDS platform involvement		
Emergency department mobile application	*P01, P02, P03, P05, P06, P10, P11, P12*	8
Patient flow dashboard	*P01, P04, P05, P07, P08, P09, P12*	7
Gender		
Male		9 (75%)
Female		3 (25%)
Clinical experience		
5-10 years		2 (17%)
10-20 years		1 (8%)
20+ years		6 (50%)
N/A		3 (25%)

The scope of the ED-based CDS was described to evolve throughout the course of the pilot, while the patient flow dashboard was not scoped in the original pilot but was quickly deployed to support the urgent needs of the pandemic. ED doctors described using the app for 3-6 months, whereas patient flow nurses described using the dashboard for only 2 weeks. We identified 4 major themes, including: system performance and design, implementation processes, organisational support and resources, and benefits of the CDS. Themes, subthemes and related NASSS domains are described below and presented in Figure 1. Barriers and facilitators to individuals' adoption of CDS within each department and ongoing adoption of CDS at the organisational level are described within themes below and presented in alignment with NASSS domains in Supplementary Table S1.

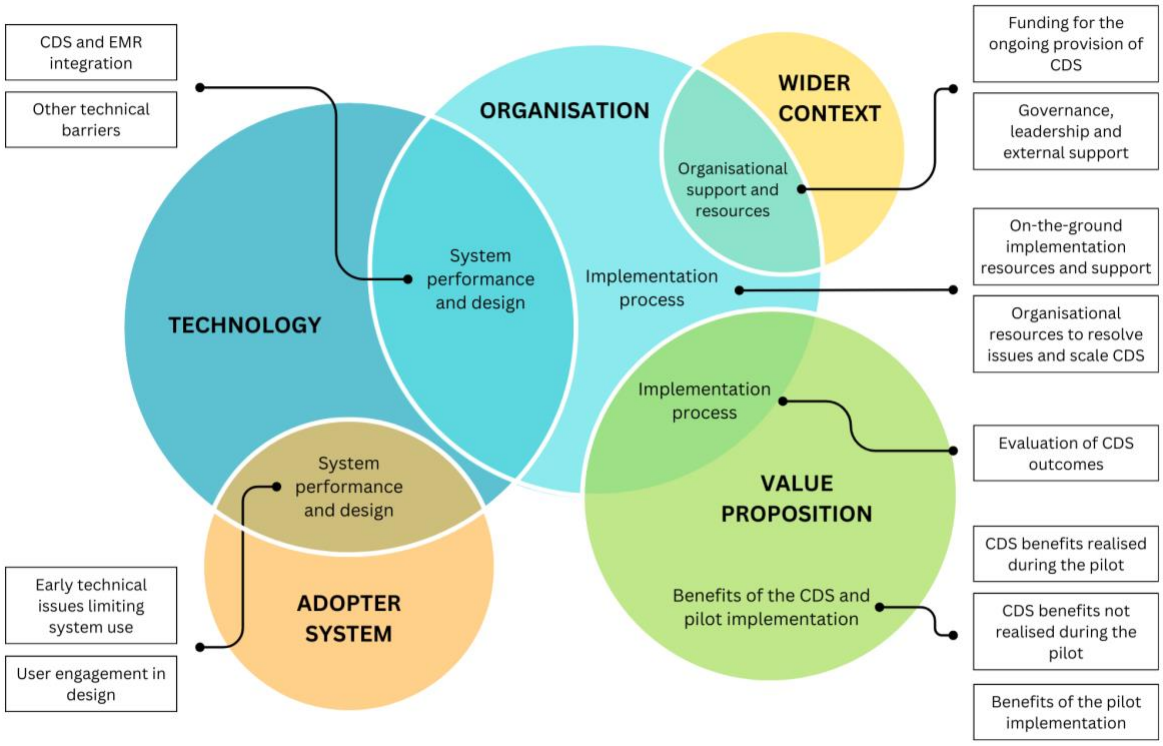

Figure 15. Summary of themes and subthemes aligned to domains of the Non-adoption, Abandonment, Sustainability, Scale-up and Spread (NASSS) framework

System performance and design

Early technical and design issues limiting use (Technology and Adopter System Domains)

Clinicians described several technical issues that hampered use of the CDS shortly after it was made available to users. A vendor participant reported that the ED-based app faced issues with data storage and servers crashing that affected system performance. Though many of these issues were believed to be resolved throughout the pilot, participants reported that several users had already stopped using the system by that stage. An ED doctor reported that "*initially, we would have had 10 or 15 users…probably 50% of them dropped off fairly rapidly. I think there were a number of people that were happy to give it a try but… perhaps couldn't see beyond its current capability*" (P02).

Similar technical challenges were reported with the patient flow dashboard, particularly regarding its integration with remote monitoring devices. For example, oxygen saturations recorded in the dashboard were reported to be inaccurate, which resulted in nurses having to constantly escalate by calling patients to confirm readings. Alerts were perceived to fire in the

dashboard inappropriately, such as when a patient removed the device or when it was out of Bluetooth range, resulting in alert fatigue. Participants felt that these technical issues were not addressed quickly enough after the system went live, contributing to nurses' lack of trust in the system. This trust was perceived to be difficult to rebuild: *"...you can't make any mistakes with the implementation. Because if you do then the trust is broken and the clinicians just won't use it*" (P04).

User engagement in design (Technology and Adopter System Domains)

ED doctors and vendor staff described working together throughout the pilot to enhance the app's design and clinical utility. Though some ED doctors stopped using the app early on, others continued to use the system as they wanted to *"improve the product and deliver what we really wanted it to… improving our processes and our patient care"* (P02). All ED doctors reported that the app was easy to use and that they could easily provide feedback to the vendor, who were quick to respond and resolve most design issues.

Conversely, patient flow nurses perceived they had insufficient input into the dashboard's design and development, contributing to their lack of trust in the system. Although participants perceived a clinical need for tools to improve remote monitoring of patients during the COVID-19 pandemic, they found the dashboard to be "*overly complex and probably overly engineered for the COVID patient cohort, which don't need 24/7 monitoring*" (P04). While participants felt that the system could have been adapted to meet their needs, the instability, unfamiliarity and urgency of the pandemic created pressure to implement a solution as quickly and efficiently as possible. Clinicians in this setting were also perceived to be less willing to participate in the design process or to use the system because "*there was no guarantees beyond the three months or six months. So a lot of the time people felt like they were putting in work for just a real short term thing*" (P04).

CDS and EMR integration (Technology and Organisation Domains)

Ongoing technical issues relating to the integration of the ED-based app and hospital wide EMR were perceived to hamper clinicians' use of the system over time. This included issues with the data feed from the EMR to the app that resulted in out-of-date data, as well as a lack of 'write back' integration from the app to the EMR. Doctors consequently needed to refer to the EMR as the source of truth after checking the app, essentially duplicating work. For

example, when viewing critical test results on the app, doctors described that "*by not having write access, the parent system had no way of knowing whether you'd looked at the information or not*" (P02). Resolving this issue was perceived to be crucial for realising expected benefits and addressing barriers to use. Although write back integration was technically possible, it was not scoped within the pilot and was unable to be addressed due to organisational approval and resourcing constraints.

Other technical issues (Technology and Organisation Domains)

Other technical barriers to using the app in the ED included the need for a separate mobile device (i.e. not a personal device) to use the app that was not used for any other purpose, as well as permissions and sign-on issues that, over time, led clinicians to discontinue use of the system. For example, doctors described forgetting to charge the device, or not bothering to reinstate logins after experiencing sign-on issues. Participants described 'black holes' in the Wi-Fi network throughout the ED and periods where the 4G network would 'drop out', causing a lag in updating of patient information, which limited system use.

Implementation process

On-the-ground implementation resources and support (Organisation Domain)

In the patient flow department, participants perceived there to be limited implementation support and resources, where a lack of change management, onboarding, and training, hindered the dashboards' use. A patient flow nurse explained: "*If we had someone to say, 'Okay, this is the device, this is how it's used. This is the database, this is how you interpret it. If you've got any questions, this is how we escalate.'… there was no real model of care around it." (P09).* This led to concerns around patient safety, where care delivery was described to "*feel unsafe" (P09).* Participants described the lack of implementation support to be especially problematic given they were not involved in the dashboard's design and therefore were unfamiliar with it. Vendor participants attributed this issue to the pilot's shift from a planned pre-production demonstration to a live production trial with real patients, where the necessary resources weren't available to support the expanded scope.

In contrast, despite describing there to be little formal training or implementation support, ED doctors felt comfortable using the system. Those who were involved in the CDS' design described championing the system, promoting it among other clinicians and teaching them how to operate it.

Organisational resources to resolve issues and scale CDS (Organisation Domain)

Several issues were described to stem from a lack of financial support, planning and staffing for the pilot. This included a lack of project management personnel that participants perceived would have been assigned if the CDS were implemented following a traditional implementation approach. One participant from the vendor organisation described there to be "*no one else there except the doctors, and some time from one of the IT (Information Technology) staff to make some of these difficult sort of technology changes that we were working through*" (P10). This caused issues, for example, where no IT specialists at the organisation had the appropriate skillset to complete the write back integration from the app to EMR. Similarly, participants described the spread of CDS to other users, such as specialists in inpatient departments, being blocked due to a lack of organisational funding and resources to expand the scope of the pilot.

Evaluation of CDS outcomes (Organisation and Value Proposition Domains)

Participants perceived there to be a lack of formal evaluation and limited time to establish and demonstrate benefits of the pilot. Consequently, the value of the system was unable to be demonstrated both to leadership in the organisation to justify ongoing costs, or to clinicians on-the-ground to drive their ongoing use of the system. One ED doctor described: "*if they had good outcomes from it, we hadn't really had feedback as end users… we never really knew the outcome… we don't know what we achieved*" (P11).

Organisational support and resources

Funding for the ongoing provision of CDS (Organisation and Wider Context Domains)

A lack of funding for the ongoing provision of the CDS was raised by a number of participants. This was often perceived as due to the organisation being a rural health service. Some participants perceived that the organisation did not have the budget available to support ongoing investment in the CDS, which they felt ultimately led to the decision not to continue with the system post-pilot. Organisational leadership described it to come down to a "*cost versus benefit decision. The time when the decision had to be made, we could not make a compelling argument to continue on*" (P01). Given the COVID-19 pandemic arose during the

pilot, some participants also attributed the resources required for the pandemic to be prioritised over resources required to support the ongoing provision of the CDS.

Governance, leadership and external support (Organisation and Wider Context Domains)

Most ED doctors perceived there to be good support for their use of the mobile app from departmental and executive leadership. However, participants suggested the project lacked appropriate governance structures within the hospital to support required approvals, for example to resolve integration issues. One staff member was frequently mentioned by participants as the driver of the pilot at the organisational level. However, this individual resigned during the pilot and participants perceived this loss to be a major barrier to the project's success: "*you lose one person and you don't have anyone who's driving that, who knows all the details through the organisation and how to pull it together*" (P05).

A lack of continued support from the state government agency responsible for the innovation initiative was also raised by vendor participants as a challenge for the ongoing provision of the system at the hospital. This was perceived to be particularly important given resources available at the local level were limited.

Benefits of the CDS and pilot implementation

Participants described a range of benefits resulting from CDS use, as well as potential or future benefits that were expected, but not realised during the pilot. Additionally, benefits resulting from the pilot implementation process were described.

CDS benefits realised during the pilot (Value Proposition Domain)

ED doctors perceived the app to improve communication and collaboration between staff, increase mobility within the department, increase accessibility to the EMR, and improve efficiency during handover. In the patient flow department, participants described instances where the dashboard had identified deteriorating patients, which enabled nurses to quickly respond. Vendor and organisational leadership participants highlighted the real-time extraction of data from the EMR for CDS use as a valuable capability demonstrated during the pilot, noting that this had not been achieved previously. Unanticipated benefits were also

raised, such as retaining access to patient information during a period of unexpected EMR downtime.

CDS benefits not realised during the pilot (Value Proposition Domain)

Potential benefits of the CDS systems, such as improved workflow efficiency, patient experience and safety, and cost-effectiveness were recognised but perceived as not being realised in the pilot due to technological, implementation and organisational barriers. Participants who described using the system for a longer period mostly stated that their motivation to continue using it was due to these larger scale benefits that they expected the system would deliver. However, they described using it less over time as these expectations were not met.

Participants who held leadership roles perceived the CDS' value to remain unrealised as it was not scaled across users, departments and hospital sites, describing that "*the benefit lies in scalability. Having it in just one department in the hospital was never going to deliver the full benefits of the system" (P01).* Limited scaling of the system was attributed to a lack of marketing across different users, departments and hospitals within the health district.

Benefits of the pilot implementation

Participants described benefits arising from the pilot process, such as facilitating the broader development of clinicians' skillsets and creating networks for the health service and individual clinicians with healthcare innovators. Those from the vendor organisation described securing new contracts following the pilot, where '*the genesis of what's in there (the contracted product) came from some of that work'* (P12).

DISCUSSION

This study provides critical insights into the opportunities and challenges associated with pilot implementations of CDS systems. Though some opportunities were identified, the current study mostly revealed challenges. We found limited added value for ED clinicians (due to unresolved technical issues), and for organisational leadership (due to the limited use and scale of the CDS across the organisation, and the departure of the pilots' champion), as key challenges contributing to the removal of the CDS system post-pilot. Technical issues,

compounded by a lack of user input into CDS design and instability during the COVID-19 pandemic, led nurses to reject the patient-flow CDS shortly after its implementation. These issues were created or amplified by the limited organisational, implementation and evaluation resources dedicated to the pilot. Though previous studies have demonstrated that CDS' level of integration,[27] perceived value,[28-30] and user input[31] can impact clinicians' acceptance of a system, this study underscores their criticality by providing evidence that CDS implementations may not be sustained when such needs go unmet.

Although the pilot did not continue to full-scale implementation, our research suggests that pilot implementations can provide valuable opportunities to involve clinicians in ongoing CDS design and to make a system's value visible within and beyond an organisation. For example, the pilot facilitated lasting networks between health services and innovators and demonstrated the technical feasibility of extracting EMR data for use in CDS systems. These outcomes laid the groundwork for further initiatives that were pursued beyond the pilot. While some benefits of both CDS' were observed during the pilot, clinicians perceived these to be of lower impact than those that were not realised, as they either had minimal direct effect on their daily work or were overshadowed by significant barriers to system use. Like previous research, we emphasise that CDS systems be designed to deliver clear, direct benefits to end-users while also addressing broader organisational and patient outcomes, with efforts made to effectively communicate these broader benefits to clinicians.[32]

Users that were heavily involved in CDS design, i.e. in the ED, found the system to be intuitive and recognised its potential to deliver valuable clinical benefits. However, key issues raised by users went unaddressed in the pilot due to organisational approval bottlenecks and resource constraints, preventing these benefits from being realised. Future pilots should therefore implement robust governance structures to facilitate the timely resolution of user-identified issues and enhance responsiveness to evolving needs.[33-35] Furthermore, while many ED clinicians were willing and able to be involved in the pilot, patient flow clinicians lacked capacity to fully engage due to the urgent demands of the pandemic. This highlights the importance of matching CDS systems and implementation approaches to the needs, capabilities and capacity of organisations, departments and users. CDS implementers may additionally consider evaluating the readiness of organisations and users to engage with the technology and pilot process.[36-38]

Another key finding was that negative user experiences early after implementation played a crucial role in shaping the long-term success of the CDS system, providing insight into why previous research has found system usage can remain low even after initial issues are resolved.[12,39] Our research suggests that, even in pilot implementations, CDS systems should be deployed with a sufficient level of maturity to prevent lasting user disengagement. Future pilots may wish to purposefully select a small group of early adopters who can participate in the iterative design process and pave the way for broader adoption by later users, who may prefer a more stable system that delivers immediate benefits.[40]

Lastly, our study expands on the unique challenges faced by pilot implementations in health service environments.[15-17,41] Like previous research, we found that clinicians viewed the pilot as a temporary initiative, which disincentivised their engagement with the system and design process.[15] Additionally, the conceptualisation of the project as a pilot meant that limited resources and organisational structures were established to support it. The pilot was therefore found to be particularly vulnerable to organisational changes, such as the departure of key personnel and shifting priorities during the COVID-19 pandemic. We recommend pilots be supported by robust project and change management, evaluation, and organisational oversight to mitigate these risks and secure the strong and sustained commitment needed for CDS success.[42-44]

Limitations of this study included the relatively small sample size, particularly in certain categories of participants such as users of the patient-flow dashboard, and the likelihood that those who chose to participate in the research were individuals more engaged with or invested in the technology. As a result, some nuances in user experiences may not have been fully captured. Additionally, our focus on a single rural hospital may limit the generalisability of findings to dissimilar settings. For example, urban hospitals are likely to have greater access to IT specialists and resources, which could mitigate technical challenges such as those relating to system integration and connectivity infrastructure that were faced in the current study. Despite this, our findings are strengthened by the information power of our sample,[23] alignment with previous research conducted on CDS and pilot implementations in other contexts, and alignment to the NASSS framework. Another limitation is that we relied on retrospective accounts from participants, which may have introduced recall bias.[45] However, this provided an opportunity to explore what unfolded following pilot cessation, offering valuable insights into its longer-term impacts. Future research may wish to validate

and expand on our findings by prospectively studying CDS pilots in differing contexts and incorporating quantitative usage metrics to evaluate actual use of CDS during pilot implementations.

CONCLUSIONS

While pilot implementations can offer a useful approach to engage users in CDS design in practice and expose the potential benefits a CDS can offer, pilots also present unique challenges and should be approached with caution. To be effective, pilot implementations must be supported by adequate organisational and implementation resources, to ensure that iterative design based on user feedback can be fully addressed. CDS implementers should carefully weigh the potential benefits and challenges of utilising a pilot approach and consider the readiness and fit of the organisation, department and its users for the technology and implementation approach.

Clinical Relevance Statement

This study provides practical insights for healthcare organisations and vendors looking to implement Clinical Decision Support (CDS) systems. CDS implementers can leverage insights from the opportunities and challenges identified to select the most suitable implementation approach. By applying recommendations, they can optimise future pilot implementations and increase the likelihood of achieving successful and sustainable adoption of CDS systems.

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Conflict of Interest

The authors declare no conflicts of interest.

Protection of Human Subjects

The study was performed in compliance with the World Medical Association Declaration of Helsinki on Ethical Principles for Medical Research Involving Human Subjects and was reviewed by the Sydney Local Health District Ethics Review Committee (#2021/STE04111).

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SUPPLEMENTARY MATERIAL

Intervention and pilot description

The project was funded as a proof-of-concept pilot in August 2018, aiming to mobilise data to improve the safety and quality of care during a patients' stay in hospital. The pilot originally intended to demonstrate Clinical Decision Support (CDS) functionality within a test environment only. However, in initial meetings with project leadership, it was agreed that real-world testing with clinicians in a clinical environment was needed to prove the functionality. The CDS systems deployed utilised the same platform, developed by a single vendor.

Emergency Department (ED) CDS

Vendor staff conducted site visits to the hospital to collect informal feedback from clinicians before and during the pilot. Additionally, they held two formal workshops with clinicians to identify the minimum dataset required and gather feedback on a live prototype before the pilot, and another two formal design workshops with clinicians during the pilot. ED clinicians had direct access to the vendor via phone call to request minor changes or report issues during the pilot.

A mobile application (app) was deployed and piloted with ED doctors, which aimed to provide enhanced access to patient information, track patient activity and notify doctors of critical test results within the ED in real-time to reduce cognitive load and increase mobility, and to enhance the accuracy of clinical coding.

- **Integration**: The app provided mobile access to the Electronic Medical Record (EMR) (Cerner), receiving real-time data through one-way integration (from the EMR to the app).
- Key **features** of the app included:
    - Ability to see all key elements of the EMR on a mobile device
    - Ability to track patients in the ED and quickly access patient lists
    - Ability to have quick access to radiology results on a mobile device
    - Ability to quickly review past visits for a patient on the mobile device
    - Ability to identify key conditions from past hospital encounters through natural language processing
- **Timeline**: The pilot implementation of the app occurred between June 2019 – February 2022.

Patient flow department CDS

A dashboard system with embedded alerts was deployed and piloted with patient flow nurses, which aimed to support the monitoring and management of patients with COVID-19 and detection of potential deterioration. Online meetings were held with operational and clinical staff prior to deployment.

- **Integration**: The dashboard received real-time data from the EMR (Cerner) and remote monitoring devices that provided continuous (24/7) monitoring of a small

cohort of patients who were diagnosed with COVID-19 in inpatient and home settings.

- Key **features**:
    - Ability to view patient details using data (e.g. name, age) from the EMR
    - Ability to continuously monitor a series of vital signs (e.g. blood pressure, respiratory rate, skin temperature, heart rate, and oxygen saturations) from remote monitoring devices
    - Ability to receive alerts from the dashboard based on incoming data from remote monitoring devices
- **Timeline**: The pilot implementation of the dashboard occurred between April 2020 - September 2021.

Interview Guide

General questions about the CDS

1. What decision support tools/products did you use? E.g. app, dashboards, logic
    a. What device/s did you use it on?

Condition

2. What illness/es or condition/s was the decision support tool/s designed for?

Technology/technologies

3. How did the tool/s support your work? i.e. what tasks did you use it for?
    a. Were there some tasks that the tool supported better than others?
4. What did you think of the decision support system's performance and dependability?
    a. How well do you think it supported the tasks it was designed for?
    b. What worked about the tool/s? What did you like about it?
    c. What didn't work about the tool/s? What didn't you like about it?
5. How did the decision support tool/s integrate with other systems?
    a. What other systems are used in your department?
        i. E.g. EMR, other devices (remote monitoring etc.), pathology

Adopter system

6. Who were the main users of the decision support?
7. How were you and other users involved in the design of the decision support?
8. How usable and acceptable did you think the decision support tool/s were to you and other users? E.g. trust, ease of use, time taken, workflow fit
    a. How often did you use the tool? Why or why not?
        i. Were there any differences in how you used the tools over time?
9. How do you think the decision support tool changed the way healthcare was delivered?

Value Proposition

10. Can you give me an example of how the decision support tool added value to patients?
    a. What was valuable about it?
11. Can you give me an example of how the decision support tool added value to you and other clinicians?
12. Can you give me an example of how the decision support tool added value to your organisation and the healthcare system?
13. Did the technology generate any negative value (i.e. any costs, risks, or disruption) for you or other stakeholders? Did the benefits of the tool outweigh any risks?

Organisation

14. What do you think of the organisation's overall capacity to take on technological innovations? E.g. leadership, slack resources, previous experience, risk-taking
    a. What about at the local departmental level?
15. How did your organisation go about implementing the DS tool? Prompts:

a. How ready do you think your organisation was for the decision support tool when it was implemented?
b. How were you trained to use the tool?
c. What supporting resources (e.g. guidelines, procedures, education) were you provided with?
d. Were leadership or other clinicians supportive of its use?

