How are meal delivery applications disrupting food environments and affecting population diets and health?

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BSc, MND

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2025

STATEMENT OF ORIGINALITY

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

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

Si Si Jia 25 March 2025

ABSTRACT

Background: Meal delivery applications ('apps') enable convenient access to takeaway foods, typically high in sodium, saturated fats, and sugars. These apps may further promote unhealthy diets and elevate risk for diet-related chronic diseases. The aim of this thesis was to investigate how meal delivery apps are disrupting food environments and affecting population diets and health.

Methods: Critical synthesis of evidence in a perspective article (Ch 2); Systematic review (Ch 3); Mobile Ecological Momentary Assessment pilot study (Ch 4), Development of the DIGIFOOD dashboard, a data-driven tool to monitor the digitalisation of food environments (Ch 5); Analysis of the DIGIFOOD dashboard using quasi-Poisson regression models to assess socioeconomic disparities in hybrid food environments (Ch 6); Systematic mapping review of evidence to inform nutrition-related policies (Ch 7).

Results: Meal delivery apps increased in use during COVID-19 (Ch 3). Of concern, meal delivery apps may impede progress towards a sustainable and healthy future (Ch 2). Chapter 4 obtained evidence on the consumption and context around meal delivery events, indicating that a bulk of orders are comprised of 'junk foods'. In an Australian context, online food outlets were most accessible in areas experiencing the least socioeconomic disadvantage (Ch 5 and 6). Existing nutrition-related policies to regulate meal delivery apps is limited (Ch 7).

Conclusion: This thesis provides evidence that meal delivery apps have transformed food environments and pose significant opportunities and challenges, to population health and diets. Research and policy must keep pace with this new digital frontier which may compromise any progress to-date in improving food environments.

ACKNOWLEDGEMENTS

“For the mind does not require filling like a bottle, but rather, like wood, it only requires kindling to create in it an impulse to think independently and an ardent desire for the truth” – De auditu by Plutarch, Vol.I of the Loeb Classical Library’s edition of the Moralia, first published in 1927.

As I reflect upon the past three and half years of my PhD journey, I am filled with immense gratitude for all those who have helped shape this important chapter in my life.

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LIST OF ABBREVIATED TERMS AND ACRONYMS

API: Application Programming Interface

ARIA+: Accessibility/Remoteness Index of Australia Plus

BMI: Body Mass Index

CI: Confidence Interval

COVID-19: Coronavirus Diseases 2019

CREMAS: Checklist for Reporting EMA Studies

DALYs: Disability-adjusted life years

EMA: Ecological Momentary Assessment

Food-EPI: Healthy Food Environment Policy Index

GBD: Global Burden of Disease

GINA: Global database on the Implementation of Nutrition Action

HDL: High Density Lipoprotein

INFORMAS: International Network for Food and Obesity and Non-communicable

Disease Research, Monitoring and Action Support

INR: Indian Rupee

IRR: Incidence Rate Ratio

IRSAD: Index of Relative Socio-Economic Advantage and Disadvantage

IRSD: Index of Relative Socio-Economic Disadvantage

LDL: Low Density Lipoprotein

MDA: Meal Delivery Application

NCD: Non-Communicable Diseases

NSW: New South Wales

NZD: New Zealand Dollar

OECD: Organization for Economic Co-operation and Development

OFD: Online Food Delivery

OFDS: Online Food Delivery Services

POA: Postal Area

PICOS: Population, Intervention, Comparison/Context, Outcome, Study Design

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews

PROSPERO: International Prospective Register of Systematic Reviews

REDCap: Research Electronic Data Capture

RM: Malaysian Ringit

SDG: Sustainable Development Goal

STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

UN: United Nations

UNCTAD: United Nations Conference on Trade and Development

USD: United States Dollar

WHO: World Health Organization

20-MN: 20-min Neighbourhood

PUBLICATIONS AND PRESENTATIONS ARISING FROM THESIS

Peer-reviewed first-author publications arising from this thesis

1. **[Chapter 2] Jia, S.**; Gibson, A.A.; Ding, D.; Phongsavan, P.; Redfern, J.; Allman-Farinelli, M.; Partridge, S.R. PERSPECTIVE: Are online food delivery services emerging as another obstacle to achieving the 2030 United Nations Sustainable Development Goals? *Frontiers in Nutrition*, 2022, 9:858475. doi: 10.3389/fnut.2022.858475

2. **[Chapter 3] Jia, S**.; Raeside R.; Sainsbury E.; Wardak S.; Phongsavan P.; Redfern J.; Allman-Farinelli M.; Fernandez M.A.; Partridge S.R.; Gibson A.A. Use of online food retail platforms throughout the COVID-19 pandemic and associated diet-related chronic disease risk factors: A systematic review of emerging evidence. *Obesity Reviews*, 2024, 1-13. doi: 10.1111/obr.13720

3. **[Chapter 4] Jia, S.**; Allman-Farinelli M.; Roy R.; Phongsavan P.; Hyun K.; Gibson A.A.; Partridge S.R. Using Mobile Ecological Momentary Assessment to Understand Consumption and Context Around Online Food Delivery Use: Pilot Feasibility and Acceptability Study. *JMIR mHealth and uHealth*, 2023, 11(1): e49135. doi: 10.2196/49135

4. **[Chapter 5] Jia SS**, Luo X, Gibson AA, Partridge SR. Developing the DIGIFOOD Dashboard to Monitor the Digitalization of Local Food

Environments: Interdisciplinary Approach. *JMIR Public Health Surveill,* 2024;10:e59924. doi: 10.2196/59924

5. **[Chapter 6] Jia S**.; Owen K.; Phongsavan P.; Allman-Farinelli M.; Gibson A.A.; Partridge S.R. Assessing socioeconomic disparities in emerging hybrid food environments: a cross-sectional analysis of the DIGIFOOD dashboard. The Lancet Regional Health – Western Pacific, 2025, 56:101504.

6. **[Chapter 7] Jia S**, Todd A, Vanderlee L, Farrell P, Allman-Farinelli M, Sacks G, Gibson AA, Partridge SR. Offline to Online: A systematic mapping review of evidence to inform nutrition-related policies applicable to online food delivery platforms. *BMC Medicine,* 2024, **22**, 542. doi: 10.1186/s12916-024-03747-8

7. **[Chapter 8] Jia S.**; Bennett R.; Gupta A. The emergence of meal delivery applications: a research agenda to advance the next decade of progress in nutrition. *European Journal of Clinical Nutrition*. 2025. https://doi.org/10.1038/s41430-025-01597-y

Additional peer-reviewed publications completed during the PhD candidature

1. **[SENIOR AUTHOR]** Tse K, Zeng MX, Gibson AA, Partridge SR, Raeside R, Valanju R, McMahon E, Ren B, Yan F, Allman-Farinelli M, **Jia S**. Retrospective analysis of regional and metropolitan school food environments using Google

Street View: A case study in New South Wales, Australia with youth consultation. *Health Promotion Journal of Australia,* 2024. doi: 10.1002/hpja.930

2. [MIDDLE AUTHOR] Partridge SR, Knight A, Todd A, McGill B, Wardak S, Alston L, Livingstone KM, Singleton A, Thornton L, **Jia S**, Redfern J, Raeside R. Addressing disparities: A systematic review of digital health equity for adolescent obesity prevention and management interventions. *Obesity Reviews*, 2024; 25(12):e13821. doi: 10.1111/obr.13821

3. [MIDDLE AUTHOR] Todd, A.R., Raeside, R., **Jia, S.**, Partridge S.R. Adolescent involvement in health research: Insights from Young People, PhD Candidates and Early Career Researchers. *Journal of Adolescent Health*, 2024, 75(4):686-687. doi: 10.1016/j.jadohealth.2024.04.031.

4. **[SENIOR AUTHOR]** Cassano S, Jia A, Gibson AA, Partridge SR, Chan V, Farrell P, Phongsavan P, Allman-Farinelli M, **Jia S**. Benchmarking Online Food Delivery Applications Against Menu Labelling Laws: A Cross-sectional Observational Analysis. *Public Health Nutrition*, 2024. doi: 10.1017/S1368980024000673

5. [SECOND AUTHOR] Raeside R.; **Jia S**.; Todd A.; Hyun K.; Singleton A.; Gardner L.A.; Champion K.E.; Redfern J.; Partridge S.R. Are digital health interventions that target lifestyle risk behaviors effective for improving mental

health and wellbeing in adolescents? A Systematic Review with meta-analyses. *Adolescent Research Review*, 2023, 9, 193–226. doi: 10.1007/s40894-023-00224-w

6. [SECOND AUTHOR] Mahawar, N; **Jia, S.**; Korai, A.; Wang, C.; Allman-Farinelli, M.; Chan, V.; Raeside, R.; Phongsavan, P.; Redfern, J.; Gibson, A.; Partridge, SR.; Roy, R. Unhealthy Food at your Fingertips: Cross-Sectional Analysis of the Nutritional Quality of Takeaway Outlets on an Online Food Delivery Platform in New Zealand. *Nutrients*, 2022, 14(21):4567. doi: 10.3390/nu14214567

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8. [MIDDLE AUTHOR] Alston, L.; Partridge, SR.; **Jia, S.**; Raeside, R. Under-investment in nutrition research for at-risk populations: An analysis of research funding awarded in Australia from 2014-2021. *Nutrition & Dietetics,* 2022, 1-9.

9. **[FIRST AUTHOR] Jia, S**, Wardak S, Raeside, R, Partridge SR, The short-term and long-term impacts of junk food consumption. *Frontiers for Young Minds*, 2022, 10:694523. doi:10.3389/frym.2022.694523

10. [MIDDLE AUTHOR] Partridge SR, Reece L, Sim K, Todd A, **Jia SS**, Raeside R, Schirmer T, Phongsavan P, Redfern J. An analysis of current obesity strategies for adolescents in NSW against best practice recommendations: implications for researchers, policymakers and practitioners. *Health Promotion Journal of Australia,* 2023, 34(2):390-397. doi: 10.1002/hpja/606.

11. **[FIRST AUTHOR] Jia, S.**; Liu Q.; Allman-Farinelli M.; Partridge SR.; Pratten A.; Yates L.; Stevens M.; McGill B. The Use of Portion Control Plates to Promote Healthy Eating and Diet-Related Outcomes: A Scoping Review. *Nutrients*, 2022, 14(4):892. doi: 10.3390/nu14040892

12. [MIDDLE AUTHOR] Raeside R.; **Jia S.**; Redfern J.; Partridge S.R. Navigating the Online World of Lifestyle Health Information: Qualitative Study With Adolescents. *JMIR Pediatr Parent* 2022, 5(1):e35165. doi: 10.2196/35165

13. [MIDDLE AUTHOR] Armstrong, M; Halim, N.K.; Raeside, R.; **Jia, S.**; Hyun K.; Boroumand, F.; Mandoh, M.; Singleton, A.C.; Phongsavan, P.; Redfern, J.; Partridge, S.R. How Helpful and What Is the Quality of Digital Sources of Healthy Lifestyle Information Used by Australian Adolescents? A Mixed Methods Study. *International Journal of Environmental Research and Public Health* 2021, 18(23): 12844. doi: 10.3390/ijerph182312844

Conference presentations arising from this thesis

Oral presentations

1. [INTERNATIONAL ORAL] **Jia S** (2024) Eat Now, Worry Later: Consumption and context around online food delivery use. *World Public Health Nutrition Congress*, London, England.

2. [INTERNATIONAL ORAL] **Jia S** (2024) Synthesising evidence to regulate online food delivery platforms for population health and wellbeing. *World Public Health Nutrition Congress*, London, England.

3. [INTERNATIONAL ORAL] **Jia S** (2024) Offline-to-online food environment policies – preliminary results from a systematic mapping review of evidence to regulate online food delivery platforms for population health and wellbeing. *Global Food Governance Conference*, Sydney, Australia.

4. [INTERNATIONAL SYMPOSIUM ORAL] **Jia S** (2023) Characterising the out-of-home food environment using big data sources, *International Society of Behavioural Nutrition and Physical Activity 22nd Annual Meeting*, Uppsala, Sweden.

5. **[INTERNATIONAL ORAL - Shortlisted for 'Best Presentation - e & m-Health'] Jia S** (2022) Using Mobile Ecological Momentary Assessment to understand food selection behaviours and dietary intake of online food delivery users: the pilot FASTERFOOD study protocol, *International Society*

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6. [INTERNATIONAL ORAL] **Jia S** (2021) How are online food delivery services changing food accessibility? Preliminary analysis using the DIGIFOOD Dashboard, *Global Food Governance Conference* 2021 (VIRTUAL)

Poster presentations

1. [NATIONAL POSTER] **Jia S** (2022) The use of online food purchasing platforms and associated dietary behaviours during COVID-19: a systematic review, *Nutrition Society of Australia Annual Meeting 2022*, Perth, Australia.

2. [INTERNATIONAL POSTER] **Jia S** (2022) How are online food delivery services changing food accessibility? Preliminary analysis using the DIGIFOOD Dashboard, *24th International Union for Health Promotion and Education World Conference*, Montreal, Canada (VIRTUAL)

3. [NATIONAL POSTER] **Jia S** (2021) The development of the DIGIFOOD Dashboard to monitor the impact of online food delivery services on the food environment, *Nutrition Society of Australia* 2021 Conference (VIRTUAL)

Additional conference presentations during the PhD candidature

1. [NATIONAL POSTER] **Jia S** (2023) Price, social life and proximity influence food choices: Engaging young people as co-researcher collaborators to better understand their surrounding food environments, *Nutrition Society of Australia and New Zealand Annual Meeting 2023*, Auckland, New Zealand.

2. [INTERNATIONAL POSTER] **Jia S** (2022) The Use of Mobile-Based Ecological Momentary Assessment (mEMA) Methodology to Assess Dietary Intake, Food Consumption Behaviours and Context in Young People: A Systematic Review, *International Congress on Obesity 2022*, Melbourne, Australia.

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Seminar and webinar presentations related to thesis

1. **[INVITED – Top 6 PhD finalist for HEART Pitch Competition] Jia S** (2024) Byte-2-Bite: The challenges and opportunities of meal delivery applications in the digital age. *NSW Cardiovascular Research Network HEART Pitch*, Sydney, Australia.

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4. **[INVITED] Jia S** & Roy R (2023) Digital food environments – *Dietitians Australia Advocacy Insights Webinar,* August 2023, VIRTUAL.

5. **Jia S** (2023) Eat Now, Worry Later: Consumption and context of online food delivery orders, *CPC Biology Seminar Series 2023*, Charles Perkins Centre, The University of Sydney, Sydney, Australia.

6. **[INVITED] Jia S** (2023) Documenting the adoption of the digital food environment, *Home Economics Institute of Australia February 2023 Webinar*, VIRTUAL.

7. **Jia, S** (2022) The use of online food purchasing platforms and associated dietary behaviours during COVID-19: a systematic review, *CPC Relaunch of Wireless Wellbeing Node 2022*, The University of Sydney, Sydney, Australia.

8. **Jia S.** & Partridge, SR (2022), The public health implications of faster food – an investigation of online food delivery, *CPC EMCR Breakfast Seminar*, VIRTUAL.

9. **[INVITED] Jia S** & Partridge SR (2021), Urban eats, Urban living, Festival of Urbanism – What's endangering public health in urban environments, VIRTUAL.

PEER-REVIEWED FUNDING AND PRIZES AWARDED

Scholarships

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5. **Jia S.** (2022) International Society of Behavioural Nutrition and Physical Activity - Partial Travel Scholarship, $600 AUD

6. **Jia S.** (2022) Postgraduate Research Support Scheme, The University of Sydney, $512.50 AUD

7. **Jia S.** (2021) Charles Perkins Centre EMCR Travel Funding Award, $500 AUD

Awards and prizes

1. **Jia S.** (2024) The University of Sydney, CPC EMCR Professional Development Award, $600 AUD

2. **Jia S.** (2024) Top 6 PhD Finalist 2024 HEART Pitch Competition, NSW Cardiovascular Research Network

3. **Jia S.** (2023) 9th Annual CPC EMCR Symposium, The University of Sydney – Best Oral Presentation – Public Health, $150 AUD

4. **Jia S.** (2022) The University of Sydney, CPC EMCR Professional Development Award, $750 AUD

5. **Jia S.** (2022) International Society of Behavioural Nutrition and Physical Activity – Top 3 Finalist in e-Health and m-Health Special Interest Group Best Presentation Award, Phoenix, United States

6. **Jia S.** (2022) The University of Sydney, School of Public Health - PUBH5217 Biostatistics: Statistical Modelling, Masters level unit of study, High Distinction

7. **Jia S.** (2022) The University of Sydney, School of Public Health - FMHU5002 Introductory Biostatistics, Masters level unit of study, Distinction

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MEDIA ARISING FROM THESIS

Full-length articles can be found in Appendix F

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CHAPTER 1 | INTRODUCTION

Chapter Overview

This chapter introduces the overarching issue of how unhealthy diets are contributing to rising rates of non-communicable diseases (NCDs). Food environments encompass structural, social, political and physical factors which are powerful influences of people's diets and subsequent health. The modern food environment is changing as individuals and communities are additionally exposed to digital settings where food can be accessed and purchased. Meal delivery applications are one such example of digital food settings which are key components of the 'digital food environment' which may have been accelerated by the coronavirus disease (COVID-19) pandemic. There is evidence to suggest that young people are the highest users of these services. Of concern, more unhealthy foods are available online and these products are aggressively marketed. The rise of meal delivery applications may also threaten decades of progress towards achieving healthy and sustainable diets. The chapter concludes by outlining the aims of this thesis to further measure, monitor and mitigate the risks that meal delivery applications pose to population health and diets.

Non-communicable diseases and unhealthy diets

NCDs are the leading causes of global deaths and disability among humans, accounting for 71% of the total number of deaths each year[1]. The top four NCDs with highest number of deaths are cardiovascular diseases, some cancers, respiratory diseases, and type 2 diabetes. Also known as chronic diseases, NCDs are medical

conditions that are long-lasting and have persistent effects[2]. The slow progress in treating NCDs result in high burdens on health systems, financial resources, and people's quality of life. For example, the global diabetes-related health expenditure was estimated at 966 billion USD in 2021. This is expected to reach 1054 billion USD by 2045[3].

The Australian Institute of Health and Wellbeing report the 10 major chronic condition groups is inclusive of: arthritis, asthma, back pain, cancer, cardiovascular disease, chronic obstructive pulmonary disease, diabetes, chronic kidney disease, mental health conditions and osteoporosis. Nearly 1 in 2 Australians (47%) had 1 or more of the 10 selected chronic diseases in 2017-18, 20% had 2 or more of these conditions and nearly 9 in 10 deaths in 2018 were associated with these diseases[2].

Physical inactivity, tobacco use, alcohol consumption and unhealthy diets are leading risk factors contributing to NCDs[1]. Unlike genetic factors which are non-modifiable, these behavioural risk factors are preventable and can be intervened in early life[4]. Concerningly, rates of unhealthy diets are growing among populations, increasing the potential risk for developing chronic diseases and subsequent burdens[5].

Unhealthy diets are generally described as the consumption of foods and beverages that provide nutrients in either insufficient or excess amounts and contribute to ill-health[6]. In contrast, most dietary guidelines across the world recommend a healthy diet that consists of a wide variety of nutritious foods from whole food groups each day. These food groups in the Australian Dietary Guidelines are i) vegetables and legumes/beans ii) fruits iii) grains and cereals iv) lean meats and alternatives and v)

dairy and alternatives[7]. Discretionary foods are foods and drinks that are not essential for health. These foods and drinks are high in energy, saturated fat, added sugars, added salts and/or alcohol and are low in fibre[7]. It is therefore recommended that consumption of these 'discretionary foods' are limited.

Despite this, research indicates that Australians are overeating discretionary foods and undereating nutritious foods from the five food groups. Data from the 2011-2012 National Health Survey, the last comprehensive population dietary assessment with 24-hour recalls, showed Australians obtained more than 35% of total energy from these discretionary foods[8]. An analysis of sales data from the food retail sector in Australia showed that in 2022-23, over one-third (38.6%) of dietary energy from food and non-alcoholic beverage sales came from discretionary foods[9]. This was similar to 2021-22 (38.5%) and 2020-21 (38.6%)[9]. Moreover, data from the 2020-21 National Health Survey with short dietary questionnaires, suggested 9 in 10 Australian adults did not consume the recommended serves of vegetables and just over half of Australians did not consume the recommended serves of fruit[10]. In 2022, these trends were deteriorating with a 7.2% decrease in adults aged 18 years and over who met the fruit recommendations, 1% decrease in those who met vegetable recommendations and 1.2% decrease in those who met both both fruit and vegetable recommendations, compared to 2017-18[11].

These trends in poor diets are also reflected in other global populations. A systematic review has found that dietary risk factors for NCDs such as high sodium intake and low intake of whole grains and fruits, have increased significantly across various regions during 1990-2019[12]. Using data and methods from the Global Burden of

Disease (GBD) study, researchers estimated that in 2015 in Australia, 29,414 deaths from NCDs and 443,385 disability-adjusted life years (DALYs) were attributable to dietary risk factors. These risk factors were diets low in fruits, vegetables, nuts and seeds and wholegrains, but high in sodium. Overall, they attributed 42.3% of cardiovascular deaths to dietary risk factors[13].

Overweight and obesity: intermediary links to NCDs and unhealthy diets

While unhealthy diets themselves can be linked directly to the development of NCDs via their inflammatory effects on the body, they are also likely to cause excess weight gain and contribute to overweight and obesity. Energy-dense and nutrient-poor foods are highly palatable, widely available, easily accessible, and heavily promoted. As such, the overconsumption of such foods is likely to cause excess weight gain and contribute to overweight and obesity. In this manner, overweight and obesity can be seen as an intermediary link between unhealthy diets and NCD's.

There are several adverse effects of overweight and obesity on health and wellbeing. Obesity aggravates nearly all the major risk factors for NCDs. Obesity is strongly linked to insulin resistance which can lead to hyperglycaemia when combined with the dysfunction of B-islet cells[14]. This results in the subsequent development of type 2 diabetes mellitus and metabolic syndrome.

A large body of evidence also shows a strong link between overweight and obesity with lipid abnormalities such as increased levels of triglycerides, increased low density lipoproteins (LDL) cholesterol and reduced high density lipoproteins (HDL) cholesterol[15]. Obesity is also notably associated with increased arterial blood

pressure, increased incidence of ventricular abnormalities and inflammation[16]. These are all risk factors for cardiovascular disease, which is the leading cause of death – accounting for nearly 20.5 million deaths globally[17] and 42,700 deaths in Australia in 2021[18].