16. Did any organisational routines, pathways and processes change to accommodate the decision support tool? How?

The wider context

17. What were some of the external challenges at the time of the implementation? E.g. political climate, professional, clinician, legal, patient, organisation?

Embedding and adapting over time

18. How long did you use the decision support tool for?
19. Could you or other users provide feedback on the decision support tool following its implementation? How?
20. Were any changes made to the decision support tool following its implementation?
    a. Did these changes accommodate yours or other users' needs? How?

Pilot cessation

21. What do you think are the main reasons that caused the decision support tool to be removed?
    a. Were there any external changes that contributed to it?
    b. Organisational changes?
    c. What caused you to stop using the decision support tools?
22. Is there anything you would do differently, or encourage others to do, if a new decision support system were being implemented? i.e. lessons learnt
23. Do you have any other comments about the decision support tool or pilot?

Supplementary Table S1: Barriers and facilitators mapped to NASSS domains

Domain	Theme	Emergency Department	Patient Flow	Organisational adoption
Technology	Integration and interoperability	-	-	-
	Alert fatigue	N/A	-	N/A
	System maturity	-	-	N/A
	User engagement in design	+	-	N/A
	Changes to made technology	+ / -	-	N/A
	Fit with clinical need	+	-	N/A
	System performance, usability, and satisfaction	+ / -	-	N/A
Organisation	Implementation support	+	-	N/A
	Departmental stability	N/A	-	N/A
	Evaluation and feedback	-	N/A	-
	Trial nature of implementation	N/A	-	-
	Organisation-wide technology infrastructure	-	N/A	N/A
	Fit with workflows	-	-	N/A
	Departure of pilot champion	-	N/A	-
	Organisational resources, structures and leadership support	+ / -	N/A	-
Value Proposition	Benefits of the system	+	+	+
	Potential benefits of the system	+	+	+
	Did not deliver expected value	-	-	-
	Benefits of the pilot implementation	+	N/A	+
Adopter System	Champions and super users	+	N/A	N/A
	Familiarity	N/A	-	N/A
	Trust	+	-	N/A

Wider Context	Impact of COVID	N/A	-	-
	Government support	N/A	N/A	-

Note: Barriers (-) and facilitators (+) to individuals' adoption of CDS within each department and ongoing adoption of CDS at the organisational level

CHAPTER 6

PREFACE

Chapter 6 explored doctors' experiences of alert fatigue, a well-documented and prevalent challenge associated with the use of alerts, the most common type of CDS used in routine clinical practice. As discussed in Chapter 1, alert fatigue is often cited as a factor that leads to the persistent disuse of CDS, representing significant threats to patient safety. However, in Chapters 1 and 2, I highlighted that limited research has qualitatively evaluated how experiences of alert fatigue develop and contribute to patterns of alert disuse over time. Chapter 6 addresses these gaps through an in-depth qualitative exploration of doctors' experiences with alert fatigue in hospital settings where alerts were routinely embedded in practice. This chapter shed light on how doctors with differing levels of experience perceive and interact with alerts, the factors that contribute to subjective experiences of alert fatigue, and how these experiences evolve as doctors become more experienced with alerts and clinical decision making. These findings build on the results and gaps discussed in Chapter 4, which identified alert fatigue as more frequently reported in later stages of implementation, and a need for further research on how new users accept and use CDS systems that are already embedded in routine practice.

Manuscript under review

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What is alert fatigue and what contributes to doctors' experiences of it? A qualitative study

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ABSTRACT

Background: Alerts, a key feature of Electronic Health Record (EHR) systems, intend to improve patient safety by providing timely information at the point of care. However, many EHR systems generate excessive alerts that are not immediately clinically relevant and that contribute to alert fatigue. Despite growing recognition of alert fatigue as a safety concern, clinicians' experiences of alert fatigue and the broader system-level factors that contribute to it being experienced are not well understood.

Objectives: Use a human factors approach to comprehensively explore how alert fatigue is experienced by doctors, identify alert fatigue's contributing factors, perceived influences and impacts, and strategies to address it in practice.

Methods: Semi-structured interviews were conducted with junior doctors working in hospitals across Australia. Data were thematically analysed using a hybrid inductive and deductive approach, informed by the Systems Engineering Initiative for Patient Safety (SEIPS) and an information processing model.

Results: Twenty doctors were interviewed. Alert fatigue was described to occur at different stages of information processing, including when alerts were not detected, superficially processed using mental shortcuts, or required excessive cognitive effort to interpret. When alerts were not detected or thoroughly processed, participants more often perceived impacts on patient safety and care quality, whereas when alerts required excessive cognitive effort; interruptions, frustration, and time and effort loss were frequently reported. Contributors to alert fatigue were reported to include technology, task, and environmental factors such as the interface design and clinical relevance of alerts, and information overload from system alerts as well as other alerts and tasks. Alert fatigue was described to be experienced differently depending on provider characteristics, such as experiences with and knowledge of alerts, mood, and personality, and organisational factors including culture, shift type and time of day.

Conclusion: Alert fatigue is not a binary concept but instead experienced on a continuum and influenced by interacting individual, technical and contextual factors. Addressing alert fatigue requires tailored interventions that target its different causes and outcomes. These could include technical and design improvements, changes to organisational practices, and individual customisation to reduce experiences of fatigue and accommodate differences in clinicians' needs.

Keywords: alert fatigue; clinical decision support systems; alerts; hospitals; doctors; human factors; digital health

INTRODUCTION

Clinical Decision Support (CDS) systems have proliferated in healthcare, forming a core component of many Electronic Health Record (EHR) platforms now used in routine practice.[1,2] Within these systems, alerts represent the primary mode of CDS delivery.[3] Alerts can interrupt clinicians' workflows during their interactions with the EHR (interruptive alerts), or passively display CDS through icons or flags that require users to actively seek information out (passive alerts).[4] While alerts are designed to support clinical decision making and enhance patient safety by providing relevant information at the point of care, many systems generate excessive alerts that are not immediately clinically relevant.[5-9]

Alert fatigue is a widely reported concern arising from excessive alerting, but as a concept it remains poorly understood and inconsistently measured.[2,10] Existing research has largely relied on observable behaviours, such as alert overrides and response times, to infer the presence of alert fatigue, assuming that clinicians experiencing alert fatigue will dismiss alerts without considering their content.[11,12] While some studies suggest that alert fatigue arises when clinicians become cognitively overloaded by alerts,[7] others report it to be driven by desensitisation that develops following repeated exposure to the same alert over time.[13,14]

These inconsistencies highlight the limitations of using behavioural proxies to measure what is fundamentally a *subjective* mental state.[15,16] Observable behaviours cannot fully capture clinicians' cognitive experiences and offer limited insight into the broader factors that contribute to fatigue.[17] Similarly, while alert fatigue is frequently identified as a barrier to clinicians' use of alerts in qualitative studies, these studies are typically concerned with overall alert experiences rather than examining alert fatigue itself and the factors that shape it.[18-20] As a result, definitions of alert fatigue and its perceived causes and impacts, remain superficial and lack a systemic perspective.

Human factors methods have been widely applied in healthcare to understand and address system-level factors that impact care delivery, patient safety, and performance outcomes.[21] These approaches are well suited to investigating complex, dynamic issues like alert fatigue, as they account for the cognitive and behavioural processes that occur during clinicians' interactions with technologies, within the broader context of the tasks, organisational settings, and environments, in which these interactions occur.[22,23] Accordingly, this study aimed to

comprehensively explore how alert fatigue is experienced by doctors, identify alert fatigue's contributing factors, perceived influences and impacts, and strategies to address it in practice.

METHODS

Study design

This study is reported following the Standards for Reporting Qualitative Research.[24] A qualitative design, using semi-structured individual interviews, was selected to explore the subjective and nuanced nature of alert fatigue within healthcare in depth.[25,26]

Theoretical frameworks

The Systems Engineering Initiative for Patient Safety (SEIPS) is a human factors model used in healthcare settings to identify and address safety concerns.[23] The SEIPS describes the 'work system', which comprises five components including the *person* (both patients and healthcare providers) at the centre of care, who perform *tasks*, using various *tools and technologies* within a *work environment* and under specific *organisational conditions*. Interactions between the components of the work system influence the delivery of care and other *process*es, which in turn impact *patient*, *employee and organisational* outcomes. The SEIPS model was used to interpret and present data.

We used an information processing model as outlined by Wickens and Carswell (2021) to further interpret the *process* by which alert fatigue was experienced by participants.[27] The model describes information processing as a sequential process involving four stages: *selecting information* (detecting stimuli from the environment), *perception and data interpretation* (recognising and interpreting the stimuli), *comprehension and cognition* (processing and integrating information with prior knowledge to assess relevance and meaning), and *action selection* (choosing and executing a response based on the processed information). This model was well suited to understanding the mental processes of alert fatigue and associated actions arising from its presence. Although alert fatigue has previously been described in the context of information processing,[28] an analysis of how alert fatigue manifests across different stages has not been explored. A schematic of the integrated models is presented in Figure 1.

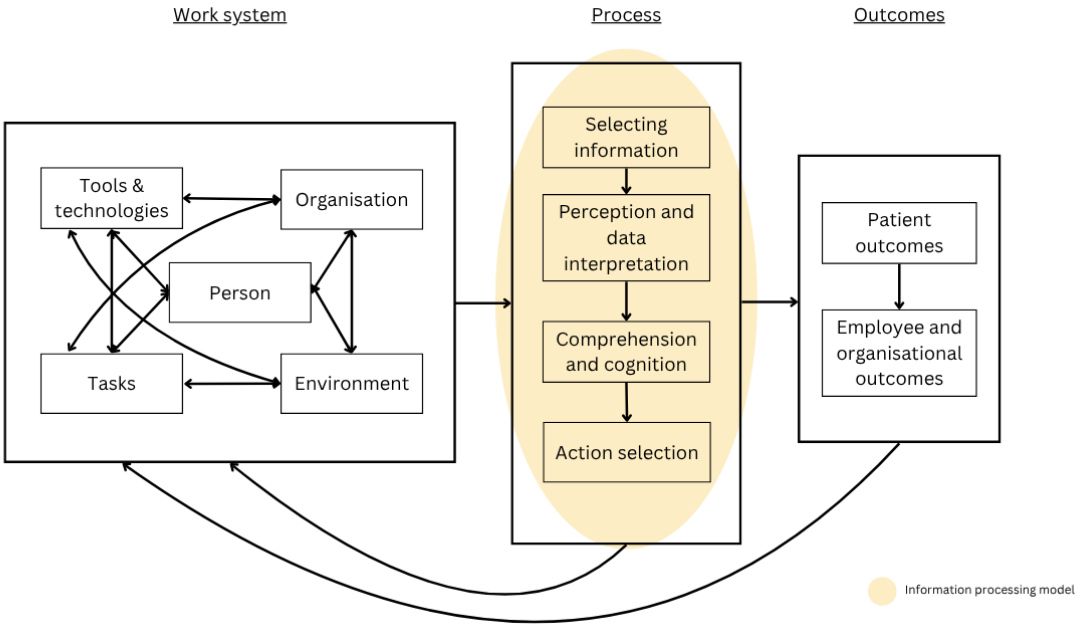

Figure 16. Schematic of the integrated SEIPS and information processing models used to interpret data

Study team

The study team included researchers with expertise across human factors, digital health, health services, sociology, and psychology; and hospital-based pharmacy directors. Additionally, two members of the study team were junior doctors, who provided lived experience insights.

Participants and recruitment

Eligible participants were current practising clinicians including Junior Medical Officers (JMO), defined as Interns (Postgraduate Year 1; PGY1), Residents (PGY2), and Registrars (PGY3+), who had interacted with alerts in clinical information systems (e.g. EHR and Electronic Medical Record (EMR) systems) in hospital settings in Australia. Junior doctors were selected for the study as they are typically the most frequent recipients of alerts in hospital settings. A convenience sample of participants was recruited by disseminating details about the study through email distribution lists, posters, and presentations at JMO training sessions, at two hospitals within the same hospital network. Additional participants were recruited via snowball sampling through the authors' professional networks, including word of mouth, LinkedIn posts, and emails to hospital contacts who circulated the study to JMO

networks. Prospective participants were encouraged to contact the researchers via email if they were interested in participating.

Data collection

A semi-structured interview guide was developed using insights from existing research on alert and alarm fatigue and discussion among all authors.[7,13,29] Two pilot interviews were conducted by one author (NN) with JMO co-researchers via Microsoft Teams, which resulted in minor refinements to the interview guide, such as adding new questions and changing the order of questions to enhance flow. Questions centred around participants' use of alerts, their perceptions and experiences of alert fatigue, factors influencing alert fatigue, the impact of alert fatigue and recommendations to reduce experiences of alert fatigue in practice (see Multimedia Appendix 1). Individual interviews were conducted with participants by one author (NN) using Microsoft Teams, Zoom or phone. Three participants were known to the interviewer prior to interviews through their professional and personal networks.

Interviews were audio recorded, transcribed using Otter AI software,[30] and checked for accuracy. Transcription and analysis occurred in parallel to data collection, allowing for further refinement of the interview guide to explore themes in depth as interviews progressed. Interviews continued until data saturation was reached i.e., no new themes emerged in the final interviews and only new examples or perspectives relating to existing themes were identified.[31]

Data analysis

Transcripts were imported into NVivo 14[32] and thematically analysed using a combined inductive and deductive approach.[33] The first 6 transcripts were independently analysed by two authors (NN and MB, AB or RF) who inductively coded quotes. Themes were deductively mapped to four categories: defining alert fatigue, factors influencing experiences of alert fatigue, the impact of alert fatigue, and strategies to reduce alert fatigue. Each pair of authors met to discuss alignment and resolve discrepancies following the coding of 2 transcripts.

Following discussions, 3 of the 4 original categories were restructured under the SEIPS model, where codes related to defining alert fatigue were moved to *processes*, factors influencing experiences of alert fatigue were moved to the *work system*, and the impact of alert fatigue was moved to *outcomes*.[23] Themes related to the process of alert fatigue were further interpreted using the information processing model.[27] Remaining transcripts were analysed by one author (NN) using the refined coding framework, adding new codes and themes to this framework as they emerged. Upon completion of analysis of all interviews, four authors (NN, MB, AB, RF) participated in a workshop to discuss the categorisation of codes and themes, which resulted in refinement of analysis, primarily through some codes being renamed, merged and/or recategorised. The coding framework was then presented to all authors and select participants for member checking, who provided input and agreed upon the final thematic structure.

Ethical considerations

Ethical approval was received from ACT Health Low Risk Ethics Committee (Protocol 2024.LRE.00024). All participants provided written informed consent to participate in the study.

RESULTS

Summary

Twenty interviews were conducted between August 2024 and March 2025. Participants included 9 interns (PGY1), 6 residents (PGY2) and 5 registrars (PGY3+), working at 10 hospital sites, across 3 Australian states (see Table 1). Interviews lasted between 18 and 56 minutes, with an average length of 33 minutes. Two interviews were conducted via phone and the remainder via video conference.

Table 6. Participant characteristics

	Participants, n (%)
Role/PGY	
Intern (PGY 1)	9
Resident (PGY 2)	6
Registrar (PGY 3+)	5
Gender	

Male	12
Female	8
Length of time at current hospital	
Less than 2 months	3
2 months to 1 year	6
1 to 2 years	4
2+ years	7
Clinical experience total (including prior clinical work)	
Less than 2 months	2
2 months to 1 year	3
1 to 2 years	4
2-5 years	5
5+ years	6
State	
NSW	11
ACT	7
SA	2
Systems used for alerts	
Commercial	18
Commercial and homegrown	2

Participants received alerts from EHR, EMR and/or electronic medication management systems. All participants were users of commercially available EHR/EMR systems (e.g., Epic, Cerner, Sunrise, Medchart), while two participants also used a similar homegrown system. Alert types included passive and interruptive alerts such as those for medications (e.g, allergy, drug-drug interactions and dosing), and best practice (e.g., VTE prophylaxis, advanced care directives and resuscitation plans). Alerts popped up during tasks such as medication ordering, opening patient charts, and opening the EHR system. Alerts outside of standard clinical information systems ('system') were also described.

In the following sections, we present clinicians' perceptions of alert fatigue (process), contributing factors (work system), impacts (outcomes), and potential strategies for addressing alert fatigue. See Figure 2 for a schematic of themes aligned to the SEIPS model.

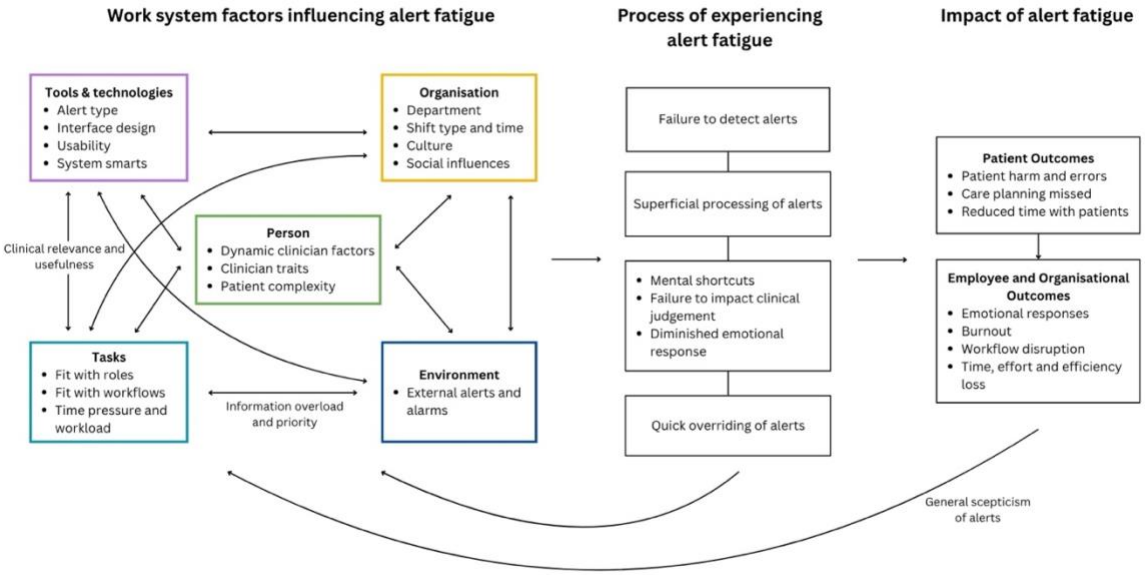

Figure 17. Schematic of themes relating to experiences of alert fatigue within the SEIPS model

The process of experiencing alert fatigue

Alert fatigue emerged across different stages of information processing.

Selecting information

Selecting information involved the detection of alerts. Alert fatigue manifested at this stage as a failure to notice alerts or detect stimuli. This occurred mainly for passive alerts, which were often described to be inconspicuous, but also for interruptive alerts:

> *"it's not really a new stimulus anymore. The idea of alerts being there is just part of the job, it's just part of the furniture…I probably at least once will miss the fact that [medications are] expiring, my eyes will gloss over it" (P1).*

Perception and data interpretation

Perception and interpretation involved recognising and processing alerts. During this stage, clinicians described superficially processing alerts by only partially viewing or reading them before responding. Participants explained that alerts were often pre-empted based on the

users' interactions with the system before an alert was triggered or identified by design features such as titles, key words, fonts, colours and layouts. Many participants felt that they could quickly and effectively recognise these alerts and often did not feel 'fatigued' to alerts that were processed in this manner: "*it's so mindless, like, you're not processing anything. All you process is, it's an ECG one, cancel, it's an ACD one, cancel. That's all you're processing*" (P14).

Comprehension and cognition

Comprehension and cognition involved assessing the relevance of alerts to inform decision-making. Participants described initially reading and actively interpreting the value of alerts. However, alert fatigue occurred where active interpretation of alerts and influence on clinical judgement ceased, and mental shortcuts instead guided responses:

> *"I would have read the alert the first time, but then…you go, 'okay, I know what this alert is about', and the next day you would have forgotten which drugs are even mentioned. I just know that this is not relevant to me" (P13).*

Emotional responses to alerts, such as anxiety and stress, were reported to be common early on:

> *"I was very scared of every single kind of alert, it's like, 'Oh my gosh. What do I do? This is telling me there's a problem and I need to do something before I can even access the file', and that's quite stressful" (P01)*

However, this diminished over time as users reported becoming desensitised and 'complacent'. Conversely, some clinicians reported experiencing alert fatigue due to the cognitive effort and time required to interpret and appropriately respond to alerts.

Action selection

Action selection comprised users' responses to alerts. Alerts that were quickly and habitually overridden signified alert fatigue at this stage. For example, participants described being "*so*

used to clicking boxes" (P06) that "*you just click through them automatically*" (P13), and "*it's like a whack-a-mole. You're just getting rid of everything as fast as you can*" (P14).

Some participants said that they broke habitual responding patterns when for example, their role changed, or they made an error due to experiencing alert fatigue. However, these patterns were likely to return: "*after a while, you desensitise yourself again after that going well, it hasn't happened for a long time, and your brain kind of becomes complacent again, with going Yes, yes, yes, through all the tick boxes*" (P18). Some alerts that were quickly overridden were however, sometimes still perceived to be useful as they prompted consideration and did not take excessive cognitive effort to process.

Work system factors influencing experiences of alert fatigue

Factors were coded to all work system domains of the SEIPS, Figure 3 shows the distribution of coded references within each domain.

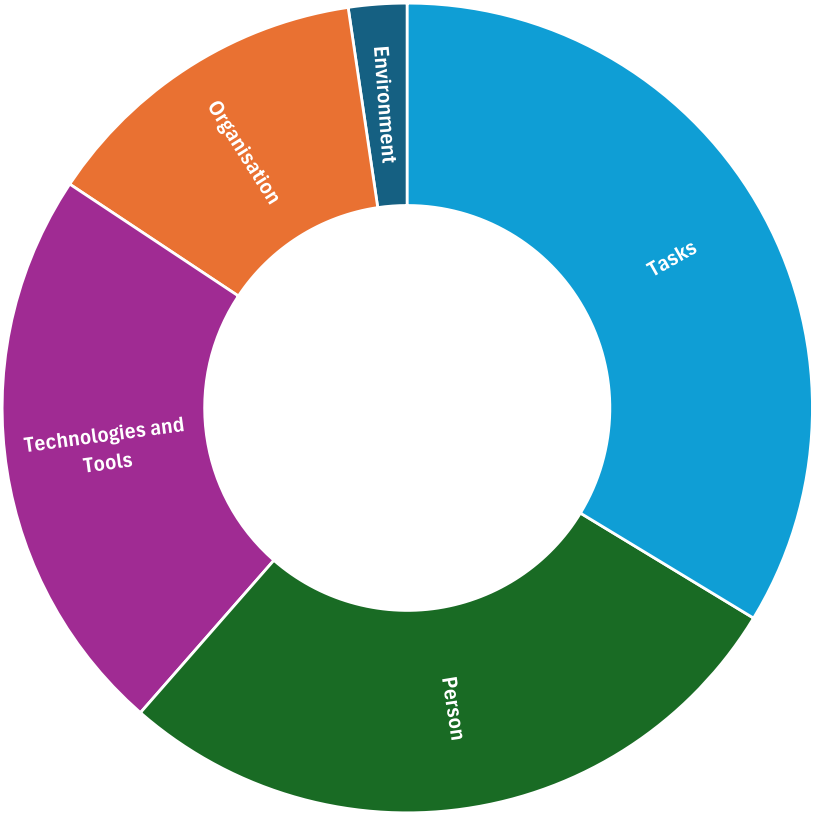

Figure 18. Proportion of coded references related to alert fatigue mapped to each SEIPS work system domain

Person

Patients' clinical complexity was reported to influence alert fatigue. Some participants described paying closer attention to alerts for unstable patients, while others described increased fatigue due to the volume of alerts that complex patients triggered.

Clinician traits, including clinician type, their clinical experience and personality, also influenced alert fatigue. While many participants believed senior clinicians experienced greater fatigue, participants who were more senior often described experiencing less fatigue than when they were junior, as they had more confidence and consequently used less cognitive effort to appropriately respond to alerts: "*when I was more junior and didn't quite understand as well, I would often just go, 'advice ignored', without really understanding the reason why*" (P13). Personality traits were also raised, where participants who were more meticulous said they paid more attention to alerts: "*for me personally, I don't like just dismissing alerts without actually thinking through it*" (P19).

Alert fatigue was influenced by dynamic factors that evolved based on individuals' experiences with alerts over time. Those who possessed a positive attitude toward alerts generally reported experiencing less fatigue: "*I just view these alerts as another opportunity to make sure you have the whole picture*" (P10), and

> *"if you think it's a pain in the ass, then it's something that's going to irritate you every time. But if your attitude is, which mine is, is- 'it's just part of the job', so you just get on with it" (P15).*

Alert fatigue was also influenced by participants' knowledge and perceived importance of the risk the alert was targeting, including personal experiences of missing information or making errors: "*if I don't understand or agree with the importance, I'm much more likely to dismiss it with so many other competing priorities*" (P17). Additionally, some clinicians explained they did not know how to correctly respond to alerts: "*no one told me how to…no one knows. So*

you just choose something that makes sense" (P2). Others described remaining cautious and attentive to alerts due to their awareness of alert fatigue.

Alert fatigue was also reported to be influenced by clinicians' emotional state, including their mood "*if I'm having a really rough day, it's probably overall going to be more annoying*" (P1), and whether they were experiencing other forms of fatigue: "*you feel more emotionally drained, less sympathetic, less compassionate, and you might dismiss things more*" (P1).

Tasks

At the task level, alert fatigue was influenced by the alignment of alerts with workflows, clinical relevance and usefulness, fit with specific roles and responsibilities, time pressure and information overload. Fatigue was often reported to occur where alerts were misaligned with organisational processes, clinicians' work and decision-making flows. Poorly timed alerts, such as those triggered upon opening a patient's chart, were typically reported to be quickly dismissed: "*I intend to view their chart with a very specific goal and updating the resuscitation right then is not a priority*" (P16). Interestingly, some participants described experiencing less fatigue due to the poor utility of alerts that they currently received: "*we do not get effective alerts from EMR at the moment, so we don't rely on those alerts, so there's no fatigue involved there*" (P16).

The clinical relevance and usefulness of alerts, with respect to clinicians' specific roles and responsibilities were often mentioned. Some alert types were seen as entirely irrelevant, while others were inconsistently useful. Fatigue also arose where relevant alerts were lacking, forcing users to manually search for information: "*it has taken me six clicks to get one answer, which is highly inefficient*" (P16). Useful alerts were described to help clinicians with cognitive unloading, save time in system interactions, and provide information that clinicians were less familiar with or that was easily forgotten, for example: "*doctors would really appreciate if there was one alert saying all the blood tests that have been ordered are now back… because we spend a significant portion of our cognitive time in the day just thinking about that*" (P16), and "*the reality is, sometimes you forget, and it is helpful if someone has already put in an allergy and the system reminds you at the time of prescribing*" (P06).

Participants stated that alerts perceived to be well aligned with roles and responsibilities often did not induce alert fatigue, even where participants would often "*end up disregarding the alert as not relevant*" (P7). This was particularly the case where clinicians had significant individual responsibility over the task they were alerted to:

> *"discharging patients is a crucial part of an intern's job. Getting them out of the hospital is really, like our number one priority… I'm always very grateful to get [discharge medications] alerts because the consequences of getting something wrong in that way can be disastrous, and it is on you legally" (P1).*

In contrast, alerts that were received by a team of clinicians created a diffusion of responsibility, which led to these alerts being deprioritised: "*if it was sent to everyone, it's everyone's job*" (P17). Participants also described automatically clicking through alerts where they had lower autonomy, for example "*someone's told you to chart that med, so you just do it"* (P13).

Situations in which clinicians faced greater time pressure and higher workloads, such as during ward rounds, were described to trigger alert fatigue even in participants who were typically unaffected:

> *"I don't feel like I'm at a stage where any alert that pops up- it's tapped into that alert fatigue. For me, it sort of comes in waves when I'm quite busy within the hospital and there's a lot of tasks that have built up" (P10).*

Information overload also contributed, with participants feeling overwhelmed by excess information or by too many alerts received at once:

> *"it'll often give you up to 10 different alerts [in a single encounter]… it's hard to tell which ones are actually worth stopping for and thinking about, and which ones you just ignore" (P4).*

Other information presented on screen, such as task lists and message functions within the system, also contributed to overload.

Environment

Only one factor was coded to the work environment, which included information overload from "*multi-sensory*" non-system alerts or individual clinicians' digital ecosystem, including pagers, emails, WhatsApp messages, auditory alarms, phone calls and in person prompts. System alerts were perceived to be:

> *"yet another thing that the junior doctor is responsible for or is bombarded with… there's just so many different ways to message a JMO about a task, or to put a task somewhere for them to do, to page us, to come and find us on the ward…there seems to be a lot of over stimulation" (P4).*

The level of priority given to system alerts over other tasks was often reported to be low, "*with the assumption that if it's automated, then it's not as pressing*" (P17).

Technologies and tools

Alert fatigue at the technology level was influenced by the alert type, interface design, system usability, and volume. Participants typically described alert fatigue to develop for specific types of alerts. However, similar looking alerts could cause confusion or take extra cognitive effort to interpret: "*allergies and drug-drug interactions often pop up looking the same, and it takes a little bit longer to work out which one it is*" (P10). Participants described interface design features, including the use of colours, font, position, and layout, that could draw their attention, however:

> *"once you get used to a certain font or format or typeface, the same problem will just happen. Regardless of whether it's in red or rainbow or purple, once you've had it pop up 20 times in one day…you just stop paying attention to it" (P13).*

Alerts with excess words and jargon were explained to contribute to alert fatigue as it could "*blur what you're actually trying to pick up on in the writing as important*" (P18), versus shorter alerts which could be quickly processed: *"the alert I pay most attention to is one that's about 10 words, regardless of the style, if it's short and something that your brain can process in three seconds, then it is probably going to be read"* (P13).

Requiring users to provide reasons for overriding alerts were perceived positively for important alerts as they forced clinicians to "*skim them because… you can't just say ignore. You've got to say, why you ignored, so they force you to put a little bit of accountability against it*" (P14). Alert importance was sometimes interpreted based on the presence or absence of additional steps to dismiss the alert:

> *"if it was so important, you couldn't click x, right? Most things in the hospital that are really important have a million and one hoops to jump through... I think everyone, whether subconsciously or consciously, knows that if it was the be all and end all, there wouldn't be a not now button" (P20).*

Poor usability of alerts and clinical information systems, such as systems being "*slow*" and "*clunky*", were reported to contribute to alert fatigue by disrupting workflows. Clinicians also described interruptions occurring where alerts blocked access to other areas of the system:

> *"it's not like it will take you to the relevant section of [the system] to gain that information. So with the allergy alerts, I need to cancel that order, stop what I'm doing, go into the allergy section and then interpret that information" (P10).*

Alerts lacking system 'smarts' for example, those flagging allergy and drug-drug interactions for patients who were already prescribed the drug in question, was described to contribute to fatigue. Constant repetition was also perceived to create a *"boy who cried wolf"* (P17) effect: "*'how can I tell if, out of the 100 times this has happened, this is the one where it matters?'*" (P13). While an excessive volume of alerts was mentioned, it was only described as problematic where alerts were repetitive, irrelevant, or where multiple alerts were received at once.

Organisation

Organisational factors included the department clinicians worked in, shift length and type, the institutional culture, social influences and team dynamics. While experiences of alert fatigue were generally consistent between departments and rotations, differences were sometimes observed between departments due to variations in the workload, time pressure, types of tasks and alerts received, and autonomy over tasks. Challenges with team flow at the start of new rotations also contributed to alerts being missed. Fatigue was described to increase on after hours shifts, as "*you're covering a number of different wards as an after-hours doctor, and the time pressure that you have in those scenarios is quite high*" (P10), and during certain times of the day, including late at night, later in the day. Participants also cited increased alert fatigue at the end of a shift due to workload demands and at the very beginning of a shift where they had insufficient information to appropriately respond.

Institutional and departmental culture, and peer behaviours shaped role expectations, which in turn impacted alert fatigue. Alerts aligned with institutional norms were not necessarily less frustrating, but reported to be more widely accepted as "*there's plenty of things we do all day that are very frustrating and difficult, but we do them because we recognise that it's an expectation*" (P7). Expectations were described to be learned informally from colleagues: "*learn on the job. You rock up and people just start asking you to do things…if you haven't been asked to do it, especially by a senior doctor on your team, then it's probably not your job*" (P17), and reinforced by observing colleagues dismissing alerts: "*if one of the registrars or the bosses is on the computer, and then they're like, 'Oh, this is so annoying.' Click, click, click. It sets the scene of 'Oh, this is just such an inconvenience.' Skip, skip, skip*" (P8). New JMOs said they often asked colleagues and senior doctors for advice on how to respond to alerts. Alert fatigue was heightened due to the "*unspoken pressure about the efficiency that you're required to have as a junior*" (P4), where alerts were perceived to decrease efficiency.

Impact of alert fatigue

Employee and organisational outcomes

Alert fatigue was associated with feelings of frustration and annoyance, and along with other work stressors, could contribute to burnout and general fatigue. Some participants additionally described experiencing guilt, for example "*you just feel as though maybe you're*

not doing as good a job…you hate to think that you're not giving 100% to your patients" (P15). While alert fatigue was often tied to specific alerts, some participants developed broader scepticism, feeling "*suspicious of alerts in general*" (P6), creating a "*sense of mistrust in the system*" (P9) after encountering many alerts that were not relevant.

Some participants felt that fatigued users might miss opportunities to streamline their workflows. However, excess alerts were more often described to disrupt workflows, resulting in a loss of time, cognitive effort and efficiency. For example, one registrar described "*when I'm already holding six pieces of information in my head, then I might lose two, which is the most frustrating aspect*" (P9). These interruptions were perceived to impact patient flow: "*if things don't move at a certain speed, the system breaks down, or patients get stuck somewhere, or miss out on discharging home at a particular time"* (P4), lead to mistakes or unnecessary responses, and shift attention away from core issues: "*it leads to uncertainty, and I think often clouds the issue that the patient's in hospital for*" (P9).

Patient outcomes

Participants felt alert fatigue could increase the risk of errors and result in actual patient harm, particularly when important alerts were missed or misinterpreted. For example, some participants observed doses being missed, patients being prescribed medications they were allergic to, and pre-emptive care planning being missed. Alert fatigue was also perceived to reduce time spent with patients: "*when there's more buttons to click or time to be spent in front of a computer, you're spending less time with the patient*" (P4), and inadvertently impact care by reducing clinicians' patience.

Strategies to reduce alert fatigue

Strategies to reduce alert fatigue included activities that were currently being undertaken by participants and their respective hospitals, as well as recommendations for future activities. Strategies discussed included technical changes such as improving the interface design, personalising and increasing the relevance of alerts; organisational strategies such as monitoring and evaluation initiatives and educating clinicians about alert fatigue; as well as personal strategies such as improving overall wellbeing and employing workarounds. A full list of strategies is presented in Multimedia Appendix 2.

DISCUSSION

Principal findings

This study provides a comprehensive exploration of junior doctors' experiences of alert fatigue in hospital settings. Importantly, alert fatigue was found to manifest at different stages of information processing where participants failed to detect alerts, superficially processed alerts, developed mental models, and used excessive cognitive effort to interpret alerts, which led to different response patterns. These experiences were perceived to have various impacts on patient safety, such as increasing the risk of errors and contributing to patient harm, and on clinician wellbeing, such as impact on emotional states, workflow interruption, and efficiency.

We also identified a range of system factors, such as those relating to alert logic and design, organisational culture, and individual traits and emotional states, that contributed to the experience of alert fatigue. The SEIPS model highlighted the complex interactions between these system components. We observed doctors at the same hospital, who received similar alerts, to experience alert fatigue differently depending on their experience, role, and personality. For example, where doctors had positive attitudes and where alerts were tightly aligned to responsibilities, even alerts that were often disregarded were not perceived as fatiguing. While poor clinical relevance remains a fundamentally important factor in the development of alert fatigue, our study reveals that doctors may have different levels of tolerance depending on these personal, organisational and task factors. We also observed feedback loops between factors contributing to alert fatigue and its outcomes. For instance, repeated exposure to low-value alerts could lead to negative attitudes, subsequently reducing trust and influencing attitudes toward future alerts.

Expanding definitions of alert fatigue

In our study, alert fatigue was rarely experienced in an all-or-nothing fashion. Instead, participants often described alert fatigue to arise only in specific contexts, such as when under time pressure or for certain alert types. While some participants reported generalised negative perceptions of alerts, none described being universally fatigued, or entirely unaffected. Similar to existing studies, we also found alert fatigue to develop for both passive and interruptive alerts.[34]

Our findings support the view that alert fatigue is not simply an action, but a mental state that is subjectively experienced at conscious and subconscious levels.[15,28] Participants described three distinct information processing pathways in which alert fatigue occurred: one where alert stimuli were not perceived at all, another in which alerts were recognised but superficially processed based on mental shortcuts, and a third where alerts required high cognitive effort to interpret and respond to. The first two pathways, in line with existing conceptualisations of alert fatigue, were often associated with alerts being rapidly dismissed.[7,11,12] Despite this, mental shortcuts were commonly perceived as an efficient and effective way to process information and were often not associated with conscious experiences of fatigue. While many participants believed they were able to rapidly interpret alerts, patient safety risks could however, still arise due to the potential to misinterpret information, particularly when alerts lacked visual distinctiveness.

In contrast, the third pathway was consistently described as fatiguing. Participants reported feeling frustrated due to the cognitive burden of alerts and related impacts on efficiency, which arose particularly where alerts were ambiguous, time consuming, or difficult to action. For certain alert types or individuals, this burden was described to gradually lead to cognitive disengagement, with clinicians eventually defaulting to rapid override as a strategy to avoid further mental effort. This finding mirrors alarm fatigue literature that suggests fatigue develops as a coping mechanism to alleviate the cognitive burden associated with excessive unactionable alarms.[29,35] While burnout is frequently linked to alert fatigue and was mentioned by participants as a possible outcome,[36] our findings suggest that burnout is likely to be experienced due to the cognitive burden associated with alerts, but not by rapid overrides. In fact, the rapid overriding of alerts may serve as a protective mechanism to help clinicians manage cognitive load and avoid burnout. Such conceptualisations align with existing literature that has found clinicians increasingly experience fatigue and burnout with longer EHR use.[37,38]

These findings suggest that override rates and response times alone are insufficient measures of alert fatigue. Aligning with prior critiques, our work confirms that frequently overridden alerts are sometimes still attended to and can be perceived as helpful.[12,39] Similarly, although quick dismissals can indicate alert fatigue, it can also represent efficient pattern recognition; while longer interactions could indicate both appropriate engagement with alerts as well as signalling cognitive burden. We therefore recommend supplementing system metrics with

clinician self-reports to better understand both conscious and subconscious experiences of fatigue. Solutions could then be appropriately applied to address the specific type or types of fatigue experienced.

Work system factors contributing to alert fatigue

In line with existing literature, we found exposure to clinically irrelevant, repetitive, and poorly timed alerts, to contribute to alert fatigue.[7,14,20,40,41] Consistent with quantitative conceptualisations, the total volume of system alerts was rarely identified as a cause of alert fatigue on its own, but instead due to the amount of clinically irrelevant and repetitive alerts received and when there were multiple alerts within a single clinical encounter.[7] We also identified novel influences, including personality traits, mood, social learning, and exposure to external alerts. Many participants described cognitive overload as a result of not just system alerts, but also notifications from pagers, emails, phone calls and verbal prompts, which cumulatively contributed to experiences of fatigue and dismissal of system alerts. While existing literature has sought to improve total alert burden to reduce alert fatigue,[42,43] our study highlights the need to consider system alerts within the broader ecosystem of alerts and tasks that clinicians receive.

Social and organisational factors are underexplored in existing alert fatigue literature but were found to collectively shape experiences in our study. Junior doctors often looked to peers to guide their own responses to alerts and expectations of their roles, learning through observation and informal discussion. These social influences affected not just alert responses but also the framing of alerts as helpful or annoying. Organisational and cultural expectations of efficiency further increased alert fatigue, as managing alerts was often seen as a barrier to achieving other clinical tasks. While alerts are likely to offer the most benefit to junior doctors, our study substantiates prior research that suggests this group experiences more fatigue than their senior counterparts.[44] Doctors with more clinical experience had greater confidence and therefore could interpret and respond to alerts with less cognitive effort, whereas junior doctors experienced more ambiguity and expended higher effort in applying information presented in alerts.

Recommendations for addressing alert fatigue

Our results highlighted several strategies for reducing alert fatigue that align with prior literature, including removing ineffective alerts and increasing clinical relevance,[45]

incorporating contextual-awareness,[46] applying human factors design principles[47,48] and implementing alerts in line with the five rights of CDS (right information, person, format, channel and time).[4,5,49,50] Our findings build on this literature by providing insight into how and why strategies are likely to be effective, and how they can be targeted to the different causes and impacts of alert fatigue. Several studies have previously tested these strategies, reporting them to be effective in decreasing the overall volume and increasing the acceptance rate of alerts.[49] However, we argue that future research must also evaluate whether clinicians' *experiences* of fatigue are reduced. Given junior doctors are likely to experience the greatest level of alert fatigue, our study highlights the importance of including this group in any redesign efforts and evaluation of fatigue reduction.

We also identify and present new strategies that could help to improve experiences of alert fatigue. These include allowing clinicians to personalise alerts, educating clinicians about alert fatigue, supporting overall emotional wellbeing, and streamlining system and other alerts. Due to the individual variability in experiences of alert fatigue, personalisation may be particularly valuable. Enabling clinicians to tailor the alerts they receive could foster a greater sense of control and responsibility, thus improving engagement with alerts they deem relevant. Further research is needed, however, to evaluate the effectiveness of personalisation and other strategies in reducing alert fatigue and improving patient safety.

Interestingly, in some cases, experiences of fatigue were not associated with the presence of alerts, but by their absence, where critical information was difficult and time consuming to locate. This finding underscores the need for balance between over and under alerting, ensuring alerts effectively address the clinical or safety need. Implementers should carefully consider the issue they aim to target, evaluating whether CDS and alerts specifically are an appropriate solution, or if different strategies or forms of CDS, such as passive alerts or search functionality, should instead be considered.[3,4]

Limitations

Our participants were junior and mid-level doctors in urban Australian hospitals who primarily used commercial information systems. Findings therefore may not generalise to other clinician groups, specialties or settings, such as rural hospitals or those using homegrown systems. Additionally, we did not incorporate observational or system usage data, which may limit insights into subconscious behaviours. Future studies should incorporate

mixed methods, i.e. both clinicians' experiences of alert fatigue and actual responses to alerts, and explore experiences of alert fatigue among different user groups to build upon the results of this study.

To our knowledge, participants in our study used only knowledge-based alerts, limiting conclusions regarding experiences of alert fatigue for smarter alerts, such as those that are Artificial Intelligence (AI)-based. Our results can however offer important considerations. Although AI-based alerts can significantly improve clinical relevance and specificity,[51] they may also increase cognitive burden if information is complex or constantly changing. Alternatively, given the fast-paced nature of the setting in which alerts are presented, AI-based alerts may be superficially processed and, due to their high positive predictive value, be automatically accepted rather than rejected due to automation bias.[52] Further research is needed to explore how alert fatigue manifests for smarter alerts in hospital settings and its impact on patient safety.

CONCLUSION

This study highlights alert fatigue as a dynamic, context-dependent experience that is not easily captured through studying behaviour alone. Our findings reinforce the need to move beyond using singular metrics to measure alert fatigue and instead address alert fatigue using tailored strategies that target the specific causes and outcomes involved. While reducing low-value alerts and improving interface design remain important, broader approaches that support clinician wellbeing, foster positive organisational culture, and consider the impact of competing priorities and tasks, may be equally critical.

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Conflicts of Interest

The authors have no conflicts of interest to declare.

Abbreviations

CDS: clinical decision support, EHR: electronic health record, SEIPS: Systems Engineering Initiative for Patient Safety, JMO: junior medical officer, EMR: electronic medical record, PGY: postgraduate year

Data availability

The data analysed in this study are available from the corresponding author upon reasonable request.

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SUPPLEMENTARY MATERIAL

Interview Guide

Use of alerts

1. What system/s do you typically receive alerts from?
2. What type of alerts do you receive?
    a. Can you give me an example of what you do that triggers an alert?
    b. How do you typically respond to alerts? What influences your response/s?
    c. On average, how many alerts would you usually receive per shift?
3. In general, what do you think of the alerts you receive? (prompt: if positive, why/why not)
4. Thinking back to your first encounter/s with an alert…
    a. What were your first impressions of the alerts you received?
    b. How did this change over time?

Alert fatigue

5. How would you define alert fatigue?
6. How would you measure alert fatigue?
7. Do you experience alert fatigue? Explain why/why not
    - If no… Given you don't experience alert fatigue, what helps you to avoid it?
    - If yes…
        a. How long ago did you start experiencing alert fatigue?
        b. Do you remember how your alert fatigue developed?
        c. How long did it take to develop?
        d. What does alert fatigue feel like? How do you know you're experiencing it?
            i. Any psychological response?
            ii. Any physical response?
            iii. What is the consequence of this feeling?
        e. What contributes to your experience of alert fatigue? Prompts:
            iv. Work complexity (/patient complexity)
            v. Workload
            vi. Relevance/accuracy of alerts
            vii. Exposure to alerts
            viii. Desensitisation over time
            ix. Personal factors e.g. mood etc.
        f. Is your experience of alert fatigue different for:
            x. Different systems?
            xi. Different departments/hospitals?
            xii. Different types of alerts?
            xiii. Different patients?
            xiv. Different contexts? E.g. ward rounds, after hours
2. How does your alert fatigue impact you and your work?
    a. How does alert fatigue affect patient care or outcomes?

    a. Have you ever missed or dismissed an alert that turned out to be important? Can you describe what happened?
8. What strategies do you take to reduce your alert fatigue?
    a. Do you have any recommendations for how alerts could be improved to reduce alert fatigue? Prompts:
        i. Would removing ineffective alerts work?
        ii. Would changing to a different kind of CDS work?
        iii. Would changing the visual/interface design of alerts work?