Obesity is a highly complex issue, and its causes are multifactorial. These range from biological factors such as genetics that control hunger and satiety cues, psychological factors such as responses to stress, social and commercial determinants such as where we live and what is marketed to us, and physical and environmental factors which influence levels of physical activity. Weight gain, however, is fundamentally attributed to an energy imbalance where energy intake surpasses energy expended.

Socio-ecological model for the determinants of health

Individuals have their own agency to make food choices in response to their individual needs, which are appropriate for their sex, age, race, ethnicity and socioeconomic status. Thus, changing dietary behaviours and intake in individuals is one strategy to reduce the prevalence of overweight, obesity and diet-related NCDs. Examples of interventions that focus on individuals include health information campaigns, life skill groups and one-to-one counselling or support[19].

Dahlgren and Whitehead in 1991, proposed the pivotal socio-ecological model for determinants of health, which outlines how individual behaviours are integrated in social and community networks, and in living and working conditions, that are overall ultimately influenced by the wider socioeconomic and cultural environments[20]. This

model has critically broadened the horizons beyond the burden on health services or individual responsibility, to address health issues[21].

In addition, a framework of obesity determinants and solutions developed by Swinburn and Sacks demonstrates that interventions which address individual behaviour patterns are easy to implement but have far smaller population impact[22]. Moreover, a systematic review of 20 studies concluded that while individual-level interventions are likely to be effective in the short-term in terms of weight loss, these have not shown evidence of long-term effectiveness[23].

As such, interventions which target individuals alone, are unlikely to have a significant impact on the growing worldwide prevalence of diet-related chronic diseases. At the environmental level, individuals are surrounded by the physical spaces where people live, work and play and the prevailing sociocultural norms can impact food availability which can impact diets and health outcomes.

The following section explores the environmental characteristics of obesity – the 'food environment' and its changing nature in an increasingly digitalised society, forming the basis of this thesis.

Food environment

The food environment is one of the strongest determinants of food choice and has major implications on dietary intake. As defined by Downs and colleagues, the food environment is the "consumer interface with the food system that encompasses the availability, affordability, convenience and desirability of foods"[24]. Swinburn and

colleagues similarly conceptualise the food environment as the “collective physical, economic, policy and sociocultural surroundings, opportunities and conditions that influence people’s food and beverage choices and nutritional status”[25].

Some research suggests that inadequate or reduced access to healthy food retail stores, such as a grocery store or supermarket, may compromise the diets and nutrition of those living in such ‘food deserts’[26]. Food deserts are conceptualised as the complex interlinkage of poor diets and health inequities related to differential access to food retail provision and social exclusion[27]. In contrast, areas with a high density of high-calorie fast food and junk food relative to healthier food options are considered ‘food swamps’[28] and leads to obesogenic food environments ‘Obesogenic food environments’ is a term that combines these concepts together to suggest that food environments which offer cheap, convenient, unhealthy food options in large portion sizes that are readily available, that is likely promote overweight and obesity. Such obesogenic food environments are considered upstream determinants of overweight and obesity[29].

Evidence of the relationship between food environments and dietary health remain inconsistent and mixed. A systematic review of 38 studies conducted by Caspi and colleagues in 2012, showed moderate evidence to support the hypothesis that neighbourhood food environments influence dietary health[30]. While many included studies reported an association between food environments and dietary outcomes, several others reported a null association[30]. These inconsistent findings are reported widely across additional systematic reviews in the field[31-33].

Despite inconclusive findings, studies generally show a relationship between living in a neighbourhood with or in close proximity to healthier food options, and better dietary quality, higher fruit and vegetable intakes, and lower risk of overweight or obesity[34]. More recent evidence from a study conducted in the United States (US) in 2022 which gathered smartphone data of over 1.1 million participants showed that higher access to grocery stores, lower access to fast food, higher income and college education were all independently associated with higher consumption of fresh fruits and vegetables[35]. Similarly, populations with lower consumption of fast food and soda had a lower likelihood of developing overweight and obesity[35].

Different types of food environments

Glanz and colleagues conceptualised four main nutrition environments[36] which influence diets and health. These are described below in Table 1.

Table 1. Main nutrition environments as defined and conceptualised by Glanz and colleagues[36].

Main nutrition environments		Description
	Organisational environments	These environments typically provide sources of food to defined groups and comprise of homes and cafeterias in schools, workplaces, churches and healthcare facilities[36].
	Community environments	At the community level, food environments encompass the number, type, location and accessibility of food outlets. These include stores and restaurants as food sources.

	Consumer environments	The availability, price and promotion of foods in stores and restaurants influence consumer environments which reflects what consumers encounter within and around a retail food outlet. Studies examining consumer environments may assess characteristics such as nutritional qualities, price, promotions, placement, range of choices, freshness and nutritional information[36].
	Information environments	Media reports and advertising which are influenced by government and industry policies, could affect attitudes and appeal of foods and encompass 'information environments'.

Measures of the food environment

The 'local' food environment is a concept closely linked to Glanz and colleagues' definition of community environments in **Table 1**. While not clearly defined in the literature, this term appears to include the location, type, and mix of food outlets within defined areas or 'neighbourhoods' where people reside[37-40]. Objective measures such as geographic analysis, are the most common methodology used to measure local food environments[41]. However, inconsistencies in measures, is a key factor contributing to the inconclusive evidence around food environments and health outcomes in the literature[30, 33].

A systematic review of food environment studies found three main types of objective geographic measures for the access to local stores and restaurants[42]. These were: density, proximity and variety. Density measures typically assess the concentration of food outlets (i.e. absolute count or number) per neighbourhood population, or geographic area[42]. Proximity measures outline food outlets such as a grocery or takeaway store available within a specified distance[42]. Variety measures reflect the composition of different food outlets within a specified area[42].

Distances used as measures of food environments:

Euclidean distances

Euclidean distances or straight-line distances, have commonly been used as the radii to investigate neighbourhoods that are 400 metres, 800 metres, 1 kilometre (km) or 1.6 km circular buffers around areas of interest[43].

Street or road network distances

Street or road network distances are defined as the distance between a specified location to a point of interest (e.g. food outlet) by a road or street. It is known to represent usual walking or travelling distances[44].

Associations between socioeconomic status and food environments

Social environments and conditions in which people are born, live, and age, have profound impacts on health and wellbeing. The World Health Organization describes these social determinants of health as factors such as income and social protection,

education, job security, housing, basic amenities, and the environment, which can either promote or undermine the health of populations[45]. Evidence suggests that health and illness follow a social gradient where health outcomes deteriorate with greater socioeconomic disadvantage[46]. Australian research has found that compared to residents in more advantaged areas, residents of disadvantaged neighbourhoods had significantly higher body mass index (BMI) and larger waist circumference, in five of eight capital cities across Australia[47]. In addition, a study using Australian survey data established a significant association between lower area-level disadvantage and higher diet quality[48].

Disparities in health outcomes of individuals living in disadvantaged neighbourhoods may be attributed to their surrounding food environment. These sub-optimal food environments may be characterised as a neighbourhood with low access to healthy and affordable food[49]. A study that analysed the diet quality of over 20,000 older Americans found an association (b = -1.35, 95 % CI: −2.06, −0.63) between living in unhealthy food environments and poor diet quality, but not with obesity risk[49]. Furthermore, a 2020 study conducted in Southeastern US found a positive association between socioeconomic disadvantage, and access to total food outlets[50]. Individuals who resided in more disadvantaged areas had greater access to both healthy and unhealthy food outlets.

The types of food outlets and ratio of unhealthy to healthy outlets, in the neighbourhood food environment may be an important factor that influences diet and health outcomes of individuals. For example, fast-food outlets sell mostly unhealthy and ultra-processed foods which increase the risk for developing diet-related non-

communicable diseases[51]. Research using UK Biobank data showed that exposure to food environments predominantly offering takeaway foods, was associated with higher odds of type 2 diabetes (Odds Ratio: 1.13, 95%Confidence Interval 1.05-1.21)[52]. An Australian study found that those in more socioeconomically disadvantaged areas had greater access to fast-food restaurants[53]. On the other hand, supermarket accessibility is often considered to enable healthier food access[54]. Another study from Australia showed a significant negative association between supermarket access and degree of remote and socioeconomically disadvantaged areas[55], indicating that more disadvantaged and remote areas had lower access to supermarket stores. In addition, research has shown that neighbourhoods of higher socioeconomic status had increased odds of greater fruit intake in Canada, New Zealand and Scotland[56]. Similarly, more advantaged neighbourhoods across Australia, Canada, New Zealand and Portugal, saw increased odds of greater vegetable intake[56].

Digitalisation of the food environment

Examining the digital determinants of health is crucial to understand the health potentials and risks emerging from the digital world including the Internet, social media and online information environments[57]. Digitalisation and technological innovations have transformed all aspects of life – including the way people can access food. Considering that 'accessibility' is a core part of how food environments are defined – digital or online access to foods is changing the concept of 'food environments'. As such, this has critical implications on the literature on physical food environments to-date, by potentially modifying the relationship between dietary health and the foods available, accessible and affordable to the population.

The term ‘digital food environments’ was first conceptualised by Granheim and colleagues in 2022 in a systematic scoping review of 357 studies[58]. Of these, 169 studies covered vendor and product properties of the digital food environment. The review identified online grocery retail and online food delivery services of fast food and other ready meals, as part of the dominant typology of food vendors in the digital food environment[58]. A narrative review has further characterised the digital food retail environment into three main components including: i) meal delivery applications (or online food delivery of fast food and other ready meals), ii) online groceries and iii) meal-kit subscription services[59].

It is evident that there are various terms used to describe online food delivery services or platforms which offer takeaway restaurant meals and/or fast food. These include meal delivery applications (apps), third-party food delivery platforms, and food aggregator apps. For consistency, this thesis hereafter will refer to these services as meal delivery apps (apps). Note: In some published chapters, other terms including ‘online food delivery platforms’ or ‘OFDS’ have been used.

Meal delivery applications

Meal delivery from online settings has existed for nearly three decades since the advent of the World Wide Web for use by the general public in 1994 and the debut of the earliest web-based food delivery site from Pizza Hut[60]. Shortly after, the World Wide Waiter (waiter.com) was established in 1995 as America’s first service offering online ordering to restaurants[61].

Over the past decade, websites and mobile applications, often referred to as ‘platforms’, have facilitated widespread exchanges of goods and services through these ‘digital marketplaces’[62]. Digital platforms offer *users* a forum for interaction with *providers*, a set of contractual rules and a secure payment method. As such, high smartphone penetration, the growth of e-commerce, Uber, and the gig economy have allowed meal delivery apps to flourish over the past decade from 2010 to present.

Meal delivery apps coordinate orders between customers and restaurants through the provision of food delivery workers who typically ride bicycles or motorcycles to transport meals. The meal delivery market worldwide is projected to reach a revenue of 435.30 billion USD in 2024[63]. The following are market-leading meal delivery apps in their respective markets across the globe[64]:

- China: Ele.me, Meituan, Dianping
- Australia and New Zealand: UberEats, Menulog**, DoorDash
- North America: GrubHub, UberEats, Postmates*
- Europe: Gorillas, Deliveroo, Flink, Just Eat**, UberEats, Wolt
- South East Asia: Grab, Gojek, Delivery Hero
- South America: Rappi, iFood
- India: Zomato

*Postmates is a subsidiary of UberEats

**Menulog is a subsidiary of the global Just Eat Takeaway.com network

Young people

Research suggests that young people aged between 16 to 35 years are the highest users of meal delivery apps[65, 66]. This age group comprised of adolescents (WHO definition 10-19 years)[67], emerging adults (18-24 years)[68] and young adulthood (25-34 years)[69], are most vulnerable to the dietary risks which meal delivery apps pose for their health and wellbeing.