Is there anything else you would like to tell me about alerts or your experience of alert fatigue?

Strategies discussed by study participants for reducing alert fatigue in practice

Technology system
Allowing personalisation and customisation of alerts by individuals
Automatically populate relevant data in alerts
Improve fit of CDS with clinical need (carefully consider whether CDS and which type of CDS is needed to address the issue at hand)
Convert interruptive to passive alerts where appropriate
Add search functionality within the EHR
Improve fit of alerts with workflows, decision-making processes, roles and responsibilities (e.g. tailoring alerts to specific roles)
Improve interface design
Clear messaging and display (e.g. clear headings, minimal words, use of bolding/colours)
Differentiate alerts
Require override reasons for highly important alerts
Tiering/grading system (and use of colour/other design features to distinguish between different tiers)
Increase clinical relevance (including removing non-clinically relevant/redundant alerts)
Smarter and less repetitive alerts
Organisational strategies
Monitoring and evaluation
Establish committees and working groups to improve alerts
Evaluate impact of alerts
Seek clinician feedback (particularly JMOs as frequent users of EHR systems)
Organisational change
Attach a consequence to alerts (e.g. disciplinary action)
Change culture and culture of practice (e.g. implement low paging hours, improve general perceptions of alerts within departments)
Streamline EHR alerts with other alerts and tasks (i.e. to reduce number of locations doctors need to check for tasks)
Organisational support
Establish communication channels for questions about alerts (e.g. in EHR itself, WhatsApp channels)
Training and education on alert fatigue (to communicate what it is and potential consequences for both patients and clinicians)
Personal strategies
Improve overall health and wellbeing
Mental reminders and self-reflection

Workarounds (e.g. developing own practices/processes for addressing tasks where alerts are triggered at the wrong point in workflows, setting personal alarms for tasks where important alerts do not exist in the system)

CHAPTER 7

PREFACE

Chapter 7 explored the relationship between clinicians' subjective experiences of alerts and alert fatigue and their actual use of alerts over time. As discussed in Chapter 1, while much research has examined CDS use, few studies have compared clinicians' self-reported acceptance with objective use data, or patterns of CDS use over time, particularly in hospital settings. Chapter 6 provided new insights into how alert fatigue is subjectively experienced by clinicians, suggesting it can arise early during system use as a result of cognitive overload, is likely to be influenced by situational factors, and can result in desensitisation toward particular alerts over time. Chapter 7 employed a mixed-methods approach, combining survey and system log data to triangulate findings from Chapter 6 and test how subjective experiences align and diverge from objective use of alerts. Additionally, as Chapter 4 highlighted the need to better understand how new users engage with existing CDS systems, we specifically explored differences in perceptions of alerts and patterns of use over time between very new, and more experienced users of CDS.

Chapter not yet submitted for publication

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Comparing doctors' perceptions of alert fatigue and their interactions with alerts over time

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INTRODUCTION

Alert fatigue is a well-documented challenge associated with the use of Clinical Decision Support (CDS) systems. It occurs when clinicians become desensitised and cognitively overloaded by alerts in clinical information systems (Chapter 6). Alert fatigue not only poses risks to patient safety, but also compromises clinician wellbeing and organisational performance (Chapter 6). In existing literature, alert fatigue has primarily been evaluated by using alert use metrics as proxy measures, such as the rate that alerts are overridden versus accepted ('override rate'), the total burden of alerts ('alert volume'); and novel measures such as 'dwell time', which relate to the time taken by clinicians to read and respond to alerts.[1-3]

An underlying assumption made by such studies is that alert fatigue is associated with a particular type of behaviour, specifically, overriding and quickly processing alerts without considering their content and context. Therefore researchers have critiqued the use of override rates as a measure of alert fatigue, due to a lack of consistency in what constitutes an "override" and the potential for alerts to provide useful information despite being overridden.[4] Dwell time has similarly been critiqued, due to its inability to represent the total cognitive load that clinicians experience.[1] Our prior qualitative research substantiates and expands on these concerns, highlighting that alert fatigue is not simply a behaviour, but a mental state that is *subjectively* experienced (Chapter 6). Accordingly, we observed cases in which clinicians reported not experiencing alert fatigue despite frequently overriding alerts, as well as cases where alert fatigue was attributed to the excess cognitive load and time required to read and manage alerts.

There exists contention in current literature around how alert fatigue develops and the factors that influence it. The two leading conceptualisations of alert fatigue include cognitive overload and desensitisation, which have each been supported using alert acceptance rates and dwell times as proxies.[4,5] With cognitive overload, it is theorised that excessive information and insufficient time or cognitive resources to distinguish between relevant and irrelevant information can lead clinicians to experience alert fatigue. On the other hand, desensitisation is theorised to occur where responses to alerts diminish as clinicians become increasingly familiar with them over time.[5,6] Other studies evaluating alert fatigue have identified work complexity, repeated alerts,[4] total exposure to alerts[7] and habitual responding toward alerts,[5,6] as key contributors to alert fatigue, again using quantitative measures to

represent alert fatigue. However, these studies have not attempted to evaluate the impact of these factors on experiences of alert fatigue. In fact, we found only one study that has previously compared perceived indicators of alert fatigue to alert exposure metrics. Despite reporting a reduction in the total volume of alerts presented to clinicians following redesign efforts, perceptions of alerts being time consuming, inappropriate, and inaccurate, remained.[8] Findings from such studies and our prior work highlight the need to test assumptions about the relationship between experiences of alert fatigue and the metrics used to evaluate it in practice (Chapter 6).

In this study, we therefore aimed to explore how doctors' subjective experiences of alert fatigue were related to their objective exposure to and interactions with alerts. Additionally, we aimed to better understand the impact of factors reported to be associated with alert fatigue in previous studies, such as desensitisation over time and cognitive overload, on experiences of alert fatigue and interactions with alerts.

METHODS

Study design

This study employed a mixed-methods design, using a survey to capture doctors' perceptions of alerts and alert fatigue, combined with analysis of doctors' exposure to and interactions with alerts as recorded in EHR log data. We developed 4 overarching research topics and sub-questions that we aimed to test using collected data (see Table 1). Questions were developed based on our prior research (Chapter 6) and existing literature on alert fatigue.

Table 7. Research topics and questions aligned to data sources

#	Question	Alert data inclusion	Survey data inclusion
Trends over time		9 months prior to participants' survey completion date	N/A
1a	Is there a linear trend in override rates over time?		
1b	Is there a linear trend in dwell times over time?		
Associations between perceptions and use		30 days prior to participants' survey completion date	Alert fatigue survey items
2a	Is there an association between doctors' perceptions of receiving too many alerts and the actual number of alerts they receive?		

2b	Is there an association between doctors' perceptions of alert fatigue and any alert metric used for assessing fatigue?		
2c	Is there an association between doctors' perceptions of relevance of alerts and their actual alert override rates?		
2d	Is there an association between doctors perceptions of thoroughly reading alerts and the time taken to respond to alerts?		
2e	Is there an association between doctors' perceptions of habitually responding to alerts and the time taken to respond to alerts?		
Factors associated with experiences of alert fatigue		N/A	Alert fatigue survey items
Differences between new and experienced users		30 days prior to participants' survey completion date	Alert fatigue survey items, participants grouped by their date of commencement at the health service
4a	Is there a difference in override rates for new versus experienced users?		
4b	Is there a difference in the time taken to respond to alerts for new versus experienced users?		
4c	Is there a difference between experiences of alert fatigue for new users versus experienced users?		
4d	Is there a difference in perceptions of reading alerts, or habitual responses, for new or experienced users?		

Setting and intervention

The study was conducted at two hospitals, one 670-bed tertiary teaching hospital (Hospital A) and one 250-bed secondary care hospital (Hospital B), within a single health service in Australia. The health service implemented an Electronic Health Record (EHR) system in November 2022, containing embedded medication and Best Practice Advisory (BPA) alerts.

Participants, recruitment and procedure

All Junior Medical Officers (JMOs), including interns (Postgraduate Year (PGY) 1), residents (PGY 2), and registrars (PGY 3+), who had received alerts from the hospital's EHR system were eligible to participate in the study. Potential participants were recruited via email, intern and resident teaching sessions, and via posters displayed at each site. Emails were distributed by education leadership at each site and contained information about the study. One member of the research team (NN) presented details of the study at two intern teaching sessions, and

one resident medical officer teaching session, to promote participation. The survey was conducted online using Qualtrics software (https://www.qualtrics.com). Participants consented to their participation in the survey and extraction of their data from the EHR in Qualtrics, before being directed to the survey instrument.

Survey development

As no standardised or validated survey for alert fatigue exists, we developed a survey instrument (see Appendix B) that included questions adapted from various validated surveys designed to measure drug-drug interaction alert effectiveness, nurses' experiences of alarm fatigue, and habit development.[9-11] The survey aimed to assess perceived levels of alert fatigue, using indicators such as perceptions of alert volume, repetitiveness, clinical relevance, perceptual and cognitive processing of alerts, and habitual responses to alerts (Chapter 6).[4] It also included questions on contextual factors reported to influence alert fatigue and responses to alerts, such as patient complexity and workload,[4] and whether participants were alone or with a consultant,[12] or on a ward round.[13]

Questions regarding the participants' start date at the hospital, level of EHR use, and role were also included. The survey had a combination of multiple choice, Likert response, and open-ended questions. Likert scale responses were on a 5-point scale from Strongly Disagree to Strongly Agree.

Data analysis

All statistical analyses were conducted in IBM SPSS Statistics 29.0.2.0.[14] Descriptive statistics, including frequencies, means, and percentages, were used to summarise all data. Any missing data were excluded from analyses. Statistical significance was assessed at the $p < 0.05$ level.[15]

Alert use data

To measure participants' exposure to and interactions with alerts, data were retrospectively extracted from the EHR system. Data were extracted in March 2025 and included all interruptive medication alerts and best practice advisory alerts shown to the doctors between October 2023 and February 2025. Only alerts shown to participants within the 9 months

preceding each participants' survey completion date were included, with values outside this range excluded. Of note, the health service had chosen not to implement drug-drug interaction alerts and thus these were not shown to doctors, therefore not included in the study. Each alert record contained information as presented in Table 2. After extraction, medication and BPA alert data were merged to calculate metrics for each category of alerts (medication or BPAs) and 'total' alerts (medication and BPAs).

Table 8. EHR variables

Category	**Variable**
Alert information	Alert type (e.g., duplicate medications, duplicate therapy, allergy, BPA type) Alert trigger Action taken (i.e., override, cancel order etc.) Time taken to respond (only available for BPAs) Time/date of alert firing Reasons for override
Clinical information	Medications involved
Patient information	Age Department/unit/ward
Prescriber information	ID

Open Ended Survey Responses

A deductive content analysis of open-ended responses was conducted using the coding framework developed in Chapter 6.[16]

Evaluation of research question 1

Trends in alert use over time

To assess trends in interactions with alerts over time, we calculated the number of months since each participant's start date as reported in the survey (relative month). Alerts were then aggregated by participant and relative month to calculate the mean volume of alerts, override rate, and mean and median dwell time, per relative month for each participant (see Table 3). These measures were selected and operationalised based on prior research.[1-3,17,18] Line graphs were used to visualise trends in alert metrics over time, and linear regression was used to assess whether any linear trends in alert use were statistically significant.

Table 9. Definitions and calculations of alert exposure and interaction measures per clinician

Alert exposure and use metrics	**Definition**	**Summary statistic**
Volume per clinician	Total number of alerts received per clinician per month	Mean
Alerts per clinician per day	Total number of alerts received per clinician per day	Mean
Override rate per clinician	Proportion of alerts overridden relative to alert volume per clinician	Mean
Dwell time per clinician	Time between alert notification and alert acknowledgement per clinician (in seconds)	Median Mean

Evaluation of research questions 2-4

Bivariate correlations were performed within and between alert fatigue survey items, alert interaction and use metrics, and users' level of experience, to identify associations between variables based on the pre-defined questions outlined in Table 2. We interpreted effect sizes using Pearson correlation coefficients, where r = 0.3-0.5 represented a moderate effect and r > 0.5 represented a large effect, based on Cohen (2013).[19] Multicollinearity was assessed based on the presence of correlation coefficients > 0.7.[20]

Associations between acceptance and use

To compare participants' current perceptions of alert fatigue from the survey with their current exposure to and interactions with alerts, only alert encounters within the 30 days preceding each participants' survey date were included in this analysis. Alert metrics included the total volume of alerts received, alerts per day, override rates, and dwell time, per clinician (Table 3). Correlation coefficients were used to identify significant relationships.

Factors associated with experiences of alert fatigue

Correlation coefficients were used to identify significant relationships between perceptions of alerts, and experiences of alert fatigue, measured using the survey item 'I experience alert fatigue'.

Differences between new and experienced users

Users were grouped into 'new' and 'experienced' according to their start date reported in the survey. New users were defined as those starting less than 6 months prior to completing the

survey and experienced users were those who started over 6 months prior to completing the survey. Correlation coefficients were used to identify significant differences between new and experienced users on perceptions of alerts and alert fatigue, and alert exposure and interaction metrics. We used bar charts to visualise differences between new and experienced users for relationships found to be significant.

RESULTS

Survey

Summary

55 completed survey responses were collected between July 2025 and February 2024. Two responses were excluded as participants indicated that they had not used the EHR system, resulting in a total of 53 usable responses. All included participants reported using the EHR system several times per day. Most participants were interns (*n* = 46; 86.8%), followed by residents (*n* = 5; 9.4%) and registrars (*n* = 2; 3.8%). Participants mainly worked at Hospital A (*n* = 35; 66.1%), and an equal number worked at Hospital A and B (*n* = 9; 17%) and Hospital B alone (*n* = 9; 17%). Most participants had been working at the health service for one month or less (*n* = 31; 58.5%), with other participants' start dates ranging from 6 months to 8 years from their survey completion date.

Perceived experiences and contextual influences of alert fatigue

Most participants (*n* = 40; 75.5%) reported either strongly or somewhat agreeing with the statement 'I experience alert fatigue', while only 4 (7.5%) somewhat disagreed and none strongly disagreed. Similarly, most participants strongly or somewhat agreed that they received too many alerts to read and respond to (*n* = 37; 69.8%), that alerts were not relevant for the individual patients in which they appeared (*n* = 35; 66%), and that they became indifferent to repeated alerts (*n* = 39; 73.6%). However, variation was observed between participants in their perceptions of thoroughly reading alerts (strongly or somewhat agree (*n* = 25; 47.1%) versus strongly or somewhat disagree (*n* = 24; 45.3%)), and responding to alerts before they realised they were doing it (strongly or somewhat agree (*n* = 27; 50.9%), and strongly or somewhat disagree (*n* = 16; 30.2%)).

Most participants strongly or somewhat agreed that they were more likely to read and respond to alerts when they were less busy (*n* = 45; 84.9%), when they were not conducting a ward round (*n* = 42; 79.3%), and when they were alone rather than with a consultant (*n* = 36; 67.9%). Participants were slightly more likely to strongly or somewhat disagree that they thoroughly read and responded to alerts that related to uncomplicated patients (n = 25; 47.1%). See Appendix B for full results on Likert scale responses.

Open-ended responses

20 open-ended responses were recorded. Participants frequently described ignoring alerts that did not fit with their workflows or decision-making processes (e.g. when opening patient charts), receiving other alerts and alarms that contributed to information overload, the excessive effort associated with actioning alerts, a lack of clinical relevance of alerts, and negative experiences with specific alert types (e.g. venous thromboembolism (VTE) alerts). Additionally, some participants reported failing to detect, and habitually dismissing, alerts. See Appendix C for thematic analysis of open-ended responses.

Alert interaction and exposure

Summary

In the 9-month period prior to participants' survey completion date, 40,089 total interruptive alerts, including 14,437 medication and 25,652 BPAs, were shown to participants. Medication alerts included those for dosing (*n* = 2178; 15.1%), drug-allergies (*n*=2579; 17.9%), duplicate medication orders (*n* = 459; 3.2%) and duplicate therapy (*n* = 9221; 63.9), with most alerts triggered when entering orders (*n* = 13,371; 92.8%). BPAs included a range of alerts, the largest proportion being VTE alerts (*n* = 20,484, 79.9%), with most BPAs triggered upon opening a patients' chart (*n* = 22,940, 89.4%).

On average, doctors overrode 85% of total alerts (*n* = 34,084), 70.1% of medication alerts (*n* = 10,118) and 93.4% of BPA alerts (*n* = 23,968). BPA dwell times were missing in 54 cases, and one outlier (53,294 seconds) was identified and excluded from further analyses. Average dwell time across the 25,597 included BPA alerts over the 9-month period was 5.44 seconds (median = 3 seconds, range = 1 to 865). Mean dwell times where an action was taken were 9.1 seconds, versus 5.2 seconds where alerts were overridden. Descriptive statistics of alert metrics are presented in Appendix D.

Research questions

Trends over time

Data were captured from 7 months before, to 97 months after participants' reported start date. Alerts received prior to a participants' start date (i.e. while they were students) were excluded. Additionally, data from relative month 11 onward were excluded to avoid skewing results toward specific participant responding patterns, as fewer than 5 participants had data available for these months. This resulted in 210 cases, representing alert data from 11 to 44 participants per month, spanning 0 to 10 months from participants' start dates. See Appendix D for the number of participants with data included/excluded at each relative month.

Figure 1 shows the linear trend in total alert, medication alert, and BPA override rates over time (Research Question 1a). No statistically significant trends in total alert override rates, or override rates for medication or BPA alerts over time were observed ($p > .05$). Interestingly, at month 3, a drop in override rates that rebounded in following months was observed across all alert types. Linear regression results are provided in full in Appendix E.

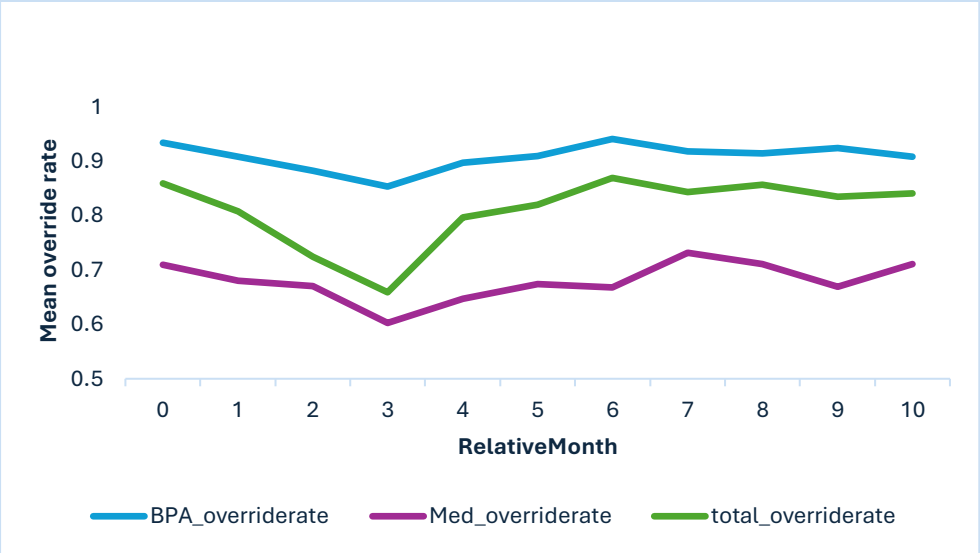

Figure 19. Mean medication alert, BPA alert and total alert override rates per relative month post participants' start date

Note. Y-axis truncated at 0.5 to highlight variation in override rates.

There was a significant negative trend in dwell times over time, using both the mean (B = -.294; $p < .05$) and median (B = -.157; $p < .05$) (Research Question 2b). With each additional month, the mean dwell time decreased by 0.29 seconds and median dwell time decreased by 0.16 seconds (Figure 3 and Appendix E). Like override rates, dwell times increased at month 3.

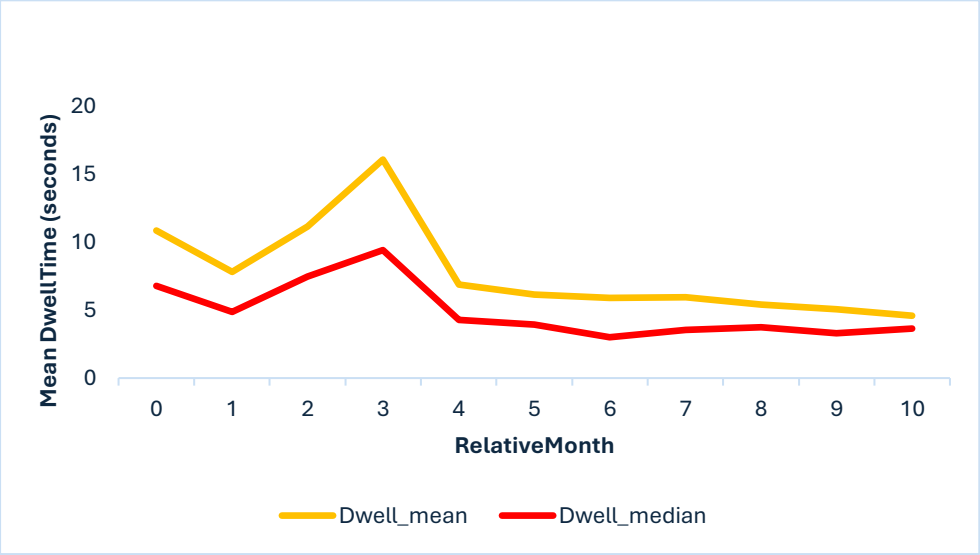

Figure 20. Mean and median BPA dwell times per relative month post participants' start date

Associations between perceptions of alert fatigue and use of alerts

Participants who received alerts on less than 5 days within the 30-day period prior to participants' survey completion date were excluded from this analysis. This resulted in 10 participants being excluded, with 43 participants included. A total of 8,735 alerts, including 2,188 medication alerts (25%) and 6,547 BPAs (75%), were presented to participants. Descriptive analyses for all alert metrics are presented in Appendix D. Over the 30-day period, each participant received a total of 203 alerts on average at an average of 13.5 alerts per day, of which 88% were overridden. BPAs had a mean dwell time of 6.2 seconds.

Correlations between survey variables and alert metrics for the 43 participants included in this analysis are presented in Table 4. There were no statistically significant relationships between doctors' perceptions of receiving too many alerts and the volume of medication, BPA, or total alerts received; or of the medication, BPA, or total alerts received per day ($p >$ .05) (Question 2a). Similarly, there were no statistically significant relationships between doctors' perceived experiences of alert fatigue and any metric outlined in Table 2 (volume,

alerts per day, override rates or dwell times) for medication, BPA, or total alerts ($p > .05$) (Question 2b). The relationship between perceived experiences of alert fatigue and the total volume of alerts received per day however neared, but did not reach, significance ($r = 0.259$; $p = 0.094$). Doctors perceptions of the clinical relevance of alerts were statistically significantly associated with BPA override rates ($r = -.318$; $p <. 05$), such that lower levels of perceived relevance of alerts to individual patients were associated with higher BPA override rates (Question 2c). There was, however, no statistically significant relationship between perceived alert relevance and medication or total alert override rates ($p > .05$). Lastly, no statistically significant relationships were observed between doctors' perceptions of thoroughly reading (Question 2d) or habitually responding (Question 2e) to alerts and dwell times using either the mean or median ($p > .05$).

Table 4. Bivariate correlations between alert fatigue survey items, alert interaction and use metrics, and users' level of experience (n=43)

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	User	1																					
2	Frequency	-0.031	1																				
3	Relevance	0.01	-0.298	1																			
4	Read	-0.137	-0.152	.336*	1																		
5	Habit	-0.046	0.143	0.093	-0.133	1																	
6	Repeat	-0.062	.303*	-.399**	-.555**	0.294	1																
7	AFexp	0.078	.618**	-0.208	-0.215	.306*	.536**	1															
8	Complex	0.025	0.125	-0.244	0.023	0.074	.311*	0.118	1														
9	Workload	-0.04	0.238	.405**	0.059	0.168	0.06	0.213	0.176	1													
10	Alone	0.054	0.274	.318*	-0.033	0.233	0.179	0.268	0.089	.717**	1												
11	WardR	-0.076	0.149	0.245	-0.075	0.273	0.147	0.25	0.134	.662**	.570**	1											
12	Med VOL	.560**	0.063	0.245	0.013	0.011	-0.143	0.181	0.12	0.182	0.151	-0.041	1										
13	Med APD	0.216	0.167	0.082	0.077	-0.005	-0.053	0.245	0.084	0.187	0.202	0.055	.767**	1									
14	Med OVR	0.257	-0.242	0.219	-0.064	0.199	-0.062	-0.028	-0.212	-0.174	0.021	-0.089	0.029	0.016	1								
15	BPA VOL	.386*	-0.019	0.16	-0.115	0.162	0.059	0.163	-0.215	0.115	0.211	0.179	.369*	0.083	0.134	1							
16	BPA APD	0.114	0.055	0.159	-0.07	0.155	0.11	0.193	-0.246	0.184	0.248	0.263	0.199	0.075	0.105	.902**	1						
17	BPA OVR	-0.027	0.051	-.318*	-0.187	-0.051	0.248	-0.053	-0.176	-0.077	0.046	0.054	-.504**	-.456**	0.003	0.142	0.19	1					
18	BPA Dwell ME	-.352*	-0.16	0.072	0.215	-0.033	-0.197	-0.203	-0.06	-0.286	-.429**	-.309*	-0.169	-0.123	-0.127	-.418**	-.490**	-0.218	1				
19	BPA Dwell MD	-0.193	-0.014	0.048	0.106	-0.101	-0.212	-0.005	0.071	-0.037	-0.29	-.309*	0.048	-0.045	-0.171	-.389**	-.498**	-.366*	.620**	1			
20	Total VOL	.479**	-0.001	0.202	-0.098	0.145	0.017	0.188	-0.16	0.146	0.223	0.148	.572**	0.262	0.125	.973**	.845**	0.001	-.410**	-.331*	1		
21	Total APD	0.201	0.102	0.195	-0.042	0.114	0.075	0.259	-0.191	0.231	0.275	0.248	.450**	.352*	0.071	.882**	.951**	0.01	-.472**	-.448**	.889**	1	
22	Total OVR	0.099	-0.087	-0.072	-0.14	0.067	0.14	-0.101	-0.192	-0.073	0.086	0.018	-.376*	-.430**	.538**	.338*	.422**	.726**	-.381*	-.452**	0.205	0.233	1

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).
Variables: 1) user: level of user experience (new versus experienced); **Survey** (perceptions of) – 2) frequency: too many alerts, 3) relevance: alert relevance, 4) read: thoroughly reading alerts, 5) habit: automatically responding to alerts, 6) repeat: becoming indifferent to repeated alerts, 7) AFexp: experiencing alert fatigue, 8) complex: patient complexity, 9) workload: workload, 10) alone: alone versus with a consultant, 11) wardR: ward round; **Alert log data** – 12) Med VOL: medication alert volume, 13) Med APD: medication alerts per day, 14) Med OVR: medication alert override rate, 15) BPA VOL: best practice advisory (BPA) alert volume, 16) BPA APD: BPA alerts per day, 17) BPA OVR: BPA override rate, 18) BPA Dwell ME: BPA dwell time mean, 19) BPA Dwell MD: BPA dwell time median, 20) Total VOL: total alert volume, 21) Total APD: total alerts per day, 22) Total OVR: total override rate

Factors associated with experiences of alert fatigue

Correlations within survey items for the 53 participants included in this analysis are presented in Table 5. Statistically significant relationships with large effect sizes were observed where participants with higher levels of perceived alert fatigue, more strongly perceived they received too many alerts ($r = .535$; $p < .05$) and were indifferent to repeated alerts ($r = .517$, $p < .05$). A moderate effect size was observed between experiences of alert fatigue on perceptions of responding to alerts before they realised they were doing it ($r = .312$, $p < .05$). There were no statistically significant relationships between experiences of alert fatigue and perceptions of thoroughly reading alerts, perceptions of alert relevance, or contextual factors influencing perceptions of reading and responding to alerts, such as patient complexity and workload ($p > .05$). No correlations exhibited multicollinearity.

Table 5. Bivariate correlations within alert fatigue survey items and users' level of experience (n=53)

	Variable	Frequency	Relevance	Read	Habit	Repeat	AFexp	Complex	Workload	Alone	WardR	User
1	Frequency	1										
2	Relevance	-.276*	1									
3	Read	-0.219	.294*	1								
4	Habit	0.237	0.131	-0.200	1							
5	Repeat	0.205	-.338*	-.486**	.292*	1						
6	AFexp	.535**	-0.156	-0.162	.312*	.517**	1					
7	Complex	0.099	-0.200	0.039	0.029	0.251	0.073	1				
8	Workload	0.255	.377**	0.004	0.168	0.108	0.236	0.152	1			
9	Alone	0.253	0.236	-0.158	0.115	0.120	0.170	0.117	.594**	1		
10	WardR	0.121	0.061	-0.123	0.117	0.166	0.215	0.071	.452**	.562**	1	
11	User	-0.075	0.099	.402**	-0.140	-.334*	-0.226	0.026	-0.102	-0.007	-0.216	1

*Correlation is significant at the 0.05 level (2-tailed).

**Correlation is significant at the 0.01 level (2-tailed).

Survey Variables (perceptions of) – 1) frequency: too many alerts, 2) relevance: alert relevance, 3) read: thoroughly reading alerts, 4) habit: automatically responding to alerts, 5) repeat: becoming indifferent to repeated alerts, 6) AFexp: experiencing alert fatigue, 7) complex: patient complexity, 8) workload: workload, 9) alone: alone versus with a consultant, 10) wardR: ward round, 11) user: level of user experience (new versus experienced)

Differences between new and experienced users

While we aimed to compare users with less experience to those with more than six months of experience at the time of survey completion, no users had started working at the health service between one and six months prior. Therefore, 'new' users were doctors who had less than one month of experience, while experienced users had more than 6 months of experience. As presented in the correlation matrix in Table 4, we identified statistically significant relationships where new users received a lower total volume of medication, BPA, and total alerts, than more experienced users. Additionally, there was a statistically significant moderate relationship between users' level of experience and mean dwell times, such that dwell times were significantly higher for new users (r = -.352; p < .05) (see Figure 3). This effect, however, was not observed with median dwell times, nor with override rates (p > .05).

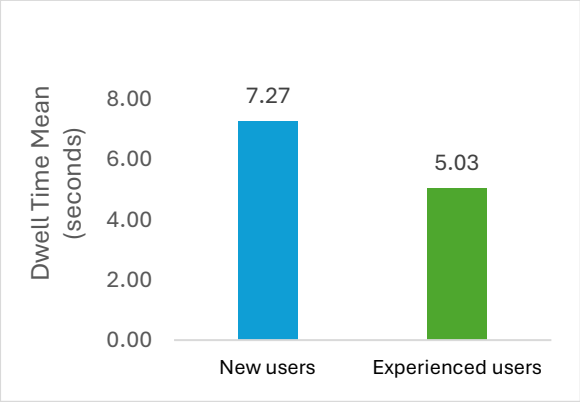

Figure 21. Bar chart showing differences in mean dwell times between new and experienced users of alerts in seconds

As presented in the correlation matrix in Table 5, we found new users were statistically significantly more likely to report that they thoroughly read alerts (r =.402; p < .05) and were less likely to report becoming indifferent to repeated alerts (r = -0.334; p < .05), both with moderate effect sizes. There were, however, no statistically significant differences between new and experienced users' perceived experiences of alert fatigue, receiving too many alerts, relevance of alerts, or habitual responding to alerts (p > .05).

DISCUSSION

Summary and integration of findings

This mixed-methods study explored how junior doctors' perceptions of EHR alerts and alert fatigue, related to their actual exposure to and interactions with alerts over time. Compared with studies of alert use in similar contexts, the volume of alerts (13.5 per clinician per day)[17,21] and override rates (85% total, 93% BPA, and 70% medication alerts) were relatively high,[22] while BPA dwell times (5.44 seconds mean, 3 seconds median) were in range of those previously reported.[5] We also found a high level of reported alert fatigue amongst our study population.

A key finding of this study, however, was that none of the alert exposure or interaction metrics evaluated were significantly associated with participants' self-reported experiences of alert fatigue. In fact, the only significant correlation observed between alert metrics and perceptions, was the increase in BPA override rates as participants reported less perceived relevance of alerts to individual patients. Although this finding aligns with prior literature that has reported the influence of relevance on alert acceptance,[23] perceived relevance was not found to be associated with experiences of alert fatigue in our study. This suggests that clinicians' judgments about relevance may independently influence responses to alerts, without necessarily contributing to alert fatigue. Similarly, we found that only doctors' perceptions of receiving too many alerts, but not the actual volume of alerts received, were associated with experiences of alert fatigue. This disconnect reinforces the view of alert fatigue as a subjective state, where clinicians possess different levels of tolerance based on individual characteristics and preferences (Chapter 6).[24]

The importance of contextual factors was also highlighted. Participants frequently reported workload, and whether they were with a senior doctor or on a ward round, to influence their ability to thoroughly read and respond to alerts. Such findings mirror previous studies using objective[4] and subjective measures.[12,13] However, we did not find measures of alert burden, which are often associated with workload, to be related to experiences of alert fatigue. This is perhaps due to the type of measures used in the current study, i.e. the total volume of alerts received by participants over a 30-day period and the number of alerts received in a day. In contrast, previous studies such as Ancker et al.[4] have demonstrated associations between workload and override rates using more acute metrics, such as the volume of alerts *per order*.

These more granular measures were not available in our dataset. This suggests that alert fatigue may be driven by more immediate cognitive burden, reinforcing the notion that it is often experienced acutely rather than gradually.

Another potentially valuable metric that was not evaluated in the current study is the total workload generated by alerts both within and outside the EHR, such as in-system messages, pagers, phone calls, and other clinical interruptions. Our prior qualitative research (Chapter 6), open-ended survey responses, and the near-significant relationship between the total number of alerts (but not BPA or medication alerts alone) and experiences of alert fatigue, support the idea that alert burden across multiple channels may better reflect clinicians' experiences of alert fatigue. Further research, particularly those using observational methods, should examine the cumulative burden of alerts from both EHR systems and external sources, to better understand their combined influence on experiences of alert fatigue and its impacts.

Interestingly, while dwell times in the current study appeared similar to those reported for other alerts presented on chart open,[6] they appeared to be lower than those previously reported for alerts presented while completing a relevant action, such as drug-drug interaction alerts.[3] Open-ended survey responses, combined with short dwell times and high override rates, highlight that alerts triggered in this manner are potentially of low value. However, as aligned to our prior research (Chapter 6), these alerts alone may not necessarily be a large contributor to experiences of alert fatigue.

In line with prior research, we found that dwell times significantly decreased over time.[5,25] We also evidenced that dwell times were higher for new versus more experienced users. However, dwell times were not found to be associated with experiences of alert fatigue, perceptions of thoroughly reading alerts, habitually responding to them, or becoming indifferent to repeated alerts. While new users were found to be significantly more likely to report they thoroughly read alerts, perceptions of thoroughly reading alerts were not associated with experiences of alert fatigue. These findings, taken in context of our prior research, provide further evidence that dwell times represent doctors' mental shortcuts of alerts that develop over time (Chapter 6). Mental shortcuts allow doctors to quickly recognise and process alerts, which can lead to them quickly dismissing alerts but not necessarily experiencing alert fatigue. The lack of increase in BPA override rates, despite decreasing

dwell times, suggests that mental shortcuts can support more efficient alert processing, without compromising doctors' responses to alerts.

There were no changes found in override rates over time. Override rates have been found to remain stable over time in some studies,[4] and decrease over time in others.[6] We believe this disparity across evidence is likely due to the focus on different alert types across different studies. While the current study focused on *all* medication and BPA alerts as a group, prior work has evaluated clinicians' responses to *specific* alert types over time. These findings suggest that desensitisation is likely to occur in a limited fashion toward specific alerts and provides further evidence that alert fatigue does not occur universally across different alert types. Additionally, the finding that new users were less likely to report being indifferent to repeated alerts than experienced users, suggests alerts susceptible to desensitisation are likely to be those that are frequently repeated and perceived to be of low value. Another complementary explanation is that differences between individual clinicians' patterns over time could result in the lack of a single pattern being observed. As has been previously reported with clinical decision support systems used in General Practice settings, distinct patterns of use can emerge between different clinicians over time.[26]

Another interesting, yet unexpected finding, was the pattern in alert interactions at month 3, where override rates dropped, and dwell times increased. Discussion with junior doctor co-researchers in our study suggested that this may reflect a transitional stage where new doctors gain a better understanding of their work and increased individual responsibility and autonomy. This timing also coincides with hospital departmental rotations, which may temporarily increase attention to alerts given the unfamiliar setting. This aligns with our current findings and prior research, that reports junior doctors are more likely to attend to alerts when alone or without senior supervision.[12] Further research should further explore this effect and whether it is replicated in other settings.

Implications

Our findings extend prior literature on alert fatigue in a number of important ways. While existing research typically uses objective alert metrics to measure of alert fatigue, we found no significant relationships between these measures and perceived experiences of alert fatigue. These findings reiterate that alert fatigue is likely to be a largely subjective cognitive

state that can present differently depending on provider, alert, and contextual factors. This highlights several implications for the design CDS systems and evaluation of alert fatigue.

Firstly, there is a need to adopt multi-dimensional approaches to measuring alert fatigue that includes both objective data and subjective experiences. While override rates and dwell times could help to identify problematic alerts, engaging clinicians to understand the subjective impact of alerts is also necessary. Clinician representatives on hospital committees may be useful to achieve this (Chapter 6).[27] Survey instruments, like the one developed in this study, can capture dimensions of perceived alert fatigue that are not typically reflected in log data and may be useful for evaluating the impact of redesign initiatives on clinicians' experiences of fatigue.

The lack of an association between perceptions and objective evaluations of conceptually similar variables, such as actual alert volume and perceived burden, further suggests that individual characteristics are likely to contribute to differences in experiences of fatigue (Chapter 6). We echo prior research that has suggested alert design and presentation must be better tailored to different users and clinical context, which may be more effective than blanket reductions in alert frequency.[28,29] Beyond this, individual personalisation, where clinicians are empowered to choose their own alerts, could also provide enhanced autonomy and reduce experiences of fatigue, but requires further research.

Limitations

This study had several limitations. First, the sample size was modest, and subgroup analyses, such as comparisons between new and experienced users and evaluations at later time points from participants' start dates, were constrained by limited participant numbers. Due to the recruitment approach, it was not possible to determine how many potential participants were invited to complete the survey, and therefore the exact response rate could not be calculated. Additionally, most participants were interns working within the same hospital network, resulting in a relatively homogenous sample that limits the generalisability of findings to other settings, clinical roles, and more experienced cohorts. Moreover, participants' responses to many of the alert fatigue items included in the survey were skewed, with most responses aligning with moderate to high levels of alert fatigue. This lack of response variability may

have limited our ability to detect statistically significant associations between subjective fatigue and objective alert use.

Second, as previously highlighted, there are multiple ways to operationalise alert metrics (e.g. alert volume, vs alerts per clinician per day, vs alerts per order), and some potentially relevant indicators could not be evaluated in the current study due to data limitations. We also did not evaluate interactions with specific alert types, which could be particularly important in driving overall alert fatigue experiences. Future studies should examine specific alert types and incorporate more granular and contextualised measures of alert burden.

Another limitation was the lack of formal psychometric validation of the survey instrument. However, its design was grounded in prior research, adapted from validated tools, and demonstrated an absence of multicollinearity, supporting its preliminary validity. Lastly, participants' interpretations of ‘alert fatigue’ evaluated in the survey may have varied, reflecting the conceptual ambiguity of the term. While this heterogeneity limits precision in interpreting self-reported alert fatigue, it aligns with the study’s aim to better understand how alert fatigue is experienced and how those experiences correspond to commonly used alert metrics.

CONCLUSIONS

Alert fatigue is a complex, individualised experience that is unlikely to be fully captured through objective alert metrics alone. Our findings reinforce the notion that subjective perceptions, such as feeling overwhelmed by the volume of alerts, encountering repetitive alerts, and developing automatic response behaviours, are more closely aligned with experiences of alert fatigue than alert exposure or interaction metrics. While log data can help to identify problematic responding patterns, we emphasise the need to incorporate clinicians’ lived experiences to contextualise responses and develop appropriate solutions. Efforts to measure and mitigate alert fatigue must therefore integrate both subjective and objective approaches.

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SUPPLEMENTARY MATERIAL

Appendix A – Survey instrument

General questions

1. Your name
2. Which [health service] site are you based at?
    - ☐ [Site A]
    - ☐ [Site B]
3. When did you start working at [health service]?
    - ☐ Drop down: Month (optional) / Year
4. How long have you used the EHR system?
    - ☐ 0-3 months
    - ☐ 4+ months
    - ☐ Since it was implemented (November 2022)
5. How often do you use the EHR System?
    - ☐ Several times per day
    - ☐ Daily
    - ☐ Several times per week
    - ☐ Weekly
    - ☐ Several times per month
    - ☐ Monthly
    - ☐ Less than once per month
    - ☐ Never
6. Are you an International Medical Graduate?
    - ☐ Yes
    - ☐ No
7. Your role
    - ☐ Intern
    - ☐ Resident
    - ☐ Registrar

Alert Fatigue Survey

The following survey questions 1-10 are to be rated on a 5-point Likert scale from Strongly Agree to Strongly Disagree. Question 11 will be open-ended.

Please answer the following questions to indicate your current views of alerts in the EHR system:

1. I receive too many alerts per day that I must read and respond to
2. Alerts are relevant to the individual patients for which they appear

3. I thoroughly read the alerts I receive
4. When I receive an alert, I start responding before I realise I am doing it
5. When I receive alerts repeatedly, I become indifferent to them

I am more likely to thoroughly read and respond to alerts when:

6. They relate to an uncomplicated patient, rather than a complex patient
7. I am less busy, rather than when I have a heavy workload
8. I am alone, rather than when the consultant is with me
9. I am not conducting a ward round, rather than when I am conducting a ward round

10. I experience alert fatigue
11. Is there anything else you would like to tell us about your experience of alert fatigue?

Thank you completing this survey.