This is a critical life stage where many health behaviours are formed[70] which are known to be notoriously difficult to undo or change in later adulthood[71]. Research suggests that early adulthood is the life stage when prevalence of overweight and obesity is increasing the fastest[72]. Adolescents especially, are also a target market for food and beverage companies as they are viewed as 'lifelong' customers to build brand recognition, brand preference and brand loyalty [73]. Adding to this, young people are 'digital natives' with excessive screentime which exposes them to extensive amounts of harmful digital marketing[74].

Normalisation of consumption and purchasing behaviours related to meal delivery apps in this new digital age may have long-lasting adverse impacts on dietary behaviours, health and may lead to a further reduction in adequate knowledge and skills in cooking.

A cross-sectional analysis lead by Wolfson *et al*., demonstrated that more frequent cooking at home is associated with better diet quality overall among both lower and higher-income adults[75]. Utter *et al*.'s longitudinal study also revealed that developing adequate cooking skills by emerging adulthood may have long-term benefits for nutrition over a decade later[76].

Additionally, an increasing number of young people aged 15-24 years have reported experiencing loneliness since 2012[77]. Concerningly, during COVID-19, meal delivery apps use was positively associated with loneliness[78]. Research shows that loneliness or social isolation may be linked to poorer dietary behaviours such as low fruit and vegetable intake, in addition to lower dietary quality[79].

COVID-19 Pandemic

The World Health Organization (WHO) declared the novel coronavirus disease 2019 (COVID-19), a worldwide pandemic on 11 March 2020. COVID-19 restrictions were implemented to reduce the spread of the disease and these approaches included closing dine-in services at restaurants and cafes, and social-distancing rules which limited the number of people eating out and shopping in person for food and groceries[80]. Such measures significantly disrupted food accessibility, and many individuals and households shifted to getting their groceries and meals delivered via 'contact-free' delivery from online food retail platforms[81, 82].

While the meal delivery application markets in countries such as China and India, were well-established prior to the COVID-19 pandemic[83, 84], other markets across the globe experienced a surge in popularity during this time. Research indicates that many new users who signed up during the pandemic, continued to use these services after restrictions were eased[85, 86]. One study suggested that consumers who formed a habitual behaviour using these services were more likely to continue their use post-pandemic[86]. Subsequently, the COVID-19 pandemic was likely a key factor accelerating the growth and popularity of meal delivery apps.

Disrupting the United Nations' global agenda for healthy and sustainable diets

Decade of Action on Nutrition

The United Nations General Assembly proclaimed the Decade of Action on Nutrition in 2016 to achieve global nutrition and diet-related non-communicable disease (NCD) targets by 2025[87]; and accelerate progress towards the 2030 Sustainable Development Goals[87]. The vision of the Nutrition Decade is to: "build an enabling environment for all countries where governments, organisations and stakeholders can work together to ensure that people at all stages of life have access to affordable, diversified, safe and healthy diets"[87].

The Nutrition Decade comprises of six key action areas including:

i) Sustainable, resilient food systems for healthy diets
ii) Aligned health systems providing universal coverage of essential nutrition actions
iii) Social protection and nutrition education
iv) Trade and investment for improved nutrition
v) Safe and supportive environments for nutrition at all ages
vi) Strengthened governance and accountability for nutrition[87].

In a mid-term review of the Nutrition Decade, focus areas for priority action and opportunities in each of the six action areas for 2021-2025 were identified[88]. For action area v) *Safe and supportive environments for nutrition at all ages*, countries were encouraged to act on three points. First, to scale-up implementation of regulatory policies by leveraging recent momentum and learnings from country

experiences such as sugar-sweetened beverage taxes, marketing restrictions and front-of-pack nutrition labelling[88]. Second, to develop and implement regulatory or voluntary approaches to increase availability of healthy choices and create a supportive environment for nutrition[88]. Third, to revitalise action in key policy areas which have stagnated or deteriorated recently[88].

These priority actions for food environments for 2021-2025 however, have overlooked the digitalisation of food environments which threaten to delay progress towards creation of healthier food environments and may interfere with existing regulatory approaches.

2030 Sustainable Development Goals

The United Nations have also urged countries to act on 17 Sustainable Development Goals (SDGs) across economic, social and environmental dimensions to promote healthy lives and wellbeing and make cities inclusive, safe, and sustainable by 2030.[89] Existing reports shows achieving the 2030 UN SDGs will require tremendous efforts ahead by governments and industries globally given the considerable setback induced by the COVID-19 pandemic.[90]

Online food delivery services or meal delivery applications may potentially impede progress towards the 2030 SDGs by impacting the way populations eat, work and care for the environment. Specifically progress towards, SDG 3 ‘Good Health and Wellbeing’, SDG 12 ‘Responsible consumption and production’, ‘SDG 13 ‘Climate action’ and SDG 8 ‘Decent work and economic growth’ may be hindered.

Emerging impacts on population health and wellbeing

Of concern, a growing amount of research indicates that meal delivery apps pose a considerable risk to population health and wellbeing and may disrupt existing progress towards achieving health-enabling food environments.

Poor nutritional quality and aggressive promotional tactics

A cross-sectional observational study on the nutritional quality of the most popular menu items on Uber Eats in Sydney, Australia and Auckland, New Zealand, classified over 88% as “discretionary” – meaning energy-dense nutrient-poor foods[91]. Similarly, a cross-sectional study in three international cities showed that foods such as “burgers”, “pizza” and “Italian” were in the top 10 of most advertised meals[92]. Research has established that these discretionary menu items were more likely to be categorised as ‘most popular’, were accompanied by a photo and offered as a value bundle on the meal delivery app[93]. During COVID-19, meal delivery app companies COVID-washed their social media posts to encourage use of these services to ‘support local businesses’ and engage in ‘social distancing’[94]. Furthermore, an 18% increase in posts which marketed unhealthy foods during the pandemic, was observed[94].

Moreover, a systematic scoping review of 57 studies conducted by Bennett and colleagues[95] has synthesised evidence from 22 studies on meal delivery apps. These studies suggest that meal delivery apps appear to have a negative impact on health by predominantly promoting the sale and consumption of unhealthy foods and beverages[95].

Increasing accessibility to unhealthy foods

Emerging research suggests that meal delivery apps allow users to order food from over 3 km away[96], with unknown impacts on how this affects observations made for 'neighbourhood' or 'local food environments' which has previously been considered as food outlets within a 1km radius of a person's home[97]. Meal delivery apps can therefore now provide individuals access to a much wider range of outlets[91, 96]. Monitoring the reach and impact these meal delivery apps have on local food environments is therefore a key research priority.

Lack of regulation

Currently, meal delivery apps operate with little government oversight. This is despite calls from public health for greater regulation in this sector[98, 99] and demonstrates an important research gap needed to mitigate the public health risks associated with meal delivery apps. The novel, dynamic nature of these platforms means that regulations targeting them will also need to be innovative, and adaptable as the platforms evolve and change over time. Importantly, while use of meal delivery apps is on the rise, access to the other traditional modes of food purchasing continue to remain relevant[100]. This indicates an opportunity to strengthen the existing regulations for conventional food environment, e.g., restaurants, for potential impact on the meal delivery apps. Importantly, applying a social determinant of health lens to the policy design can enhance the success of initiatives.

Thesis overview and structure

The emergence of digital food environments is changing traditional physical food environments with important implications on the existing evidence base to-date.

As such, there is evidently a need for further research to measure, monitor and mitigate the risks which meal delivery apps pose to population health and diets. The aim of this research is to contribute further evidence on the emerging impact of meal delivery apps, as part of the digital food environment, on population diet and health.

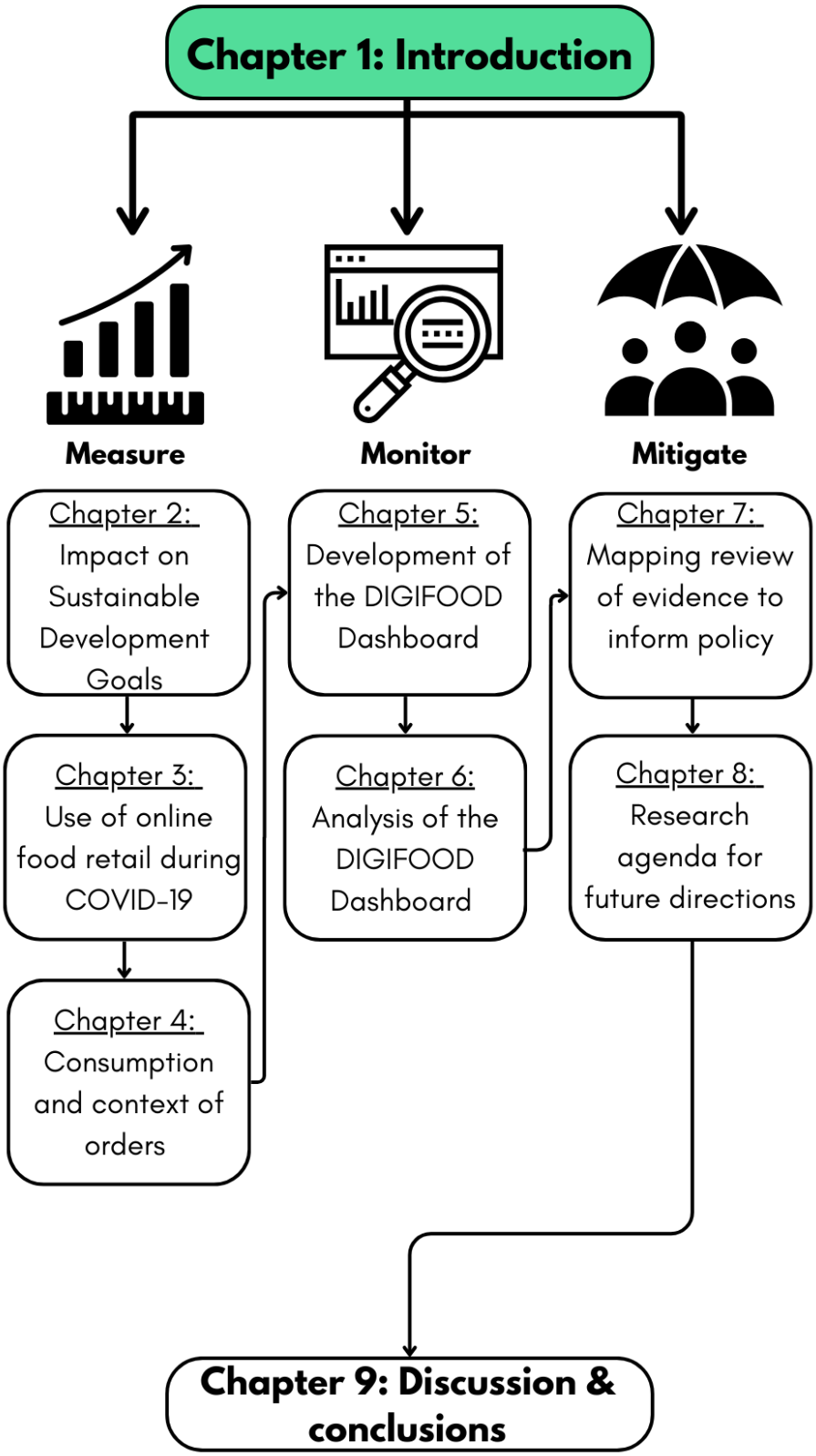
Overarching research question that this thesis aims to address is:

How are meal delivery applications disrupting food environments and affecting population diets and health?