-----This survey is complete-----

Appendix B – Responses to Likert scale items (n=53)

	Strongly disagree	Somewhat Disagree	Neither agree nor disagree	Somewhat Agree	Strongly agree
Current views of alerts in the EHR system:					
Frequency (too many)	0 (0.0%)	6 (11.3%)	10 (18.9%)	24 (45.3%)	13 (24.5%)
Relevance	2 (3.8%)	9 (17.0%)	7 (13.2%)	28 (52.8%)	7 (13.2%)
Read	7 (13.2%)	17 (32.1%)	4 (7.5%)	21 (39.6%)	4 (7.5%)
Habitual response	4 (7.5%)	12 (22.6%)	10 (18.9%)	23 (43.4%)	4 (7.5%)
Repeated alerts	1 (1.9%)	4 (7.5%)	9 (17.0%)	17 (32.1%)	22 (41.5%)
Alert fatigue experienced	0 (0%)	4 (7.5%)	9 (17.0%)	26 (49.1%)	14 (26.4%)
More likely to thoroughly read and respond when:					
Uncomplicated patient	4 (7.5%)	21 (39.6%)	13 (24.5%)	14 (26.4%)	1 (1.9%)
Less busy	2 (3.8%)	2 (3.8%)	4 (7.5%)	24 (45.3%)	21 (39.6%)
Alone	2 (3.8%)	7 (13.2%)	8 (15.1%)	27 (50.9%)	9 (17.0%)
Not on ward round	2 (3.8%)	3 (5.7%)	6 (11.3%)	16 (30.2%)	26 (49.1%)

Appendix C – Open ended survey responses

Response	Code/s
Sometimes young nurses especially EEN they keep messaging or create medical tasks not necessary urgent thing	• Other alerts and alarms
harder to find on epic - confusing peripheral screens - sticky notes better	• Failure to detect alerts
I have not received many alerts that are actually clinically relevant. Eg. There is an alert that arises when >1 antiemetic is prescribed, when it is actually best practice to prescribe more than one. The alerts seem to be created by someone who has no idea what we do.	• Clinical relevance • Fit with workflows • Trust
The lack of consistency in appearance and management of alerts also contributes to fatigue. Eg. Different VTEp reminders and the manner in which you can/cannot dismiss them. Also the arrangement of alerts/inappropriate or not clinically relevant alerts eg. Checking electrolytes in a patient with liver failure, all the LFT and some EUCs are bright red, which is important but not newsworthy and just makes it harder to distinguish the ones you actually care about	• Interface design • Clinical relevance
Hard stops on alerts make me dismiss them as I cannot do the job I opened the patient file to do without responding - so it gets dismissed.	• Alert type • Fit with workflows
I find myself responding to low BGL, MEWS criteria immediately. But VTE is often charged by registrars while in ED, so the form can't be completed by them at the time. I also find that I get fatigue for VTE because it is another interruption in work flow, when we already have so many others such as pages, calls, NS entering doctors space, medical tasks, direct messages. It would be better to set aside a time for the alerts that aren't immediately necessary - e.g. end of shift towards hand over. VTE often given at 8pm anyways	• Habitual response • Fit with workflows • Interruptions • Other alerts and alarms
Some alerts lose meaning because of different ways DHR is used by different users. For example they may already be addressed by someone else in practice but not addressed in the system.	• System not up to date
The VTE pop up is so intrusive that I reflexively dismiss it. The process to do the right things takes many steps so it's easier to dismiss.	• Habitual response • Cognitive overload and effort to appropriately respond
I actually would prefer if I received alerts for "medical tasks". At the moment nurses can submit medical tasks but I will only see the medical tasks if I remember to regularly check medical task board - means it is very easy for these tasks to get missed	• Failure to detect alerts • Useful alerts not present

Sometimes they are have already been addressed but the system hasn't recognised it eg: VTE prophylaxis prescribed outside of the order set	• Lack of system smarts
Alerts that appear when I open the chart are almost always ignored without reading them.	• Superficial processing of alerts • Fit with workflows
Alerts that appear when I am performing an action e.g. prescribing I am much more likely to process / read.	• Fit with workflows
Alerts which are a forced stop - are still disregarded if there are too many. Also, if there are multiple steps required to rectify an issue (often with errors cropping up within this flow) then it is more and more likely the alert will be ignored. Furthermore, some alerts are inaccurate - for e.g. the "sepsis" warning on pt files is largely inaccurate - I'm not sure on what parameters this is based.	• Volume • Cognitive overload and effort to appropriately respond • Lack of system smarts
There's also now message alert fatigue - nurses with DHR can now easily alert you to dozens of updates on the patients every day and many of them seem inconsequential / aren't medically relevant which can get really overhelming	• Other alerts and alarms • Information overload
The VTE prophylaxis alert is the worst!!	• Alert type
At some point red becomes another colour and not an alarm colour	• Failure to detect alerts (desentitisation)
We are trying to learn a whole new system so timing of alerts and appropriate escalation is important e.g. intern vs reg choice	• Fit with workflows
Too many low value alerts that are typically non urgent or not clinically relevant and require repeated responses (e.g IVC past 72 hours in a pt with difficult access. - alert triggering every time you open the chart). Would be better as side bar pop up reminders rather than requiring an action. However the system also picks up on very useful and important alerts and overall that does likely benefit pt care. May be beneficial to have the alerts appear different based on the typer of alert e.g purple for less urgent like a cannula in for 73 hours, red if your prescribing a medication the patient has an allergy too - in an attempt to improve response to more serious or time critical alerts.	• Clinical relevance • Repetition • Fit work workflows • Useful alerts • Interface design and alert tiering
There are many kinds of alerts, and messages I find the most distracting. VTE alerts get ignored most, despite being very important.	• Other alerts and alarms • Interruptions • Alert type
Other senior doctors drive behavioural responses to alerts - they often tell you to ignore xyz alert.	• Socially informed response

Appendix D – Descriptive statistics

Table D.1. Descriptive statistics of alert metrics total (0-9 months prior to participants' survey completion)

Alert metric (total)	Valid N	Min	Max	Sum metric	Mean metric	Std. Deviation
Medication alerts (override)	14437			10118	.7008	.45791
BPA alerts (override)	25652			23968	.9344	.24767
Total alerts (override)	40087			34084	.8503	.35683
BPA dwell time (seconds)	25597	1	865	139334	5.44	16.156

Table D.2. Descriptive statistics of alert metrics per provider (0-9 months prior to participants' survey completion)

Alert metric (per provider)	N (provider)	Minimum	Maximum	Mean	Std. Deviation
Medication alert volume (n)	53	1	1180	272.40	340.210
Medication alert override rate (mean)	53	.33	1.00	.6962	.14252
BPA alert volume (n)	53	6	2228	484.00	582.125
BPA override rate (mean)	53	.58	1.00	.9373	.06609
BPA dwell time (seconds, mean)	53	3.29	14.37	6.6480	2.29001
BPA dwell time (seconds, median)	53	2.00	7.00	3.4340	.93046
Total alert volume	53	12	2942	756.36	874.370
Total override rate	53	.70	1.00	.8718	.06808

Table D.3. Average number of alerts received by providers per relative month

Relative Month	Total alerts per provider (mean)
0	74.5
1	45.84
2	88.87
3	84.73
4	266.53
5	268.13
6	290.75
7	345.27
8	214.25
9	279.42

10	128.82

Table D.4. Participant frequency per relative month and inclusions

Relative Month		Participants	Percent	Valid Percent	Cumulative Percent	Inclusion/ exclusion
Valid	-7	8	2.6	2.6	2.6	Excluded
	-6	7	2.3	2.3	4.8	Excluded
	-5	8	2.6	2.6	7.4	Excluded
	-4	6	1.9	1.9	9.3	Excluded
	-3	12	3.9	3.9	13.2	Excluded
	-2	2	.6	.6	13.8	Excluded
	-1	2	.6	.6	14.5	Excluded
	0	36	11.6	11.6	26.0	Included
	1	44	14.1	14.1	40.2	Included
	2	15	4.8	4.8	45.0	Included
	3	15	4.8	4.8	49.8	Included
	4	15	4.8	4.8	54.7	Included
	5	15	4.8	4.8	59.5	Included
	6	16	5.1	5.1	64.6	Included
	7	15	4.8	4.8	69.5	Included
	8	16	5.1	5.1	74.6	Included
	9	12	3.9	3.9	78.5	Included
	10	11	3.5	3.5	82.0	Included
	11	3	1.0	1.0	83.0	Excluded
	12	4	1.3	1.3	84.2	Excluded
	13	4	1.3	1.3	85.5	Excluded
	14	4	1.3	1.3	86.8	Excluded
	15	4	1.3	1.3	88.1	Excluded
	16	4	1.3	1.3	89.4	Excluded
	17	4	1.3	1.3	90.7	Excluded
	18	4	1.3	1.3	92.0	Excluded
	19	2	.6	.6	92.6	Excluded
	20	2	.6	.6	93.2	Excluded
	21	1	.3	.3	93.6	Excluded
	22	1	.3	.3	93.9	Excluded
	23	1	.3	.3	94.2	Excluded
	62	1	.3	.3	94.5	Excluded
	63	1	.3	.3	94.9	Excluded
	64	1	.3	.3	95.2	Excluded
	65	1	.3	.3	95.5	Excluded

	66	1	.3	.3	95.8	Excluded
	67	1	.3	.3	96.1	Excluded
	68	1	.3	.3	96.5	Excluded
	69	1	.3	.3	96.8	Excluded
	88	1	.3	.3	97.1	Excluded
	89	1	.3	.3	97.4	Excluded
	90	1	.3	.3	97.7	Excluded
	91	1	.3	.3	98.1	Excluded
	92	1	.3	.3	98.4	Excluded
	93	1	.3	.3	98.7	Excluded
	94	1	.3	.3	99.0	Excluded
	95	1	.3	.3	99.4	Excluded
	96	1	.3	.3	99.7	Excluded
	97	1	.3	.3	100.0	Excluded
	Total	311	100.0	100.0		

Table D.5. Descriptive statistics of alert metrics per provider (0-30 days prior to participants' survey completion)

Alert metric (per provider)	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Medication alert volume (n)	43	14	200	50.88	42.608
Number of days with at least one medication alert	43	5	21	10.26	4.919
Medication alerts per day (mean)	43	2.00	10.89	4.6466	2.25713
Medication alert override rate (mean)	43	.33	.96	.7126	.13340
BPA alert volume (n)	43	17	761	152.26	152.493
Number of days with at least one BPA alert	43	6	23	12.91	4.844
BPA alerts per day (mean)	43	2.13	33.09	10.5605	6.58646
BPA override rate (mean)	43	.67	1.00	.9418	.06042
BPA dwell time (seconds, mean)	43	3.00	20.65	6.2251	3.22007
BPA dwell time (seconds, median)	43	2.00	5.00	3.3837	.65317
Total alert volume	43	33.00	855.00	203.1395	172.82245
Number of days with at least one alert	43	7	23	14.09	4.985
Total alerts per day	43	3.00	37.13	13.5067	7.19840
Total override rate	43	.70	.98	.8796	.06871

Appendix E – Linear regression results

Variables tested	R^2	Adj. R^2	F	p	B (slope)	SE (B)	β (Beta)	t
Mean total alert override rates per provider, predicted by relative month	.007	.002	1.395	.239	.004	.003	.082	1.181
Mean medication alert override rates per participant, predicted by relative month	.000	-.005	.093	.761	.001	.004	.022	.304
Mean BPA override rates per provider, predicted by relative month	.000	-.005	0.021	.886	.000	.003	.010	0.143
Mean BPA dwell times per provider, predicted by relative month	.248	.061	13.604	<.001*	-.610	.165	-.248	-3.688
Median BPA dwell times per provider, predicted by relative month	.035	.030	7.501	.007*	-.359	.131	-.187	-2.739

*significant at the .01 level

CHAPTER 8

General Discussion

SUMMARY OF FINDINGS

This thesis explored clinicians' acceptance and use of Clinical Decision Support (CDS) systems over time. Chapter 3a synthesised the approaches used in existing literature to involve clinicians in CDS development and found that co-design was rarely examined in terms of its impact on post-implementation acceptance and use. Chapter 3b reviewed the methods used in existing research to evaluate CDS acceptance and use over time and revealed a lack of longitudinal research and qualitative studies post-implementation. In Chapter 4, a systematic review identified and mapped 132 factors reported to influence CDS acceptance and use at different points in time following implementation and demonstrated how clinicians' needs evolve over time. A pilot approach to implementing two CDS systems in a rural hospital was qualitatively evaluated in Chapter 5, revealing important insights on clinicians' early acceptance and use of CDS with different levels of user involvement. Chapter 6 focused on alerts embedded in Electronic Health Record (EHR) systems that were used in routine practice, and qualitatively explored junior doctors' experiences of alert fatigue and factors influencing their routine use and disuse of alerts. Junior doctors' perceptions of alerts and alert fatigue were compared with their actual exposure to and interactions with alerts in Chapter 7, revealing a lack of association between subjective and objective measures. Chapter 7 also revealed similarities and differences in perceptions and actual use of alerts between very new and more experienced users.

A core contribution of this thesis is the demonstration that clinicians' acceptance and use of CDS evolves over time, as shaped by complex interactions between individual, technological, and organisational factors. In Chapter 1, I introduced the concept of time and proposed that time can be considered not only through formal implementation stages (e.g., planning and analysis, design, implementation, and maintenance), but also by users' levels of exposure, familiarity, and experience with CDS systems (e.g., pre-adoption, early use, routine use).

These trajectories often, but do not always, align. The next sections outline key experiences found to influence *early* acceptance and use, followed by those influencing *routine* acceptance and use. Different strategies that can be taken to improve experiences and opportunities for further research are highlighted throughout these sections. Differences observed between experiences for new users of *newly implemented* systems and new users of *routinely embedded* systems are also described throughout. The chapter then highlights how strategies could be practically employed during CDS selection, development, implementation, and maintenance, to anticipate and address issues found to impact acceptance and use as they emerge and evolve. Lastly, the chapter concludes with a discussion of the strengths, limitations and conclusions of this work.

EARLY ACCEPTANCE AND USE: A FUNDAMENTALLY IMPORTANT TIME

The importance of clinicians' early impressions of CDS was emphasised throughout this research. Chapter 4, 5 and 6 showed that negative early impressions of CDS can have lasting impacts on clinicians' acceptance and use over time.[1,2] This finding appears to somewhat contradict literature discussed in Chapter 1 that has explored the acceptance and use of other clinical information systems, such as Electronic Health Records (EHRs) and Computerised Provider Order Entry (CPOE), over time. While studies evaluating these systems have reported clinicians' acceptance to decrease immediately following implementation and later stabilise as clinicians adjust their expectations and adapt to system flaws,[3-5] the research reported in this thesis suggests that early dissatisfaction with CDS systems typically leads to long term disengagement. Unlike EHRs or CPOE systems, which are mandatory and essential for completing core clinical tasks, users may be less inclined to persist with a CDS if they do not have positive early experiences with it.

There is therefore a need to ensure early experiences with CDS are positive. Findings across chapters suggest that early acceptance and use is shaped by a complex interplay between clinicians' prior exposure to and experiences with CDS systems and processes, their individual characteristics, and their early experiences of using the system within the implementation context. These themes are further discussed in the sections below.

The influence of prior experiences, exposure, and expectations on early acceptance and use

In line with concepts introduced in the first chapter, previous experiences with different systems and processes, as well as prior exposure to the CDS system being implemented, contributed to clinicians' expectations of CDS before use.[6,7]

Exposure to different systems or processes

In Chapter 4, studies conducted in the first 6 months following implementation reported that exposure to different systems or processes which CDS replaced, influenced acceptance and use. This occurred for example, where hospitals had transitioned from alerts within a homegrown EHR, to a commercial EHR system with embedded alerts based on standardised knowledge bases.[8] Interviews on alert fatigue in Chapter 6 similarly revealed that doctors who were new to a hospital often had pre-existing expectations of CDS based on their interactions with systems in other settings. Some doctors who had previously used EHRs without alerts for example, expressed a preference for their current system that utilised alerts. Interestingly, some junior doctors perceived that having no experience with other systems made them more tolerant and accepting of alerts, as they had no alternative frame of reference.

Clinicians in Chapters 5 and 6 discussed how negative experiences with the CDS systems contributed to general negative perceptions of CDS and influenced attitudes toward CDS systems they subsequently interacted with. This effect appeared to be stronger when the new system closely resembled the one in which they had had the prior negative experience with. For example, in Chapter 5, a manager expressed concern that the failure of the dashboard to support nurses' management of COVID-19 patients undermined their trust and made it more difficult to convince them that a different system could support these needs. Similarly, in Chapter 6, frequent encounters with alerts that were not helpful, led some doctors' to be more sceptical of new alerts they encountered. In line with these results, a recent study in primary care highlighted that clinicians' perceptions and use of CDS could be shaped by negative prior experiences with digital technologies in general.[9] Taken together, these findings suggest that negative experiences with clinical systems can influence early interactions with newly encountered CDS systems.

Exposure to CDS through planned implementation activities

Some clinicians were introduced to CDS through planned implementation activities such as co-design (Chapters 3a and 5). Interestingly, co-design appeared to serve a dual purpose. While it is primarily used as a method to improve the CDS' fit with users' characteristics and needs,[10] we found that co-design provided an opportunity for clinicians to gain early exposure to the CDS, better understand the intent of the system, and increase their buy in and ownership.[11] In Chapter 5, interviews revealed that co-design created a chance for ED doctors to form positive perspectives about not only the CDS, but also the vendor, who were responsible for developing and implementing the system. Trusted relationships were established through the incorporation of incremental changes based on clinician feedback, which was described to enhance positive perceptions of the CDS during early use. These findings align with prior research on clinical information system implementations, which suggests trusted relationships, such as those with implementation teams, are foundational for early success.[12-14]

Exposure to CDS through social influences

Social influences appeared to be particularly important for shaping early perceptions of CDS systems, particularly among new users and later adopters. For example, in Chapter 5, specialists in different departments of the hospital formed positive perceptions of the ED mobile app by observing clinical champions in the ED use the tool in practice. In contrast, Chapter 6 found new junior doctors were often negatively inducted to alerts, observing senior doctors and colleagues rapidly dismissing and expressing their frustration with alerts. These findings are aligned with the Unified Theory of Acceptance and Use (UTAUT) and Diffusion of Innovations (DOI) discussed in Chapter 1, which identify social influence as an important factor in system acceptance among less experienced users and later adopters.[7,15] These findings also highlight a need to develop or apply strategies that could help to continue fostering positive culture around the use of CDS systems over time and is an important area for future research.

Interestingly, exposure to CDS also occurred through social networks *between* organisations. In Chapter 5, when the first dashboard failed to support patient flow nurses in managing COVID-19 patients, they initially lost confidence in CDS. However, after hearing stories from nurses at another hospital who were successfully using a different dashboard for the

same purpose, they became more open to trialling the alternative system. No study identified in Chapter 4's review however discussed the impact of broader social networks on exposure to CDS and early acceptance, suggesting this should be further explored in future research.

The influence of individual characteristics and adopter curves on early acceptance and use

In Chapter 4, individual differences between clinicians were found to moderate CDS acceptance and use, however as this result was mainly identified in quantitative studies, the reasons behind these differences were not explored in depth. In Chapters 5 and 6, individual characteristics such as digital literacy, openness and readiness for change, and personality traits, contributed to differences observed in early acceptance and reported interactions with CDS. In Chapter 5, participants who were involved in co-design of the ED mobile app described themselves as "technophiles", who were more confident with technology and open to innovation. This aligns with the adopter categories described in the DOI theory discussed in Chapter 1, which characterise early adopters as individuals who are open to innovation, abstract in their thinking, and hold positive attitudes toward science and technology.[7] In contrast, doctors who were described as more sceptical of technology and slow to adopt change, were reported to be less receptive to using the system, less interested in being involved in co-design, and exhibited lower tolerance of system flaws. While DOI suggests that later adopters tend to avoid trialling innovations early due to the investment typically required, findings from Chapters 5 and 6 showed that even later adopters engaged with CDS early on, as these systems were easily available and accessible.[7] However, this meant that negative early impressions formed quickly and were not easily overcome.

Given the tendency of early adopters to seek out information about innovations, identifying clinicians with these traits to contribute to early system design and serve as champions could support more effective CDS integration. Their involvement could help to ensure the system aligns with clinical needs from the outset and provide visible evidence of its effectiveness in practice, which is often critical for encouraging uptake among later adopters.[6,7,16]

Interestingly, new users of CDS alerts in Chapter 6 often mentioned personality traits to impact how they perceived and interacted with alerts. Those who self-described to be more cautious and meticulous, characteristics that align with the personality trait of

conscientiousness,[17] described attending to alerts more than their colleagues. One explanation for this is that conscientious clinicians view alerts as tools that help to ensure thoroughness and reduce risk, prompting them to engage more fully. This distinction suggests that personality traits may shape not only attitudes toward CDS, but also how clinicians evaluate its usefulness during early interactions. In line with these findings, a thesis exploring the relationship between personality and continued EHR use, found that a higher level of both openness and conscientiousness promoted users' intentions to continue using the system.[18]

This was, however, somewhat contradictory to patient flow nurses in Chapter 5, who were perceived as being both open to technology and cautious yet still rejected the dashboard. These conflicting findings are likely due to differences in the fit and maturity of systems.[18] In Chapter 6, the CDS systems examined, i.e., interruptive and passive medication and best practice alerts, were not innovative technologies. These types of alerts are now a standard component of most EHRs, and most clinicians often enter clinical environments where such alerts are already established. Thus, in Chapter 6, doctors who were more cautious viewed alerts as an opportunity to support patient safety, while nurses in Chapter 5 perceived the dashboard to impede their ability to safely monitor patients.

Overall, these findings reinforce the need for targeted approaches to selecting, designing and implementing CDS systems, that accommodate different personality profiles and adopter types. By aligning strategies with the diverse preferences, expectations, and engagement styles of users, long-term acceptance and use of CDS systems is likely to be improved.

The influence of early experiences on early and ongoing acceptance and use

CDS system performance and maturity

Consistent with technochange theory, many CDS systems were found to struggle with early performance issues that emerged during the 'shakedown' stage.[19] Issues identified in Chapter 4's review included poor integration with existing technologies, system glitches, and inaccurate data, which were more often reported to impact acceptance and use early post-implementation. As previously discussed in Chapters 4 and 5, these issues left clinicians sceptical of CDS and contributed to lasting disengagement.[1] This effect appeared to be amplified for clinicians that already held negative expectations, as evidenced in Chapter 5. Such findings highlight how individual and CDS system factors can interact during the early

phases of use, where clinicians who hold negative mental models of CDS or possess characteristics associated with later adopters of technology, may simply reject the system upon encountering these issues as they confirm their existing beliefs.[20,21] Improving CDS system design and attitudes toward CDS prior to implementation, and quickly addressing unresolved challenges in the early stages of implementation, are likely to help mitigate this problem.

Lack of familiarity and reduced efficiency

A recurring theme was how clinicians new to using CDS, faced challenges relating to self-efficacy. Chapter 4's systematic review found perceptions regarding clinicians' lack of self-efficacy to use CDS to be particularly prevalent during the first 6 months post-implementation. Studies often reported a lack of experience with CDS, and limited knowledge of its features and in what situations it would be useful for, to influence clinicians' early acceptance and use.[14,22,23] In Chapter 5, patient flow nurses struggled to use the dashboard due to a lack of familiarity with the system and insufficient knowledge around how to interpret the information presented, as well as a lack of familiarity with clinical process changes introduced by the dashboard. This appeared to be less pronounced for new users of existing CDS systems, supported by Chapter 5 and Chapter 6, where doctors relied on peers with established knowledge of how to use CDS effectively and efficiently within local workflows (to be discussed further in *Routine use: Workflow integration and organisational culture*).

Simultaneously, negative outcomes of CDS for clinicians, such as reduced efficiency, were commonly reported during early use of CDS (Chapter 4, 6 and 7). Clinicians in Chapter 6 described expending more cognitive effort and greater uncertainty in interpreting and applying information presented in alerts when they had less clinical experience. The lack of familiarity with the clinical issue the alert was targeting led to a lack of confidence in decisions and appropriate actions to take, which appeared to be influential in junior doctors' early experiences with alerts. For example, a doctor described receiving a drug-drug interaction alert but lacking experience to decide whether the interaction was concerning or clinically indicated. Due to a combination of the cognitive burden and follow up actions required to fully interpret the alert and the fast-paced environment of the hospital and junior doctors' roles, the alert was ignored. These findings are supported by Chapter 7, where new

users took significantly longer to respond to alerts but reported similarly high levels of alert fatigue when compared to more experienced users. These findings demonstrate how a lack of familiarity with both the CDS system, and with the information provided, can contribute to an increased amount of time and effort that clinicians spend using CDS (Chapters 4, 5, 6 and 7).

Findings from this research builds on prior literature by demonstrating the impact of familiarity with CDS systems on acceptance and use during early implementation.[5,24,25] It also introduces new findings that are likely to be specific to systems designed to support decision making, in contrast to systems such as CPOE and EHRs, which tend to focus on process-based tasks. In particular, familiarity with the clinical issue and decision targeted by the CDS appears to be uniquely important in influencing acceptance and use of *CDS*, as junior clinicians require more time to interpret and assess the relevance of recommendations. Without sufficient familiarity, these systems may be perceived as burdensome, increasing the risk that clinicians disengage after only a few encounters and before the potential value of CDS is recognised (to be described further in a later section on *CDS usefulness and value*).