Specific aims of this thesis were to:

1. Synthesise evidence in a perspective piece on the wider implications of online food delivery services impeding progress towards the 2030 United Nations Sustainable Development Goals [Chapter 2];
2. Systematically review the literature to understand changing food environments and dietary behaviours in a digitally accelerated, pandemic-stricken world [Chapter 3];
3. Investigate what foods and beverages are ordered from meal delivery applications and the contextual factors surrounding an online food ordering event; Test the feasibility of capturing order data using mobile Ecological Momentary Assessment [Chapter 4];
4. Develop a data-driven dashboard to monitor the impact of the 'digital food environment' on the 'local physical food environment' using an interdisciplinary approach [Chapter 5];

5. Analyse the data from the DIGIFOOD dashboard to investigate how meal delivery applications are changing food environments across the socioeconomic gradient [Chapter 6]'
6. Review emerging evidence and policy options to regulate meal delivery applications [Chapter 7]
7. Examine the evidence for meal delivery applications in the context of the United Nations Decade of Action on Nutrition and propose a research agenda on its population health impacts, to advance the Nutrition Decade into the future [Chapter 8];


Chapter 1: Introduction
Measure
Monitor
Mitigate
Chapter 2: Impact on Sustainable Development Goals
Chapter 3: Use of online food retail during COVID-19
Chapter 4: Consumption and context of orders
Chapter 5: Development of the DIGIFOOD Dashboard
Chapter 6: Analysis of the DIGIFOOD Dashboard
Chapter 7: Mapping review of evidence to inform policy
Chapter 8: Research agenda for future directions
Chapter 9: Discussion & conclusions

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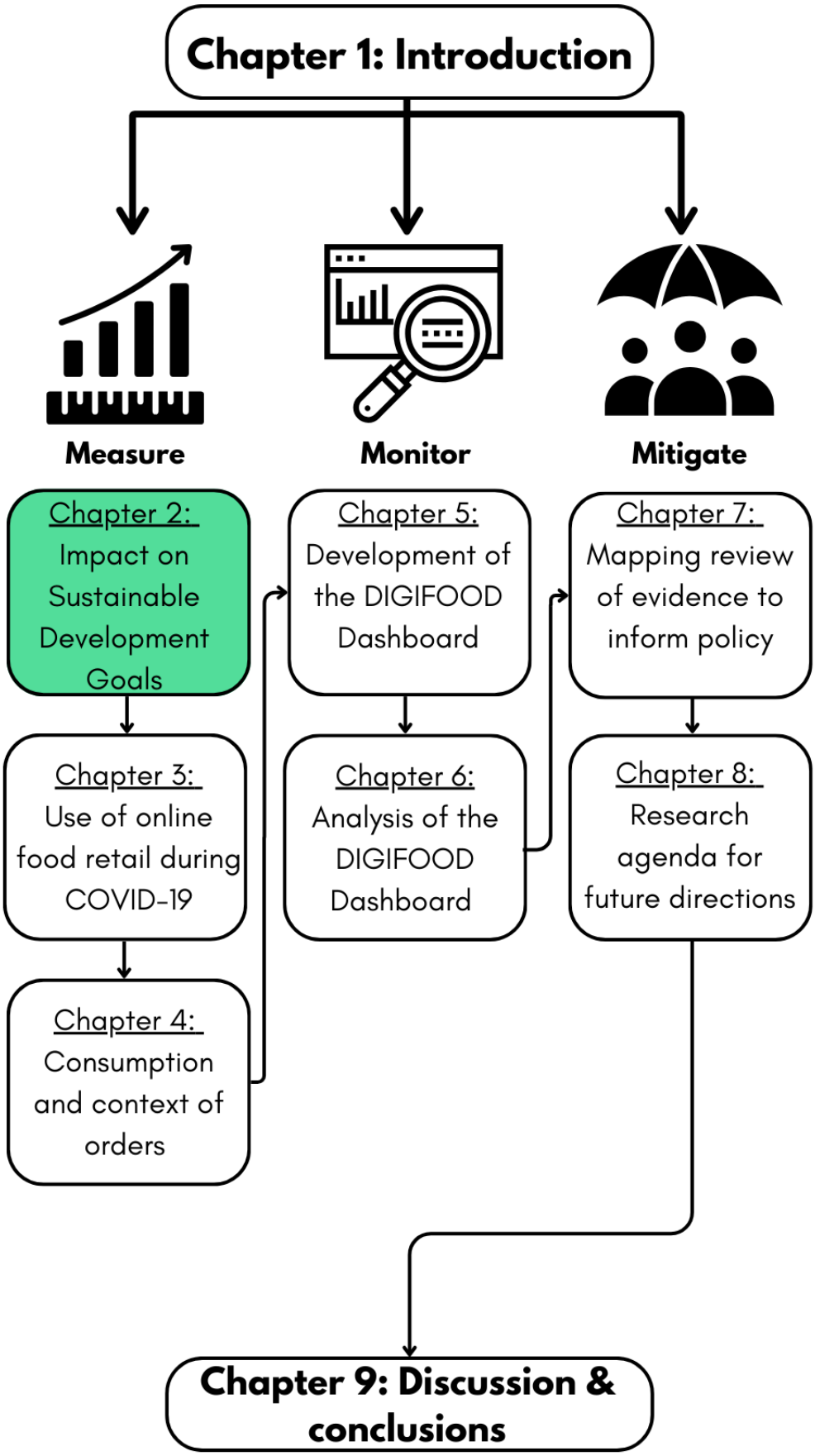
Chapter 1: Introduction
Measure
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Chapter 2: Impact on Sustainable Development Goals
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CHAPTER 2 | IMPACT ON SUSTAINABLE DEVELOPMENT GOALS

Preface to the chapter

Chapter 2 presents a perspective article which identifies the potential implications these 'online food delivery services' have on impeding progress towards the 2030 United Nations Sustainable Development Goals. This chapter thereby addresses Aim 1 of the thesis and contributes to the sub-theme of 'measuring risks which meal delivery applications pose to population diets and health'. This article has been peer-reviewed (submitted 20th January 2022, revised 7th February 2022) and published (3rd March 2022) in *Frontiers in Nutrition*.

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Author attribution statement

This statement is to specify the contribution made by Si Si Jia in the preparation and submission of the following manuscript included in this chapter: “Perspective: Are Online Food Delivery Services Emerging as Another Obstacle to Achieving the 2030 United Nations Sustainable Development Goals?”.

As first author, Si Si Jia was primarily responsible for conceptualisation, creating the tables and figures and writing the draft manuscript and subsequent revisions.

The individual roles of all co-authors are listed below:

Task	**Role of co-authors**
Conceptualisation	SJ
Writing – Original Draft	SJ
Writing – Revision	SJ, SRP, AAG, DD, PP, MAF, JR
Tables and Figures	SJ
Supervision	SRP

Si Si Jia 25 March 2025

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

Dr Stephanie Partridge 25 March 2025

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PERSPECTIVE
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Perspective: Are Online Food Delivery Services Emerging as Another Obstacle to Achieving the 2030 United Nations Sustainable Development Goals?

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Online food delivery usage has soared during the 2019 novel coronavirus (COVID-19) pandemic which has seen increased demand for home-delivery during government mandated stay-at-home periods. Resulting implications from COVID-19 may threaten decades of development gains. It is becoming increasingly more important for the global community to progress toward sustainable development and improve the wellbeing of people, economies, societies, and the planet. In this perspective article, we discuss how the rising use of these platform-to-consumer delivery operations may impede advances toward the United Nations 2030 Sustainable Development Goals (SDGs). Specifically, online food delivery services may disrupt SDGs that address good health and wellbeing, responsible consumption and production, climate action and decent work and economic growth. To mitigate potential negative impacts of these meal delivery apps, we have proposed a research and policy agenda that is aligned with entry points within a systems approach identified by the World Health Organization. Food industry reforms, synergised public health messaging and continuous monitoring of the growing impact of online food delivery should be considered for further investigation by researchers, food industry, governments, and policy makers.

Keywords: online food delivery, sustainable development goals, global health, public health, systems approach

INTRODUCTION

Unhealthy diets, non-communicable diseases, urbanization, and climate change are recognized as significant challenges to global health (1). The United Nations have urged countries to act on 17 Sustainable Development Goals (SDGs) across economic, social and environmental dimensions to promote healthy lives and wellbeing and make cities inclusive, safe, and sustainable by 2030 (2). Online food delivery services (OFDS) are potentially impeding our progress toward the

SDGs—impacting the way we eat, work, and care for the environment. Defined as "platform-to-consumer delivery operations" of ready-to-consume meals, OFDS offer delivery of a wide variety of takeout foods and beverages from kitchens to doorsteps (3).

The OFD industry is now widespread across the globe and big multinational corporations are dominating the market. Billion-dollar companies such as UberEats, DoorDash, and Just Eat operate in thousands of cities and show no sign of slowing down. Globally, OFDS market revenue increased by 27% in 2020, reaching $136.4 billion USD (4). These services are likely to proliferate further, as UberEats estimates that despite the return to dine-in restaurants, consumers are now spending three times more on OFDS compared to pre-pandemic levels (5). Furthermore, Just Eat or otherwise known as Menulog, reported a 79% increase in total orders between 2020 and 2021, across its 17 operating countries including UK, Germany, Canada, and Netherlands (6).

Considering the growing prevalence and market influence of OFDS, it is important to track the impact of OFDS on key public health challenges, such as increasing accessibility of unhealthy foods, promotion of excessive consumption, poor working conditions of delivery couriers in a gig economy and the environmental implications of takeout food packaging. This perspective piece will discuss how OFDS may disrupt progress toward SDGs that address good health and wellbeing, responsible consumption and production, climate action and decent work and economic growth.

JUNK FOOD ON DEMAND: IMPACT ON NUTRITION, HEALTH, AND WELLBEING

OFDS may pose a considerable risk to the aim of SDG 3 to "Ensure healthy lives and promote wellbeing for all at all ages". Research has shown that these OFDS have an abundant offering of menu items that are of poor nutritional quality. From an investigation of 680 popular food outlets on the market leading OFDS in Sydney, Australia, 37.6% (256/680) of popular outlets were classified as a "fast-food franchise" store, and out of the 2,463 most popular menu items identified, 2,358 (95.7%) were identified as "discretionary foods" (7), characterized as high in saturated fat, sodium and sugar, and not essential for health.