This emphasises the importance of supporting early use and promoting familiarity through co-design, champions, and education on the system *and* clinical issue targeted.[26] Prior research has highlighted how ongoing, experiential learning, that emphasises practical skills, can help to improve self-efficacy in the early stages of use.[13] Importantly, our findings also highlight the need to reduce burden on clinicians who are new to using CDS systems, primarily junior clinicians who may lack familiarity with clinical processes and nuances in clinical decision making. Organisational initiatives, such as protected time to complete administrative tasks, have been previously reported to reduce overload and burnout among resident physicians.[27] Similarly, initiatives like low-paging hours were perceived positively by participants in Chapter 6 to help manage their task list. Organisational practices such as protected time have not been evaluated in context of CDS implementation or for junior doctors' use of CDS and should be explored in future research.

<u>CDS system usability and perceived ease of use</u>

The usability and perceived ease of use of CDS systems also emerged as a recurring theme during the early stages of implementation (Chapters 3a, 4 and 5) and early use (Chapter 6). Findings from this research, when considered in the context of the UTAUT, indicate that

strong usability can help to mitigate the effects of limited familiarity and reduced efficiency that are associated with the early use of CDS. The UTAUT proposes that experience moderates the influence of effort expectancy, i.e. the users' belief about how easy or difficult the technology will be to use, on system acceptance and use.[15] As reported in prior studies conducted during early use of CDS and in line with the DOI theory, a more usable and intuitive system can speed up the process of familiarisation.[7,28,29] My findings suggest that CDS usability should not only support intuitive technical interactions, but also make it easy for clinicians to understand the advice provided and access additional relevant information to further guide their decisions.

Additionally, usability appears to be particularly important when the benefits of using a system remain unclear (as will be further discussed in the next section '*CDS usefulness and value'*).[28] In Chapter 6, doctors described continuing to engage with alerts that were perceived to be usable and easy to process, even where they at first, did not see the value. In Chapter 5, ED doctors perceived the mobile app to be highly usable, which promoted further engagement. As aligned with prior research,[30] Chapter 5's findings however, suggest that while usability is important during the early stages of use, it is not enough to *sustain* use alone. We found that when doctors' expectations of the CDS' value were not met over time, they gradually stopped using the system.

Chapter 3a found that co-design is likely to be effective in improving perceptions of CDS usability, where many studies employing co-design approaches reported ease of use as a facilitator to acceptance and use, primarily in the first year following implementation. Similarly, as reported in Chapter 5, the co-designed ED app was perceived as being easy to use and intuitive, while the patient flow dashboard with limited co-design was perceived to be difficult to use. Literature has suggested that the interface design, logic and data underlying CDS, and timing and presentation in workflows, must be co-designed to meet clinicians' needs for usability.[31,32] Taken together, these findings advocate for the use of co-design to improve CDS system usability and improve early and consequently, long term acceptance and use.

CDS usefulness and value

Consistent with prior reviews, CDS' usefulness and value were found to be key factors driving acceptance and use.[33-35] While *perceived usefulness* refers to the extent to which clinicians believe a CDS system can enhance their job performance,[36] *perceived value* reflects a clinician's broader judgment of whether the system delivers sufficient benefits, relative to the effort required to use it.[37] Chapter 4's review showed that perceptions of usefulness could impact clinicians' acceptance and use of CDS immediately after implementation and continue to be important over time. Interestingly, perceptions of usefulness could be both anticipated, where clinicians thought the CDS *could* offer value, or provide actual value, where clinicians observed benefits resulting from using the system.[38] Across all chapters, it was evident that the value, or at least potential value, of CDS had to outweigh the barriers to using it. Where barriers to use were greater than the CDS' perceived value, clinicians reported ignoring or abandoning the system.

Chapters 4, 5 and 6, highlighted that useful CDS systems were those that targeted an issue that clinicians viewed as important *and* those that were perceived to effectively target the issue. For example, while the dashboard in Chapter 5 met criteria 1 (nurses perceived a need for increased support in virtually monitoring COVID-19 patients), it did not meet criteria 2 (nurses felt the dashboard was overengineered for the purpose of monitoring COVID-19 patients). The usefulness of a CDS could however be interpreted differently for different users.[37] For example, as previously discussed, doctors with more conscientious personality types in Chapter 6 found alerts to be useful as they were perceived to improve their thoroughness in caring for patients.

In Chapter 6, several participants described forming rapid judgments about the relevance and value of an alert based on their first few encounters, which often dictated their use of that alert over time. Although doctors reported reading and actively engaging with alerts during initial encounters, they often quickly formed judgements about each alerts' value in a particular context. For some users, once a negative conclusion was drawn, it appeared that they would no longer actively interpret the alert and its value, but rather rely on their mental model of it to guide future behaviour. This was further supported in Chapter 7, where decreasing dwell times were observed over time and newer users more often reported thoroughly reading alerts than more experienced users.

As observed in Chapters 4, 5 and 6, the benefits of CDS were not always immediately apparent to clinicians and the challenges during early use could often be immense. We found that benefits often emerged over time as users became more familiar with the system and its capabilities, gained experience using it in different clinical scenarios and thus, developed an increased understanding of when and how it could be useful. This finding parallels the process referred to in information systems as 'appropriation', which argues that users refine their use of technology over time based on experience and evolving needs.[39] It is only through appropriation that users are considered to find value in system use. In line with design in use approaches discussed in Chapter 1, the authors argue that technology design is therefore not complete when a system is launched but is instead completed in use, as users appropriate (adapt, configure, and repurpose) technologies to fit their practices.[7,39,40]

Interestingly, in Chapter 5, by utilising the pilot implementation approach as a way to encourage appropriation and ongoing design of the CDS in use, ED doctors were found to be more willing to use CDS based on anticipated value rather than observed value in the early stages of use. Because the CDS was constantly being adapted and iterated to meet doctors' needs as the systems' value became more apparent, they continued to engage as they were invested in its potential, anticipated value. For some doctors, it was only once this process ceased, and the system had not yet met their expectations, that they stopped using it. Continued co-design of CDS throughout implementation is therefore recommended to support ongoing adaptation of the system as users discover new ways it can provide value in practice.

Another important observation is how the benefits of CDS were sometimes perceived for other stakeholders, such as the hospital, patients, or other clinicians, but not the primary users of the system. Given the intended role of CDS systems to *support clinicians'* work, it is worth considering whether a CDS system that is not expected to provide any benefit back to the clinician using the system (in addition to other stakeholders), should be implemented at all. In Chapter 6, doctors highly valued efficiency and a common driver of alert fatigue (ignoring and/or becoming frustrated by alerts) was where alerts negatively impacted efficiency and resulted in a loss of time and effort. Useful CDS systems on the other hand, were described to improve efficiency by supporting doctors with cognitive unloading, saving time in their interactions with the EHR, and providing information that was easily forgotten. These were

notably all benefits that could improve patient safety and performance, but also provided some direct benefit to clinical users. We therefore recommend that all CDS systems be designed to provide benefits directly to clinicians as well as other stakeholders, which could be achieved by involving clinician end-users in CDS selection and design.

'Fit' between CDS and the organisational context

Consistent with prior research, we found CDS acceptance and use to be heavily influenced by the fit of the system with the local context. In Chapter 5, for example, the innovativeness and immaturity of the patient flow dashboard clashed with the organisational instability caused by the COVID-19 pandemic. The introduction of an innovative system, without sufficient technical maturity or organisational support, such as training and guidelines, during this unstable time led to rapid rejection among users. Similarly, the ED app and pilot approach lacked compatibility with the hospitals' technical infrastructure, such as Wi-Fi availability, and organisational resources including a well-resourced information technology team, which was needed to address user feedback. This appeared to be particularly impactful given the rural context of the hospital. These findings highlight the need to procure and design CDS systems that match organisational readiness requirements, which could include assessing and mapping factors like digital maturity, infrastructure and resources, as well as individual and organisational readiness for change.[41] Additionally, like prior research, we recommend that CDS implementation processes and support be appropriately tailored to suit the context, system complexity, and degree of change, expected.[42,43]

Workflow fit, on the other hand, emerged as a concern shortly after implementation and continued to influence CDS acceptance and use over time. In Chapter 4's review, workflow fit was often identified as a barrier to use. Challenges relating to workflow included CDS being presented at the wrong point in time or to the wrong users, and lacking fit with existing systems, clinical pathways and decision-making processes (evidenced in Chapters 4, 5, 6, and 7). Prior research has shown that many issues relating to workflow can be anticipated and addressed while developing CDS. For example, using methods such as interviews, observations, and contextual inquiry can help to map clinicians' existing workflows and decision-making processes, and inform the development of systems that are intuitively designed and presented according to these needs.[44,45] Other challenges relating to workflow however, could be more difficult to predict until clinicians begin using CDS in real-world

settings. Salwei et al. (2023) conducted a retrospective analysis of issues arising during the co-design process, as compared to those experienced post-implementation of CDS.[32] The authors found that challenges relating to the physical environment, organisation and teamwork, were rarely discussed during co-design, if at all.[32] In Chapter 6, issues such as information overload from the environmental and organisational context, such as other alerts, alarms and tasks, time pressure and expectations of efficiency, were found to impact doctors' use of alerts. These represent conditions that are difficult to replicate and fully imagine the impacts of without using CDS in practice, further emphasising the need for ongoing co-design and adaptation of CDS throughout implementation.

Organisational commitment and implementation resources

Clinicians' perceptions of organisational commitment to CDS and appropriately resourcing its implementation also emerged early on. This was particularly evident in Chapter 5, where several clinicians perceived the CDS as a short-term pilot with unclear long-term viability, reducing their willingness to invest time and effort into using the system. While this Chapter presented a somewhat unique case, where the CDS was implemented as a pilot, a review of CDS systems used in regular practice (i.e. excluding pilots) also highlighted organisational support as a key factor influencing success.[46] The influence of organisational commitment in early CDS implementation aligns with broader research on innovation commitment, which highlights the importance of visible, sustained investment from leadership to foster use and build trust in new systems.[47] Research has shown that when CDS use is *not* expected or rewarded by the organisation, this negatively impacts acceptance and use.[1] Efforts to communicate the importance of the CDS in relation to broader organisational goals could help to improve perceptions and priority given to the system. Effective communication from hospital managers and leadership has been reported to improve early perceptions of other clinical information system implementations.[12]

Furthermore, providing additional implementation support during the early stages of use could help to overcome barriers experienced during this time. Providing ongoing experiential training, incentives and implementing initiatives like protected time may help to improve early acceptance and use. Findings from this thesis also echo prior research highlighting the importance of clinical champions and super users in implementing CDS.[6,48-51] Champions can help to foster positive perceptions and increase exposure to CDS systems. In addition, they

play a critical role in enhancing other users' understanding and self-efficacy by demonstrating how systems can be effectively used to perform tasks in local settings.[50] Prior research has found champions often act as intermediaries, relaying feedback from less engaged users to IT staff and vendors, thereby bridging gaps between frontline clinicians and system developers to improve systems for all users.[52] Chapter 4's review identified a handful of studies that reported that champions and peer recommendations improved CDS acceptance and use, and these were unsurprisingly used only in the early stages of implementation.[2,53,54]

Conversely, the absence of organisational and on-the-ground implementation resources was found to negatively impact clinicians' initial engagement with CDS in Chapter 5, a finding that also emerged in Chapter 4. In line with previous research, Chapter 5 found clear governance and leadership support to guide the provision of these resources to be particularly important.[55,56] It is therefore recommended that appropriate governance structures be instituted to support and monitor the allocation of resources and respond to emergent needs.

ROUTINE ACCEPTANCE AND USE

Of the issues arising during early implementation and use, some appeared to dissipate and others continued to be problematic during later stages. For example, a lack of familiarity and the importance of usability were more commonly associated with the early stages of implementation and for new users of existing CDS systems, than during routine acceptance and use. In contrast, some issues like workflow fit, usefulness, and individual differences, continued to be reported over time. In particular, individual and organisational factors became increasingly prevalent over time in Chapter 4's review, which was also reflected in the results that were uncovered in Chapter 6.

Three broad explanations can be put forward for the recurrence of similar themes across early and routine acceptance and use. In line with technochange theory, which discusses the concept of exported problems, some issues that were apparent in earlier stages were never addressed and so remained in later stages of implementation.[19] For example, in Chapter 6, many alerts that doctors described encountering long after implementation were perceived to have never been useful. Secondly, some general themes remained stable but were experienced differently in routine use. As demonstrated in Chapters 4 and 6, self-efficacy and mental models initially arose during early use in relation to limited understanding, skills, and pre-

existing conceptions of CDS. Over time, however, these progressed to enhanced self-efficacy and more informed attitudes, shaped by clinicians' actual experiences and interactions with the system. Lastly, new challenges that related to previously encountered problems, such as issues with the systems' performance, could resurface over time.

Other themes arose during routine use but were not often described during early implementation or use. These themes arose based on increasing users' familiarity and experience with the CDS, enhancements in system maturity and the systems' fit with the local context, and changes to the work system, that naturally occurred over time. Routine use was, in large part, influenced by the experiences and satisfaction of users with the CDS during early use and through the embedding of CDS into routine work, which occurred not just through individual users, but through shifts in organisational practice and culture. This was reflected in Chapter 4's systematic review, where factors relating to individuals and the inner setting were observed to increase over time. Themes included habits and mental shortcuts, experienced use of CDS, integration of CDS into routine decision-making and workflows, and unintended uses of CDS systems that became entrenched over time. Notably, these themes are not as often discussed in existing CDS literature or reviews.[33,35] A likely explanation, as supported by Chapters 3b and 4, is that routine use of CDS has been studied far less than early use, accounting for the underrepresentation of these factors in the literature. As demonstrated in the following sections, these themes play a critical role in shaping how CDS is sustained, adapted, or resisted in everyday practice.

The influence of integration into individuals' ways of working on routine acceptance and use, and disuse

Self-efficacy, experienced and individualised use

Clinicians' self-efficacy to use CDS appeared to increase with more experience and familiarity with both system features and the information presented (evident in Chapters 4, 5 and 6). Experienced users were able to more efficiently and effectively assess which CDS features were helpful for what purpose, and when information could be safely disregarded. As discussed in Chapter 4, a number of studies found clinicians became more aware of system limitations and inaccuracies in CDS output over time, and were better able to distinguish appropriate situations in which to use their own judgement over system recommendations.[54,57] Interestingly, in Henry (2022) for example, clinicians did not fully

understand the technical build of the CDS, which was a Machine Learning (ML) based model, but the observation of its performance in different contexts was sufficient to build confidence and trust in the system.[54] As reflected in Chapters 4 and 6, clinicians observed how CDS performed for different patients in different scenarios, which contributed to them routinely using, or not using, CDS in different contexts.

Another facet of self-efficacy that emerged was where experienced users actively sought CDS out and found value by engraining its use into different tasks and workflows. A study identified in Chapter 4 for example, found individualised dashboard use varied both within and between departments, where general medicine nurses used it intermittently to monitor patients, while doctors integrated it into specific workflow tasks.[1] In Chapter 5, frequent users of the app found value by using it for specific purposes. For instance, one doctor described finding value in using the app during handovers, and another described it being helpful in showing and discussing imaging results with patients. In Chapter 6, there was evidence of individualised use in experienced *EHR system* users, who described mastering the system over time and creating their own alerts for information they viewed to be important. This included for example setting up passive icons that displayed when patients' test results were returned. Doctors who had set up these types of alerts perceived them to be the most useful alerts they received.

Aligning with prior research, these findings suggest that individual differences and preferences in the use of CDS become more pronounced as users become more familiar with the system and find ways to most effectively utilise it .[28,58,59] It is therefore recommended that CDS systems be designed to accommodate different user types and allow flexibility for users to decide how and when CDS is used. While the importance of tailoring CDS to clinicians' specific roles has been previously reported,[60] there has been limited discussion on designing CDS systems that can be personalised by clinicians. Personalised decision support systems have been proposed to improve autonomy and enhance value to users in other information systems domains, but have not been trialled in clinical settings.[61,62] AI could also present opportunities to improve CDS personalisation, where it could be applied to learn clinicians' interactions with CDS and ultimately suggest relevant and timely information in line with clinicians' individual ways of working, thus strengthening benefits returned to users over time. Further research is needed to explore different mechanisms by which personalisation could occur and its impact on CDS acceptance and use.

In Chapter 6, in cases where alerts were seen as useful but appeared at the wrong point in time, doctors often described developing workarounds, such as setting alerts and alarms on personal devices, and writing tasks and reminders down on paper, before actioning these items at a different time. This was evident for example, where certain departments were described to require junior doctors to complete VTE assessments for each patient. However, given the VTE alert appeared upon opening a patients' chart and doctors viewed charts with a different intention, they reported routinely ignoring these alerts. In Chapter 4, workarounds were often observed long after CDS was implemented, suggesting that users develop strategies to overcome system or workflow limitations as they become more aware of them over time. Similarly, as reflected in prior research of different clinical information systems, clinicians described picking up workarounds by observing colleagues' behaviours.[63,64] This reinforces how workarounds promoting CDS disuse can become further engrained in an organisation and become more difficult to resolve over time.[65] Although workarounds can enable improved efficiency where CDS does not meet clinicians' needs, they can also present safety risks and diminish any potential benefits of CDS.[66,67] For example, some doctors in Chapter 6 described losing paper that they had written tasks on, or using 'mental reminders' to come back to tasks but forgetting to do so. It is therefore important to continue monitoring CDS use and actively engage with clinicians to identify opportunities for improving system design and integration with workflow needs over time.

As an important caveat, increased self-efficacy and experienced use emerged only where clinicians *used* the system. This aligns with prior research on adopter types and patterns of use discussed in Chapter 1 and may explain why previous studies have found some groups of clinicians increase their use of clinical information systems over time, i.e. as they build self-efficacy, develop experienced and individualised use, and observe increased benefits, while others stop using the system early and consequently are never exposed to its benefits.[44,45] Promoting anecdotal evidence of CDS benefits, by communicating how experienced users have found value from the system, may help to build later adopters' trust in CDS and convince them that the system is worth trialling.

General attitudes toward CDS

Clinicians' attitudes toward CDS systems were observed to play an important role in shaping use over time. As previously described, pre-existing attitudes informed early interactions with CDS, and early interactions with CDS in turn informed updated attitudes that guided ongoing use. In line with theories and studies discussed in Chapter 1, findings from Chapter 6 suggest that attitudes eventually stabilise with routine use.[68-70] Interestingly, doctors who held more positive attitudes towards alerts were observed to generally be more aware of the impact of CDS on the clinical issue it was aiming to address, and/or of digital health systems in general. For example, some described recognising the complexities of tailoring CDS embedded in EHRs from large commercial vendors, and thus reported being less frustrated by alerts. Doctors often described being made aware of these clinical and system related issues through their participation on hospital committees and audits, including digital health committees and those for specific clinical issues, such as Venous Thromboembolism (VTE). Being involved in these committees appeared to increase both their understanding of the issue, by for example observing data that showed the negative impacts of missing relevant alerts on patients, and their ownership in resolving them.

However, negative attitudes could also become engrained, leading to routine disuse of CDS. While much research has attempted to understand how pre-existing and early negative attitudes toward CDS and other systems can be reshaped, strategies for reversing long-standing negative perceptions remain underexplored. Findings from this research suggest that when clinicians have negative prior experiences with CDS, their attitudes can become more deeply entrenched, leading to heightened scepticism that the system can meet their needs. Addressing these attitudes is therefore likely to require tailored strategies that focus on rebuilding trust and demonstrating value.

Habits of CDS use and disuse

Habits appeared to emerge over time, both for routine use *and* disuse of CDS. Habitual disuse of CDS was reported in Chapters 6 and 7. In Chapter 6, doctors described forming mental shortcuts of an alert's value based on initial interactions, that contributed to them habitually dismissing these alerts over time. Similarly, many doctors in Chapter 7 reported responding to alerts before they realised they were doing so. This finding supports existing research that theorises the disuse of CDS can become habitual and expands upon prior work by further

clarifying the conditions under which these habits can emerge.[71] Prior literature on information system habits suggests they develop over time in response to specific repeated contextual triggers, but are not generalised across all situations.[72] In Chapters 6 and 7, these contextual triggers appeared to include specific interactions with the EHR, such as ordering a specific medication combination or when opening a patients' chart, or specific environments such as on a ward round. When these contextual triggers were present and apparent, clinicians described habitually dismissing alerts. Notably, it is suggested that this habitual behaviour may be specifically related to *interruptive* CDS, given other forms of CDS may simply be ignored.

Chapters 6 and 7 revealed that while the initial window for shaping engagement with alerts appeared to be brief, there were situations in which changes to contextual triggers disrupted clinicians' established patterns of overriding alerts. These included rotating to a different department or where the importance of an alert became more salient, such as making an error due to dismissing a clinically relevant alert. Junior doctors discussed how their use of alerts could sometimes change in different rotations, such as between the ED, inpatient and surgical units, where the environmental pressure, workflows, autonomy, or patient complexity in each department varied. Changes in contextual triggers that disrupt behaviours are consistent with habit literature and provides clues as to how routine disuse behaviours could be addressed. For alerts in which persistent use habits have developed, purposefully changing contextual triggers such as alert design features and taking other steps to reiterate the importance of alerts or clinical issues that alerts target, may disrupt these behaviours. In line with this, studies have cited improvements in clinicians' use of alerts following redesign of alert interfaces and logic.[73]

Although this evidence reveals how habits are *perceived* to occur and be disrupted, habits typically emerge subconsciously.[74] This may explain findings from Chapter 7, which found no significant association between users' perceptions of habitual behaviour and their actual use of alerts. Additionally, while Chapter 7 found dwell times to decrease over time, override rates did not change. As previously explained, this could be due to the focus on all medication and BPA alerts as a group, rather than evaluating the use of specific alert types, in particular contexts, which may be more susceptible to effects of habitual behaviour and desensitisation. Thus, further testing of habitual disuse of specific alert types, given specific contextual

conditions (as reported in Chapter 6), should be conducted using objective and/or observational data.

Habits that *encouraged* system use were also observed across chapters. In multiple studies identified at around one year post CDS implementation in Chapter 4's review, habits were described to increase use, where the more a clinician used CDS and the more familiar they became with it, the more habitual and routine the use of the system became.[2,75] As discussed in an earlier section on '*self-efficacy, experienced and individualised use*', some clinicians developed habits around using CDS for particular interactions in their workflows. In Chapter 6, some alerts and the broader EHR system were described to be interacted with habitually, which was perceived positively as it allowed them to find and process information more efficiently. Interestingly, even disuse habits were often perceived positively as they allowed clinicians to more efficiently process alerts. Habits and mental shortcuts thus appear as an adaptive strategy in both routine use and routine disuse of CDS, that arise to improve efficiency and reduce cognitive burden over time.