Moreover, the two leading OFDS (UberEats, Menulog) in Australia are partnered with the top 10 fast food franchise stores (Subway, McDonalds, Dominos, KFC, Hungry Jacks, Red Rooster, Nando's, Pizza Hut, Zambero, Oporto) (8). This signifies the dominance of fast-food franchise outlets on these platforms which are now another additional avenue for consumers to access their menu items. It is well-known that offerings from fast food franchise outlets are "energy-dense and nutrient poor" (9) and evidence has highlighted the strong association between high fast-food consumption and obesity (10). Furthermore, research has shown that diets high in inflammatory foods such as refined grains, sugary drinks, processed meats and other "junk foods", have been associated with increased inflammation in the body and can elevate subsequent risk of heart disease by 46% and stroke by 28% (11). These highly inflammatory foods are widely available on these online food delivery platforms as shown in findings from a recent cross-sectional study (12). From over 196 independent takeaway food outlets available on UberEats in Sydney, Australia, discretionary cereal-based mixed meals was the largest category found within complete menus (42.3%, 5849/13,841). These include foods such as pizzas, burgers, pides, pasta, wraps, and sandwiches (12).

A Canadian study analyzed the full menus of retailers partnering with a large OFDS and similarly found low Healthy Eating Index-2015 scores—ranging from 19.95 to 50.78 out of 100 (with a score of 100 being the healthiest) (13). This study also found a mean delivery distance of 3.7 km or 2.3 miles measuring from postal codes in Ontario to online food retailers (13). Australian research has likewise, demonstrated that the mean delivery distance from food outlet to suburbs was 3 km, and around 90% of delivery distances were greater than 1 km (7)—a distance that typically defines the neighborhood food environment. The neighborhood food environment reflects the spatial extent of an individual's typical shopping behavior which could be reasonably walked by an adult in 15–20 min (14). As such, these platform-to-consumer services may be expanding local neighborhood food environments.

Altogether, findings suggest OFDS are expanding the traditional definition of the neighborhood food environment, increasing the accessibility of food outlets which mostly offer items with poor nutritional quality.

OVER-CONSUMPTION AND EXCESS PROMOTION

In addition to increasing accessibility of food outlets, OFDS further encourage excessive consumption with aggressive marketing and promotion tactics. Macromarketing researchers are wary of the current marketing systems which promote an era of excess as business models choose to "create" rather than "address" consumer needs, without consideration of the waste generated from overall consumption (15). OFDS may add further burden to unsustainable practices of mass consumerism which threaten progress toward SDG 12: "Ensure sustainable consumption and production patterns".

UberEats and Menulog frequently distribute promotional vouchers that offer free meals, discounts, and free delivery (16, 17). These are often disseminated through emails to past customers signed up to the OFD platform (18) or handed-out in person at high-traffic locations such as train stations (19). Moreover, there is evidence that OFD companies "COVID-wash" their social media promotions—a practice where companies align themselves with social or health issues of COVID-19 to enhance their own image (20). In a content analysis of Instagram posts from leading OFDS in 2020 during the pandemic, the most used COVID-19 marketing strategy was related to "combatting the pandemic" (76/123, 62%) (21). This theme helped brands position themselves to be "in this together" and encourage consumers to "support their local businesses". These findings were echoed in another content analysis study conducted in New

Zealand. The most used theme in 36% of all COVID-19 related social media posts intended to generate feelings of community support during the challenging time. Fast-food brands were also found to be the largest proponents of COVID-washing, accounting for 46% of all COVID-19 posts (20).

Furthermore, during the pandemic, an increase in social media posts promoting "junk foods" from leading OFD brands was observed. In a recent study, we found junk foods accounted for 69.1% of all food and beverage items featured, compared to 58.3% in 2019 (21). Similarly, a study from Brazil indicated widespread presence of unhealthy food advertising as ultra-processed beverages such as soft drinks were among the most shown in advertisements for OFDS throughout COVID-19. Free delivery also prevailed in advertisements of junk food items such as ice cream, candy, high sodium snacks, and pizza (22). More research found that menus offering unhealthy meals had more photos and discounts compared to meals offering unprocessed and/or minimally processed foods (23). Taken together, OFDS continue to facilitate fast-food delivery at heavily discounted prices and excess promotions, perpetuating the culture of excessive consumption.

UNSUSTAINABLE PLASTIC WASTE AND CO2 EMISSIONS

Plastic waste is a key global environmental concern with annual plastic consumption currently at over 300 million tons, which is expected to double in the next 20 years (24). High volumes of online food delivery consumption exacerbates plastic waste and adds to the increasing contamination of natural environments such as the ocean, freshwater systems, and terrestrial areas (25). Subsequently, OFDS may have a huge climate cost and are another impediment to SDG 13: "Take urgent action to combat climate change and its impacts".

Takeout meals ordered from OFDS can come with extensive quantities of plastic material, namely food containers, cutlery, napkins, and plastic bags among others (26). These materials are often single-use, requiring large quantities of energy and raw materials to produce, transport, and be disposed (27). A study on the environmental impacts of takeout food containers revealed that single-use polypropylene containers are the worst packaging material for takeout food, with many negative impacts on the environment (26). In China, researchers found that the total amount of packaging waste from food delivery surged from 0.2 million metric tons in 2015 to 1.5 million metric tons in 2017 (28). Plastic containers made from polypropylene and polystyrene foam accounted for approximately 75% of the total food delivery packaging waste in weight. COVID-19 lockdowns further aggravated China's plastic waste dilemma: during the lockdown in Wuhan, an average of 130,000 takeout orders were made per day, which totaled to more than 279,500 m of lunchboxes over a 6-week period (29).

Excessive energy consumption and carbon emissions are associated with the waste produced from food delivery. Based on annual online food delivery data of 179.2 million active users, a 2016 Chinese study found an average ordering frequency of 2 times/week and average delivery distances of 25 km (30), which resulted in an estimated Green House Gas (GHG) emission of 73.89 Gigatonnes (Gt) carbon dioxide-equivalent emissions (CO_{2eq}) (30). In Australia, COVID-19 lockdowns led to a 20% increase in household solid wastes, partly due to a surge in food deliveries which contributed sizeable amounts of paper, plastic packaging waste and single-use waste (31). Another study found in 2018, the disposal of single use packaging from online food orders in Australia led to 5,600 tons of CO_{2eq} (32). With online food orders expected to increase to 65 million in 2024, researchers project a 132% rise in carbon emissions to 13,200 tons of CO_{2eq} (32). As such, the environmental threat of OFDS is progressively evident and needs to be considered as governments globally move toward carbon emission reduction targets.

FUELLING THE GIG ECONOMY

Instead of steering toward the SDG 8: "Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all", OFDS stimulate the gig economy and may veer away from sustainable economic growth that will create quality jobs. While OFDS have facilitated new job opportunities and increased flexibility of work, the quality of these jobs is questionable with little-to-no employment rights and poor work health and safety conditions (33).

Advances in online technology have fuelled the rise of the "gig economy"—a free market system in which mobile apps or websites connect consumers with individual workers providing services. Gigs are denoted by short-term, one-off employment contracts mediated by online platforms which include online food delivery. Although spending on gig economy in Australia declined severely during the period of early COVID-19 lockdown restrictions in March 2020, it increased to 40% above pre-lockdown levels. This growth was almost entirely driven by the online food delivery sector, which itself increased by more than 100% between August and October 2020 (34). Indeed, UberEats Australia, a leading OFDS, has reported providing 59,000 work opportunities during 2020 which is an eight-fold increase since 2016 (5).

In a report on digital platform work in Australia, it has been revealed that food delivery workers choose to work with OFDS for flexibility and to supplement existing income streams (35). However, food delivery workers are more dependent on income generated from meal delivery compared to gig workers on other digital platforms (35). This report also suggests food delivery workers were more likely to work longer hours in a week and were more likely to say the income was essential for meeting basic needs (35). Moreover, food delivery platforms may vary in their contractual agreements where workers may be independent contractors rather than employees. This places workers at risk of insecure income, no insurance, personal or paid leave, no workers compensation, superannuation or certain taxes. Over a long term, gig work as a food delivery worker may be financially untenable. A gig worker who spends 5–10 years in the gig economy full

TABLE 1 | Proposed action points to mitigate negative impacts of online food delivery services and address the 2030 UN Sustainable Development Goals and entry points identified in the WHO Meal Delivery Apps Report.

	Action	UN sustainable development goal	WHO MDA entry point	Current and emerging research
1	Advocate for major reforms to the gig economy sector to recognize full employment rights for food delivery workers to improve working conditions	SDG 3 SDG 8	Labor, Road Safety	Menulog Australia has started a pilot employment program around Sydney's Central Business District—giving their worker's rights to a minimum wage and superannuation contributions by directly employing them (42)/ New Zealand's second-largest private sector trade union, "FIRST Union" has launched a class action lawsuit against Uber to seek better conditions and security of rideshare and food-delivery work (43).
2	To create healthier neighborhood food environments by developing cycle-friendly or convenient and walkable pathways within transport networks and city infrastructures.	SDG 3 SDG 8 SDG 13	Labor, Physical activity, Environment	To improve potential access to healthier foods and reduce the reliance on getting takeaway meals delivered, a "15-min" city may be a possible solution. Proposed by Moreno and colleagues, a "15-min city" is an urban planning concept that advocates for the provision of basic urban amenities at distances that would take local citizens no more than 15 min to access by foot or by bicycle (44). This urban planning concept has inspired many cities to embrace becoming more cyclable and walkable. The city of Paris is leading the "15-min city" transformation (45) while other cities have also seen notable action such as Melbourne (46), Shanghai (47), Singapore (48), Portland (49), and Bogota (50).
3	Disincentivise unhealthy food and beverage choices through regulatory pressure to limit promotions such as monthly subscriptions and junk food advertising on social media while promoting healthier food options on these platforms.	SDG 12 SDG 3	Alcohol consumption, Nutrition	Research on the monitoring of social media food marketing content targeted toward children and adolescents is still in its infancy. However, this is a high priority for global bodies such as the World Health Organization. Further research may benefit by aligning with the proposed tools and initiatives from WHO to monitor food and beverage marketing to children via television and the Internet (51). In addition, the UK government has announced a ban on junk food advertising online and before 9 p.m. on TV from 2023 (52). This ban will affect all paid-for forms of digital marketing—from Facebook ads to paid search results on Google, text message promotions, and paid activity on sites such as Instagram and Twitter. More work should also focus on the potential benefits of online food delivery services—as many healthier food options can be promoted and selected instead. Digital nudging interventions have shown promising results with improvement to the nutritional quality of online school canteen lunch orders (53). Intervention participants had significantly lower energy content and saturated fat content than control lunch orders.
4	Generate clear public health messaging on both the nutritional quality and environmental impacts of OFDS usage in relation to sustainability.	SDG 3 SDG 12 SDG 13	Nutrition, Environment	Adding nutritional labeling requirements to online food delivery service platforms may be a feasible policy option to inform individuals of the nutritional quality of menu items. The UK has expanded its menu calorie-labeling policies to all restaurants, cafes and takeaways—including online food delivery and this will be implemented in April 2022 (54). Ecolabeling, a method of identifying products or services that are environmentally preferable (55), may also be a potential avenue to changing individual dietary choices while also advocating for environmental sustainability. A recent systematic review has shown promising results to suggest ecolabeling is associated with the selection and purchase of more sustainable food products (56).
5	Investigate sustainable and food safe takeaway packaging options and implement across food outlets partnered with OFDS	SDG 3 SDG 13	Environment, Food safety	Research on sustainable packaging is also growing and there have been suggestions that reusable packaging systems have better environmental benefits over single-use systems. There is an increasing number of companies now providing alternatives to single-use cups for restaurants and cafes—CupClub (U.K.), Meu Copo Eco (Brazil), Globelet (Australia), ReCup (Germany), and Revolv (Indonesia). Companies such as GoBox (US), recircle (Switzerland), Returnr (Austria), Ozarka, and Sharepack (The Netherlands) are leasing reusable containers to restaurants, cafes, bars, and food trucks. It remains unclear however, how this could be applied to all online food delivery outlets considering the need for customers to return empty packaging that will be cleaned and refilled for future use (57).

time, could potentially be $40,000–$100,000 AUD worse off in accumulated superannuation at retirement compared to a minimum wage earner (34). Major reforms of OFD work in the gig economy are required to increase the quality of these jobs, improve the livelihood of workers and be sustainable in the long term.