An important distinction however is that although clinicians developed habits for consulting the system in a particular context, there was no evidence that habits resulted in the *automatic acceptance* of CDS recommendations in Chapters 4, 6 or 7. As discussed in an earlier section on '*self-efficacy, experienced and individualised use*', findings from this research instead suggested that users became more aware of system flaws and became better at critiquing information with increased system and clinical experience. This finding aligns with literature discussed in Chapter 1, that those with more domain specific experience are less susceptible to automation bias. It also builds on prior evidence, suggesting that more experience with the *CDS system* can decrease overreliance over time.[76]

The influence of institutional embedding and evolution on routine acceptance and use, and disuse of CDS

Workflow integration and organisational culture

Another important finding of this thesis was that many routinely embedded CDS systems appeared to be used, or not used, due to social or institutional expectations. In studies conducted years after CDS implementation in Chapter 4 and in Chapter 6, certain CDS systems were described as being used by default. That is, not just due to individual habits, but

because they had become part of the way that work was done in a particular department or organisation.[77] Chapter 4's review found few outcomes or benefits perceived or observed to result from CDS system use beyond the first-year post-implementation, suggesting outcomes become less of a driver of CDS use as increasingly normalised as part of routine clinical practice. This finding aligns with theories discussed in Chapter 1, that describe how systems and system use becomes normalised within organisations over time.[65,78] Doctors in Chapter 6 instead often described using social and organisational norms to guide what was expected of them in their roles and how CDS could effectively support them to achieve these expectations. This phenomenon was described clearly by one participant in the alert fatigue study, who explained: "*once you reach a critical mass, it then becomes part of the institutional culture that certain aspects of the system are used in certain ways… The main thing that matters is purely whether users believe there is an institutional expectation to do that, because there's plenty of things we do all day that are very frustrating and difficult, but we do them because we recognise that it's an expectation as part of our job.*" In routine practice, it therefore appeared that clinicians derived value from CDS where it was aligned with their core roles and responsibilities and could tolerate a degree of inefficiency when this was the case.

In contrast, where alerts were perceived to not be conducive to meeting organisational and specific job expectations, they were often described to be disregarded in the face of other competing priorities. Communication from hospital and departmental leadership that reinforces the significance of the clinical issue, and the role of clinician end-users play in addressing it, may therefore help to strengthen and sustain engagement with CDS. In line with this, a study identified in Chapter 4's review found that when the clinical issue targeted by CDS, such as VTE assessments was viewed as a priority by the organisation, acceptance and use were positively influenced.[79] This recommendation is further supported by a recent review, which found that organisational commitment and mandates were key characteristics of CDS systems that were used in regular practice.[46]

However, developing an organisational culture that promoted CDS use was also perceived to carry risks where CDS was viewed as not being important or useful and rather, as a distraction to core clinical care. As noted in Chapter 1, when systems are used out of obligation rather than perceived value, the risk of making incorrect or unnecessary decisions is increased. This was reflected in Chapter 6, where doctors sometimes perceived alerts to

contribute to them making decisions that were overly cautious, increasing the likelihood of performing unnecessary actions and detracting away from other tasks that were viewed as being more important.

Evolution of the work system over time

Finally, this research program highlighted that the routine acceptance and use of CDS systems could be disrupted by the ongoing evolution of the broader work system. As previously discussed, the continuous influx of new clinicians in hospital settings introduced important considerations for CDS systems that are embedded in routine practice. In addition to workforce turnover, other changes to the digital environment were observed disrupt CDS use. As described in Chapter 4, several studies reported that the introduction of new information systems or upgrades to existing systems altered clinical workflows, led to unintended disruptions in the use of existing CDS systems.[77,80] This again underscores the importance of continued monitoring and adaptation of CDS systems to ensure they remain aligned as clinical workflows inevitably change over time.

Similarly, in Chapter 6, participants often mentioned the addition of new systems or system features that did not directly impact CDS workflows but added cognitive burden through an increasing number of information and task inputs. This general overload diminished the time and mental resources clinicians could devote to CDS. These findings underscore the need to consider how new implementations, including CDS, interact with existing workloads and highlight the importance of de-implementing systems or processes that provide limited value.[81] Organisations should also explore avenues by which to streamline information inputs. Without ongoing responsiveness, CDS and other systems can accumulate over time and have potential to contribute to overload and burnout.[82,83] Additionally, while it is likely that changes to clinical guidelines, evidence, and shifting organisational priorities occur and can impact the ongoing utility of CDS systems, neither the review nor subsequent chapters explicitly identified this to impact clinicians' acceptance and use of CDS over time. It is recommended that future research further explore these factors in the long-term use of CDS.

Given the inevitable evolution of the work system over time, it was highlighted across all chapters that continuous monitoring of CDS is required both early and long after implementation. Prior research has suggested multiple strategies for monitoring and

optimising alerts post-implementation. These include using multidisciplinary hospital committees, dashboards that track CDS use, and simple in-system feedback options, all of which have been shown to support the identification of ongoing and emergent problems and facilitate improvements to CDS.[73,84-87] In a systematic review of 16 studies reporting improvements made to alerts through optimisation efforts, less than half reported the impact on clinicians' use of alerts and only one evaluated clinicians' perceptions following optimisation.[73] While studies measuring use mainly reported improvements, the single study evaluating perceptions found no changes.

Although prior research has described ways to identify and implement changes to alerts, such as inactivating alerts, adjusting trigger thresholds and the interface design, there is little reported about how improvement efforts are communicated to clinicians.[73] Considering many users may have already disengaged from CDS, as discussed in the previous section, efforts that go beyond design changes may be required to improve perceptions and attitudes. Given the earlier finding that negative experiences with similar systems can contribute to ongoing scepticism, redesign may present greater challenges than initial implementation. This underscores the importance of clear communication and efforts to rebuild trust during optimisation efforts. One study using in-system feedback options to identify and action improvements for alerts, reported that clinicians were informed when their feedback was used for improvement.[88] While the study did not evaluate how the improvements or feedback processes affected clinicians' acceptance and use, findings from this thesis suggest that approaches such as these could enhance engagement and should be explored in further research.

These findings align with previous research on the longitudinal appropriation of information systems, which emphasises that system stabilisation is only temporary, and that continued adaptation is necessary as user needs and organisational contexts evolve.[89] Optimisation of CDS post-implementation will therefore always be required to some extent, but has not been comprehensively researched. Importantly, this thesis reinforces that supporting CDS acceptance and use demands significant ongoing investment beyond development and implementation. Given the resources required to maintain CDS relevance and effectiveness, organisations should be selective about the CDS systems they adopt, recognising that without continued alignment with clinical and organisational needs and workflows, systems are likely to be ignored and ultimately ineffective.

SUMMARY AND RECOMMENDATIONS FOR IMPROVING ACCEPTANCE AND USE ACROSS THE CDS SYSTEM LIFECYCLE

In summary, this thesis demonstrates that clinicians' acceptance and use of CDS systems is a dynamic process. Key themes influencing acceptance and use shifted over time in response to changes in individual and collective exposure to CDS, CDS system maturity and fit, and the broader work environment. Acceptance and use during the early stages of CDS implementation and use were often shaped by expectations that formed prior to implementation. As users gained first-hand experience with CDS, first impressions, usability, evolving perceptions of value, and fit with the organisation and user needs, dictated how ongoing and routine use of CDS developed. Many considerations for early acceptance and use extended beyond the implementation phase, remaining important as new clinicians entered organisations where CDS systems were already embedded in routine practice. Routine use, and disuse, of CDS were associated with factors relating to individuals, such as self-efficacy and habits, and organisational factors including how CDS was embedded within organisational workflows and culture. Importantly, routine use of CDS could be undermined when it failed to be adapted as other elements of the work system evolved.

These findings align closely with the theoretical perspectives introduced in Chapter 1, which emphasise the evolving nature of user and organisational needs and the different strategies that should be taken to address these needs over time.[7,19,78] This thesis challenges conventional approaches to CDS implementation that mainly target pre-implementation stages and assume that use will stabilise or improve over time without continued support.[33] Instead, supporting clinicians' acceptance and use of CDS systems, requires more adaptive strategies, targeted to different stages of the system lifecycle that account for changes in experience, maturity and integration. As aligned with technochange theory, this research found many of the acceptance and use needs identified during early and routine acceptance and use could likely be targeted by shifting the implementation focus upstream and addressing issues before they manifest at the point of use.[19] For example, challenges relating to the poor CDS utility, design and workflow fit, are likely to stem from poor system selection, misaligned expectations, or lack of readiness. This research similarly found that such issues became more engrained in individual and organisational workflows and culture, and thus more difficult to fix over time.[65]

In the following sections and Table 1, practical strategies that can be taken by implementers to meet the needs of users at each stage of the CDS lifecycle are summarised. Consistent with the theories and frameworks outlined in Chapter 1, this research emphasises that the early and sustained acceptance and use of CDS is often dependent on how successfully needs are met during earlier stages of the lifecycle.[7,19] Strategies that have been previously evidenced to improve the specific needs identified in this thesis at different stages of CDS implementation (either in prior literature or prior chapters), and those that have been reported to address these needs in implementations of other clinical information systems or systems in different contexts, are highlighted.[90,91] Some general principles should be applied across the system lifecycle, for example, clinician involvement can help to resolve issues that appear at every stage. Additionally, CDS governance to ensure appropriate monitoring and allocation of resources, and effective communication from organisational leadership, is required over time. Though not as often explored in CDS implementations, interorganisational networks to share learnings and common pitfalls could also help to improve acceptance and use needs across the lifecycle.[92,93]

Table 1. Overarching goals and examples of strategies to promote acceptance and use during different stages of the CDS lifecycle

	Problem identification, CDS selection and procurement	**CDS design, development and implementation planning**	**CDS Implementation**	**CDS Maintenance**
Overarching goals to promote CDS acceptance and use	• Understand the clinical need from clinicians' perspectives • Determine if CDS can address the clinical need and if value will be provided to users as well as other stakeholders • Select the right vendor and type of CDS for the clinical need, organisation, department/s and clinical users	• Design or adapt the CDS system to fit the local clinical need and workflows • Promote positive exposure to the CDS and implementation team, building trust between implementers and clinical users • Plan for CDS implementation and resources, ensuring the level of support fits with context (users and setting), innovativeness and change required	• Identify and quickly resolve problems that arise • Encourage CDS use, promoting self-efficacy, experienced use and positive habits • Encourage appropriation and adapt the CDS to better fit user designed workflows • Promote positive exposure for later adopters	• Evaluate CDS, reflect on benefits and address outstanding challenges • Continue to monitor system use, user concerns, changes to the digital and organisational environment, and make continuous improvements • Support new users
Example strategies to target acceptance and use needs	• Qualitative research and engagement with clinicians • Assessments of organisational and individual readiness • Digital health maturity assessment • Resources to support appropriate CDS procurement • User involvement in CDS procurement • Communities of practice • Identify and develop plan for addressing context specific implementation barriers	• Meaningful co-design with CDS users • Contextual inquiry, workflow and decision-making process mapping • Usability testing (including in simulated environments) • Pre-implementation training • Organisational communication and change management • Success stories in similar settings	• Ongoing co-design with CDS users • Staged implementation, e.g. pilot to full scale • Clinical champions, super users, clinical informaticists • Experiential training • Academic detailing • Feedback on system value and achieving objectives • Incentives and competition • Organisational communication and change management • Multi-pronged strategies (e.g. education about issue) • Protected time e.g. low paging hours	• Feedback from users through simple in-system mechanisms • Multidisciplinary committees and other CDS governance • Access to ongoing training and education (on CDS and clinical issue, particularly for junior staff) • Protected time e.g. low paging hours (particularly for junior staff) • Monitor CDS use through dashboards • Streamline CDS with other task-based systems • De-implementation of low value CDS

			• Multidisciplinary committees and other CDS governance	• Evaluate CDS and document outcomes • Organisational communication • CDS redesign • Feedback to users on redesign efforts

Problem identification, CDS selection and procurement

Fundamentally, effective CDS begins with clearly identifying the clinical problem and assessing whether CDS is an appropriate solution. This requires engaging clinicians early to understand their perspectives on the clinical issue and the potential of employing a CDS to address the issue. Deploying CDS without a clear fit with a clinical need, or where the benefit to users is unclear, can undermine acceptance and use from the outset. Qualitative methods such as interviews or focus groups with end users can help surface unmet needs, determine whether and what type of technology-based solution is warranted and if so, identify any potential barriers to system implementation.[94,95] Organisations should also consider evidence of CDS' effectiveness in improving the targeted issue.[96] In parallel, assessing the organisational readiness can support appropriate matching between CDS and the local context.[97] This could include for example, evaluating the infrastructure, staff capacity, leadership support, digital maturity, and whether the clinical issue is recognised as a priority across these different levels.

Once the clinical need and organisational readiness is well understood, guidance to support procurement, such as structured evidence-based evaluation, can further help decision-makers to compare options and select vendors that align with these needs. Prior research has however, reported a lack of existing resources to support CDS procurement.[98] Findings from this research suggest that the selection process should consider the level of fit between the CDS' purpose, cost, customisability, and technical infrastructure, with the needs and resources of the proposed users and organisation. For example, large commercial EHR systems may provide direct integration of CDS within workflows but provide less opportunity for customisation. Homegrown or bespoke plug-in systems on the other hand can offer more adaptability but may be limited in their level of integration and/or require stronger internal support.[99] Similarly, interruptive and passive CDS are likely to be beneficial for different purposes.[100] Involving CDS' proposed end-users in procurement decisions could help to improve fit with local needs and workflows and promote early buy-in and trust.[56] The level of implementation support based on readiness and the CDS system selected should additionally be scoped during this stage.[101] Critically, the level of implementation support provided should match the CDS system's complexity, innovativeness, and required behaviour change. By addressing these foundational issues early, organisations can reduce mismatches

between CDS tools and user needs that continue to appear across time, avoid wasted investment, and lay the groundwork for long-term use.

CDS design and development

This research program highlighted the importance of activities undertaken during the CDS design and development stage for facilitating sustainable use. A fundamental strategy to improve early acceptance and use was the meaningful involvement of clinicians in system design (Chapters 3a, 4 and 5). Importantly, co-design should focus not only on improving CDS' usability and fit with workflows, but also on promoting clinicians' buy-in, and building trust in the CDS and the implementing team. Additionally, given the individual differences in users' needs for CDS, early design decisions should consider opportunities for CDS personalisation and individual customisation where feasible.

Additionally, exposing users to CDS through hands-on demonstrations or pre-implementation walkthroughs can help to build self-efficacy and positive expectations of how the system will be used in practice.[102] As aligned with prior research, the findings from this thesis support the need for pre-implementation training to target user attitudes, awareness, and self-efficacy to use CDS, but warns against overly complex training that could overwhelm users.[3,103] Presenting clinicians with examples of CDS success or evidence of its effectiveness in similar settings may also help shift attitudes, particularly of clinicians who hold negative mental models of CDS. Overall, this stage should not only focus on improving system functionality, but also on building trust and readiness for implementation across the organisation and intended users.[13,104]

CDS implementation

This thesis demonstrated that the implementation stage represents a pivotal window for shaping clinicians' long-term engagement with CDS.[65] While some issues can be addressed during earlier stages, new challenges often emerge only once the system goes live. Therefore, implementation should be seen as a period of adaptation and refinement, where technical and workflow-related problems are quickly identified and resolved, and where users are supported to develop familiarity, confidence, and positive habits around system use. Pilot implementations for example, can help to surface unanticipated barriers with a smaller

number of early adopters and improve CDS for broader use (Chapter 3a, 5). Another approach, academic detailing, involving tailored one-on-one educational outreach with clinicians following implementation, provides promise in addressing some of the key issues commonly identified in this stage. As demonstrated in Barton et al. (2024), academic detailing following the implementation of a CDS system enhanced clinicians' understanding of the system and allowed for the collection of user insights to inform iterative refinement of the system and implementation strategies.[105] Additionally, the value of clinical champions should not be underestimated. This research strongly supports the deliberate identification of individuals well-positioned to serve in these roles and recommends that champion responsibilities be formally integrated into their work duties.[12,106]

This thesis also suggests that effective organisational communication could improve early acceptance and use by promoting the value of CDS. For instance, sharing stories of success where clinicians have effectively incorporated CDS into workflows and providing feedback on actual evidence of benefits (Chapter 5). This may be a particularly useful strategy for encouraging uptake among later adopters who typically seek clear evidence of benefits from peers before trialling technologies themselves.[7,16,107] These efforts can not only help address any lingering issues exported from earlier phases, but also foster self-efficacy, individualised use patterns, increasing observation of benefits, and prioritisation of CDS in clinicians' workflows.

CDS maintenance

As highlighted in this thesis, routine use should not be viewed as a fixed endpoint, but rather as a dynamic period where continuous adaptation is required to ensure the system remains useful, usable, and well-integrated into clinical workflows. Maintaining CDS therefore requires ongoing support, monitoring and adaptation to ensure value continues to be reaped in the face of evolving clinical environments, workforce turnover, and organisational priorities. Monitoring can be supported by dashboards to monitor CDS use, collecting quick in-system feedback from clinicians, and using multidisciplinary committees.[88] To act on user feedback effectively, organisations must demonstrate flexibility and implement strong governance structures to support timely improvements. Redesigning CDS is likely to require not only system improvements, but also strategies designed to disrupt habitual behaviours and regain users' trust.

Continued access to training and education on CDS for new users, is essential. This may include onboarding sessions, demonstrations in practice, and resources accessible within the system. Additionally, mechanisms to reduce cognitive burden, such as providing protected time (e.g., low paging hours) and streamlining task management across systems, can create space for new and junior clinicians to meaningfully engage with CDS.

During routine use, a CDS system becomes one of many tools available to clinicians, and thus continued engagement depends on the CDS' relevance and alignment with their perceived roles and responsibilities in everyday practice. In some cases, de-implementation of low-value CDS may be warranted, especially where the targeted issue is no longer an organisational priority or has been incorporated into processes that make CDS redundant.[82] Ultimately, maintenance requires not only system monitoring but also organisational investment to ensure CDS remains prioritised, reduces clinician burden, and meaningfully contributes to patient care.

STRENGTHS, LIMITATIONS AND CONCLUSIONS

Strengths

A key strength of this thesis is its comprehensive, mixed-methods exploration of clinicians' acceptance and use of CDS systems over time, making significant contributions to a topic that has previously been underexplored. First, using a systematic approach, this thesis was able to holistically identify themes and gaps in existing literature over time. In the following chapters, the use of interviews, survey and log data analysis, allowed for the further exploration of these themes and gaps in depth. By studying experiences arising during the early stages (Chapter 5) and routine use stages (Chapters 6 and 7) of implementation, common challenges and facilitators in achieving long-term acceptance and use were identified across the continuum. Using established frameworks within chapters, enhanced rigour in the analysis of findings and generalisability to other implementations. Additionally, the use of pioneering theoretical models, such as diffusion of innovations and technochange, provided conceptual rigour and enabled comparisons of the findings against well-established patterns and mechanisms that drive technology acceptance and use at both individual and organisational levels.

Furthermore, the findings were situated across diverse clinical and geographical settings, such as rural and urban, and the ED, inpatient, virtual care, and outpatient departments. Across chapters, a wide range of CDS systems were studied, with many different types of CDS identified in the systematic reviews, and diverse CDS systems including alerts and visual displays that were further explored in depth in subsequent chapters. In addition, these systems had different levels of integration with EHRs, were developed by vendors with diverse characteristics (large commercial versus bespoke), and focused on diverse clinical issues. Together, this provided a robust understanding of experiences and enhances the transferability of findings, providing a rich foundation for future CDS implementations across contexts.

Limitations

While this thesis offers many important insights, several limitations must be acknowledged. First, while the reviews offered insights into different clinical users' acceptance and use of CDS over time, subsequent chapters focused primarily on the experiences of doctors. This means that the experiences of other user groups, such as pharmacists, nurses and allied health professionals, were not as deeply explored. Thus, the findings may be less transferrable to these groups. Similarly, although the review chapters considered evidence from AI-based CDS, the empirical studies in later chapters largely examined rule-based systems. This is an important limitation given the rapid growth of AI in clinical practice. Nonetheless, it is expected that the principles and recommendations outlined in this thesis will remain highly relevant to the development and implementation of AI-based CDS. For instance, beginning with a clear definition of the clinical problem and confirming that an AI-based CDS is the appropriate solution, involving clinicians in the design process, supporting clinicians to build self-efficacy in using the system, and monitoring for workflow changes that may affect ongoing use are likely to be equally, if not more, important for AI-based CDS.

Second, although experiences were explored across multiple time points in both the reviews and subsequent chapters, studies and chapters were mainly cross sectional in nature. It is worth noting that while this thesis originally intended to use a longitudinal approach, studying acceptance and use at different points from the time of implementation to long-term use, priorities of the health services in partnership with this thesis shifted over time, affecting implementation timelines that subsequently affected the focus of this thesis. These challenges

reflect the nature of applied research in health service settings. In response, this thesis adopted a retrospective and comparative approach to explore how clinicians' perceptions of CDS developed and evolved over time. However, future research that prospectively examines acceptance and use at multiple time points within a single study is still needed. While the retrospective design enabled reflection on longer-term use, it may have introduced recall bias.[108] Similarly, the comparative nature of this research means that contextual differences across implementations could have influenced the outcomes observed, rather than time alone.

Finally, while this thesis evaluated clinicians' needs for the acceptance and use of CDS systems, the implementation and evaluation of proposed strategies to address these needs, aside from codesign, were largely beyond the scope of this research. As such, further research is needed to prospectively evaluate whether these strategies, used at the specific stages of the CDS lifecycle outlined in this thesis, can effectively meet identified acceptance and use needs and successfully promote routine use of CDS. Likewise, further research is needed to identify best practices for balancing the time, effort, and resources required to implement these strategies with their impact on clinicians' acceptance and use of CDS.

Conclusions

This thesis expands our understanding of clinicians' acceptance and use of CDS systems, reinforcing that it is not a one-time outcome but a dynamic, evolving process that requires ongoing attention, adaptation, and support. Findings across chapters consistently demonstrate that early experiences matter. Unlike systems required for core clinical tasks, voluntary CDS systems must overcome early use challenges to realise intended benefits. This thesis demonstrated that shifting conditions, including new users, and evolving workflows, organisational, and clinical priorities, can impact acceptance and use over time. Consequently, the implementation of CDS cannot be considered complete once a system goes live, nor when it is successfully embedded into routine practice.

Our findings demonstrate the substantial resource implications for successfully implementing CDS. The cost of implementing and maintaining relevant, usable, and valuable CDS systems extends beyond software licensing or system development, including significant time, personnel (clinical and technical), and infrastructure to maintain system alignment with user and organisational needs and expectations. This reinforces the need for health services to be

highly selective in their CDS investments and to avoid implementing systems that lack a strong use case or perceived value for clinicians. Poor implementations not only lead to waste but can also contribute to the formation of negative mental models that undermine future acceptance of CDS more broadly.

In conclusion, we presented specific needs that were experienced by clinicians and can be addressed at different stages of the CDS lifecycle. These experiences were grounded in theory, evidence and real-world experiences. By providing practical, stage-specific recommendations to address these needs and thereby improve CDS acceptance and use over time, we hope these findings help to reduce waste and ensure that CDS systems meaningfully improve patient care.

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