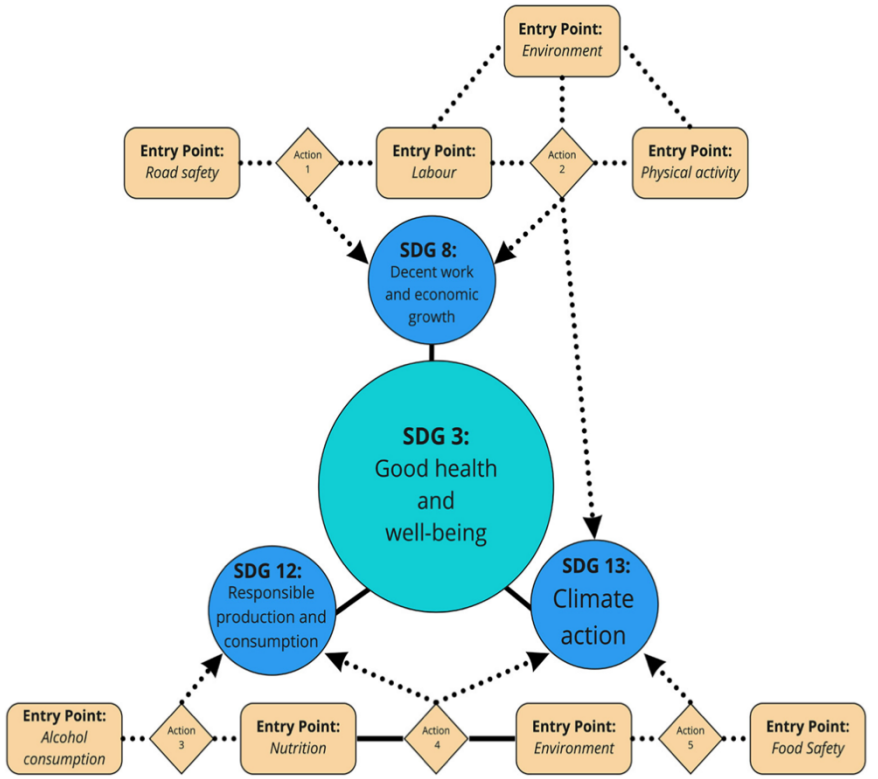

FIGURE 1 | Conceptual diagram identifying areas for entry points and Sustainable Development Goals relating to online food delivery services to merge, forming action points to ultimately address SDG 3 Good Health and Wellbeing. Actions are defined and described in detail in **Table 1**.

DISCUSSION

Existing reports shows achieving the 2030 UN SDGs will require tremendous efforts ahead by governments and industries globally given the considerable setback induced by the COVID-19 pandemic (36). A systems approach to the complexities of public health issues has been proposed by notable researchers—as outlined in the 2011 and 2015 Lancet Series on Obesity (37, 38) and has been a developing research area to inform the National Institute for Health and Care Excellence guidelines on obesity prevention (39). The synergising of goals and targets within and between systems affecting health including manufacturing, financial, transportation, and food, may be essential to meaningful progress. The EAT-Lancet commission on Food, Planet, and Health is an example which shows the power of goal alignment (40). This report has outlined the role of diet with human health and environmental sustainability—addressing both the rise in unhealthy diets, the targets of the UN Sustainable Development Goals and the Paris Agreement. As research on the impacts of OFDS is still in its infancy, robust solutions to resolving the issues outlined in this perspective have yet to be developed. However, using a similar systems-based approach, the following calls to action identify areas for existing systems to merge.

PROPOSED CALLS TO ACTION

The World Health Organization (WHO) (41) has now acknowledged the growing impact of online food environments on people's diet choices. In a recently published report, WHO Europe has proposed the use of a systems approach to make informed decisions on potential interventions and/or regulation of these OFDS or otherwise known as "Meal Delivery Apps" (MDA). Taking a systems approach, several entry points to change were identified. These include Nutrition, Physical Activity, Alcohol consumption, Labor, Road Safety, Food Safety which are key elements that use existing mechanisms to solve complex issues (41). The entry points align with the SDGs discussed in this perspective and may benefit from collective action by food industry, governments, policy makers and researchers.

In **Table 1**, we propose a research and policy agenda with action points that address SDGs and entry points from the WHO report. We have also illustrated examples of current and emerging research across these action points. **Figure 1** was designed to demonstrate how these action points can work together to strive toward SDG 3: "Good Health and Wellbeing" for the benefit of public health. The proposed action points may also later converge with

recommendations outlined from WHO Europe's commentary piece (58).

As research on the impact of OFDS continues to grow, ongoing monitoring and evaluation is critical to the development of policy options for regulating the digital food environment. Dashboards are considered as useful tools to help users visualize and understand complex information in a snapshot. They have been developed to monitor global food systems (59) and food environments (60) and may also be essential to tracking progress of online food delivery services. We therefore also propose the inclusion of online food settings within existing monitoring and evaluation frameworks of food systems and food environments (60).

CONCLUSION

In a world now grappling with ongoing repercussions of the COVID-19 pandemic, resulting societal and environmental changes exacerbated by COVID may further derail the trajectory toward meeting the SDGs set by the United Nations. OFDS are likely to proliferate, providing valued convenience in an increasingly fast-paced modern society. However, the potential disruption to our health and the environment is substantial, interfering with overarching SDGs. Food industry reforms synergised public health messaging and continuous monitoring of the growing impact of OFDS may be part of the solution to collectively address the issues of sustainability, environmental health, decent work and economic growth and nutrition. Multidisciplinary action and research are urgently needed to further investigate such solutions.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

SJ and SP contributed to the conceptualization of the manuscript. SJ wrote the first draft of the manuscript and designed all tables and figures included in submission. SP provided primary supervision of SJ, reviewing the first draft of the manuscript. AAG, DD, PP, MA-F, and JR edited and reviewed the manuscript drafts. All authors contributed to manuscript revision, read, and approved the submitted version.

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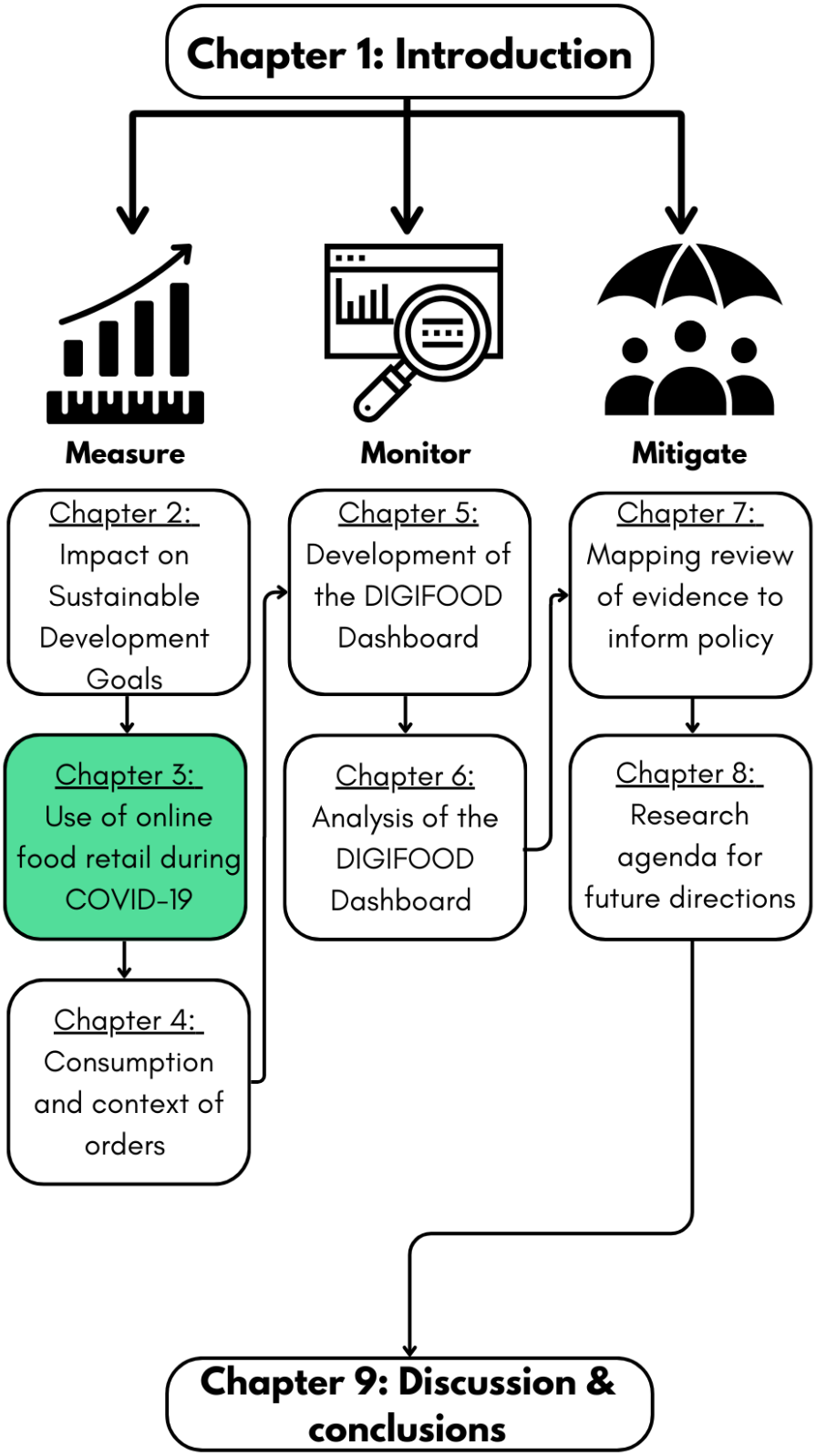
Chapter 1: Introduction
Measure
Monitor
Mitigate
Chapter 2: Impact on Sustainable Development Goals
Chapter 3: Use of online food retail during COVID-19
Chapter 4: Consumption and context of orders
Chapter 5: Development of the DIGIFOOD Dashboard
Chapter 6: Analysis of the DIGIFOOD Dashboard
Chapter 7: Mapping review of evidence to inform policy
Chapter 8: Research agenda for future directions
Chapter 9: Discussion & conclusions

CHAPTER 3 | USE OF ONLINE FOOD RETAIL PLATFORMS DURING COVID-19

Preface to the chapter

Chapter 3 has systematically reviewed the existing literature to understand changing food environments and dietary behaviours in a digitally accelerated, pandemic-stricken world. This chapter thereby addresses Aim 2 of the thesis and contributes to the first sub-theme of 'measuring risks which meal delivery applications pose to population diets and health'. This systematic review has been peer-reviewed (submitted 15th February 2023, revised 28th November 2023) and published (18th January 2024) in *Obesity Reviews*. Author contributions to this paper are outlined in the authorship attribution statement. Supplementary material can be found in Appendix A including A.1 Full Medline Search Strategy, A.2 Quality assessment using the Joanna Briggs Institute checklists, A.3 PRISMA 2020 Statement and A.4 Data extraction table.

Published peer reviewed manuscript

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Author attribution statement

This statement is to specify the contribution made by Si Si Jia in the preparation and submission of the following manuscript included in this chapter: “Use of online food retail platforms throughout the COVID-19 pandemic and associated diet-related chronic disease risk factors: A systematic review of emerging evidence”.

As first author, Si Si Jia was primarily responsible for formulating the research question, performing the literature search, screening for studies against inclusion and exclusion criteria, extracting data, critical appraisal of studies, writing the draft manuscript and subsequent revisions.

The individual roles of all co-authors are listed below:

Task	**Role of co-authors**
Conceptualisation of research question	SJ, SRP, AAG
Systematic search of the literature	SJ
Screening – Title and abstract, full-text	SJ, RR
Data extraction	SJ
Validation of extracted data	SW

Critical appraisal	SJ, ES
Writing – Original Draft	SJ
Writing – Revision	SJ, ES, SW, PP, JR, MF, MAF, AAG, SRP
Supervision	SRP, AAG

Si Si Jia 25 March 2025

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

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REVIEW

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Use of online food retail platforms throughout the COVID-19 pandemic and associated diet-related chronic disease risk factors: A systematic review of emerging evidence

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Summary

Food accessibility was considerably impacted by restrictions during the coronavirus disease 2019 (COVID-19) pandemic, leading to growth in the online food retail sector, which offered contact-free delivery. This systematic review aimed to assess the change in use of online food retail platforms during COVID-19. The secondary aim was to identify diet-related chronic disease risk factors including dietary intake, eating behaviors, and/or weight status associated with the use of online food retail platforms during the pandemic. The review was registered in the International Prospective Register of Systematic Reviews (PROSPERO) (CRD42022320498) and adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Nine electronic databases were searched between January 2020 and October 2023. Studies that reported the frequency or change in use of online groceries, meal delivery applications, and/or meal-kit delivery services before and during the pandemic were included. A total of 53 studies were identified, including 46 cross-sectional studies, 4 qualitative studies, 2 longitudinal cohort studies, and 1 mixed-methods study. Overall, 96% (43/45) of outcomes showed an increase in the use of online groceries during COVID-19, while 55% (22/40) of outcomes showed a decrease in meal delivery applications. Eight of nine outcomes associated the use of

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online food retail with weight gain and emotional eating. Further research is needed to investigate the links between online food retail and obesity.

KEYWORDS
COVID-19, digital technology, food delivery, food environments, healthy diets, online food retail

1 | INTRODUCTION

The coronavirus disease 2019 (COVID-19) pandemic has inflicted a profound effect on health systems, economies, and livelihoods.[1] As governments across the world actioned social-distancing measures and stay-at-home orders to mitigate the spread of the disease, many people's lifestyle behaviors were significantly disrupted.[2] These measures restricted people's ability to exercise,[3] increased stress and anxiety levels,[4] and heightened demand for unhealthy foods.[5] The World Health Organization (WHO) has reported that rates of weight gain have risen during the COVID-19 pandemic and that this increase was likely attributed to more "obesogenic" changes to the food environment[6] including a surge in promotion of fast-food, alcohol, and sugar-sweetened beverages on social media platforms.[7,8]

Systematic reviews on the impact of the COVID-19 pandemic on food consumption have revealed adverse changes in eating habits. González-Monroy et al.[9] reported increased snack frequency and preference for sweets and ultra-processed food instead of fruits, vegetables, and fresh foods and a decreased adherence to healthy diets. Similarly, Neira et al. observed an increase in food consumption, weight, and body mass index (BMI).[10] A meta-analysis of six studies across Italy, Spain, Poland, Turkey, and Australia and cohorts from Asia, Africa, and Europe showed that body weight change from March to May 2020—the first phase of restricted movements during the pandemic—observed a significantly higher body weight in the post-lockdown period compared to a period before the lockdown. The weighted mean between-group difference was 1.57 kg (95% confidence interval [CI]: 1.01, 2.14).[11] Although this change in weight may not appear to be a clinically meaningful result of ≥2 kg,[12] it is noteworthy to consider the rapid rate at which this weight gain occurred within a few months of the pandemic.

The United Nations has also acknowledged the significant impacts of the COVID-19 pandemic in further undermining the food security and nutritional status of millions of households across the world.[13] Due to food supply chain issues and restricted store opening hours, an individual's access to food was significantly altered during this time.[14] In a systematic review conducted by Éliás and Jámbor, most (78%) studies reported an increase in household food insecurity during the first year of the COVID-19 pandemic.[15] Research has shown that food insecurity is associated with poorer diet quality[16] and increased risk of obesity[17] and chronic diseases such as hypertension and type 2 diabetes.[18]

Social-distancing measures have contributed to increased demand for e-commerce and contact-free delivery[19] through online food retail platforms. A recent review outlined three distinct categories of online food retail platforms with the greatest implications for public health including online groceries for fresh produce and pantry staples (e.g., Amazon Fresh®), meal delivery applications (apps) for ready-made takeaway meals (e.g., Uber Eats®), and meal kits with ingredients for cook-at-home meals (e.g., HelloFresh®).[20]

The United Nations Conference on Trade and Development (UNCTAD) reported globally that the online share of total retail sales increased from 16% to 19% in 2019–2020, a three-percentage point rise compared to a two-percentage point rise between 2018 and 2019.[21] UNCTAD also indicated that throughout the COVID-19 pandemic, online retail sales increased substantially in the countries that comprise half of the global gross domestic product (GDP) including China and the United States—growing from $2 trillion USD in 2019 to $2.9 trillion in 2021.[22] An analysis of Google search interest in "delivery" in the Organisation for Economic Co-operation and Development (OECD) countries such as the United Kingdom and Germany found that interest doubled in a short period before and after COVID-19 confinement measures were implemented.[19]

Online food retail platforms were therefore likely an important method to access food for many people during the COVID-19 pandemic and potentially contributed a significant portion to the growth in total online retail sales. The full extent of the adoption of online food retail throughout the pandemic, however, remains underexamined. It is important to understand how usage of these online sources of food may have changed during lockdowns and to consider what impact these platforms may have on people's diets. There are signs from the growing body of literature that indicate that meal delivery applications are causes of concern for health due to the poor nutritional quality of foods offered online[23,24] and lack of energy labeling on menu items to inform consumers.[25] Moreover, results from a recent systematic review on the evidence gaps in assessing the healthiness of online supermarkets also indicate that there is an advanced ability to disguise healthier products and promote unhealthier products through marketing strategies in an online grocery retail setting.[26]

As such, the primary aim of this systematic review was to examine people's change in use of online food retail platforms during the COVID-19 pandemic, including their lived experiences and their access to food during COVID-19 lockdowns. A secondary aim was to identify diet-related chronic disease risk factors including dietary intake, eating behaviors, and/or weight status associated with the use of online food retail platforms during the pandemic. Unhealthy dietary behaviors developed during COVID-19 may elevate the risk of obesity and associated chronic diseases. Thus, the findings from this review have the potential to inform policy planning for future pandemics in

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terms of dietary behaviors related to ordering food from online platforms.

2 | METHODS

Systematic review was conducted under the standards established in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA).[27] The review protocol was prospectively registered in the International Prospective Register of Systematic Reviews (PROSPERO) (Registry Number CRD42022320498).

2.1 | Eligibility criteria

Quantitative studies including cross-sectional and longitudinal studies, qualitative studies, and mixed-methods studies published in peer-reviewed journals were included. In addition, studies were included if the following criteria were satisfied: (i) conducted during the COVID-19 pandemic (from January 1, 2020, onwards)[1] and (ii) covered the subject of online food retail platforms including online groceries, meal delivery applications, and meal-kit subscription services. Studies that reported on the frequency of online food retail use and at least one of the following outcomes in association with online food purchasing during the pandemic were included: (i) diet-related chronic disease risk factors such as dietary intake, food consumption behaviors, eating context, and/or weight status and (ii) lived experiences of online food access during COVID-19 lockdowns.

Dissertations or theses, study protocols, conference proceedings, systematic reviews, narrative reviews, gray literature, and commentaries, editorials, or opinions were excluded from the review. Studies were also excluded if they (i) were conducted in a clinical setting and (ii) included participants with an existing mental health diagnosis, who were pregnant or post-partum, and who had an acute illness or other significant chronic disease that required a specific diet and/or physical activity management. The following study outcomes were not of interest and excluded: (i) consumer behaviors not related to health such as behavioral intent, (ii) health impacts of essential workers and gig economy workers, (iii) environmental impacts, (iv) food safety concerns, and (v) marketing and food promotion of online food delivery services. Please see Table 1 for more detailed information on the PICOS criteria used for this review.

2.2 | Information sources

Nine electronic databases including MEDLINE via Ovid, Embase, WHO COVID-19, Business Source Ultimate, CINAHL, PsycINFO, Scopus, ProQuest, and Web of Science were searched in March 2022. The search was updated in October 2023.

TABLE 1 Population, Intervention, Comparison, Outcome, and Study Design (PICOS) inclusion and exclusion criteria.

	Include	Exclude
Population	General population of any age and country of residence	Participants free from an existing mental health diagnosis, not pregnant or post-partum, and free of acute illness or other significant chronic disease that requires specific diet and/or physical activity management (type 1 diabetes, cancer, etc.)
Intervention	The exposure in this research question is the COVID-19 pandemic, and as such, only studies conducted during COVID-19 were included. Only studies from 2020 onwards were considered. The cut-off date of 2020 was selected as the first known case was only identified in December 2019	Not applicable
Comparator(s)/control/context	Before and during the COVID-19 pandemic	Not applicable
Primary outcome(s)	Use of online food ordering platforms and frequency of online food purchasing before and during COVID-19	• Health impacts on online food delivery workers/drivers • Environmental impacts • Food safety concerns • Marketing/food promotion of online food delivery services
Study design	Only peer-reviewed journal articles were included such as cross-sectional studies, cohort studies, qualitative studies, quasi-experimental studies, and randomized controlled trials	Study protocols, case study, conference abstracts, theses or dissertations, narrative reviews, systematic reviews, gray literature including news articles, market reports, and commentaries/editorials/opinions

Abbreviation: COVID-19, coronavirus disease 2019.

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2.3 | Search strategy

An experienced academic librarian was consulted to formulate the search strategy. In consideration of the small volume of literature around online food retail during the COVID-19 pandemic, a broad search strategy was applied. The following search term categories, combinations, truncations, and synonyms were used: "COVID-19" or "SARS-COV-2" AND "stay-at-home order" or "lockdown" or "restrictions" AND "digital platforms" OR "mobile applications" OR "internet" AND "online food delivery" OR "online food shopping" OR "online food ordering" OR "meal delivery." The full search query for the MEDLINE via Ovid database search is provided in Table S1.

2.4 | Selection process

Search results from all databases were retrieved and merged using Endnote X9 reference management software (Clarivate Analytics, Philadelphia, USA) and imported into Covidence (Veritas Health Innovation Ltd, Melbourne, Australia), a web-based collaboration software platform used to streamline the systematic review process. In Covidence, duplicates were removed, and studies were first selected from title and abstract screening. This was performed independently by two authors (S.S.J. and R.R.). Full texts were retrieved for the studies included from the title and abstract screening process and assessed against the inclusion criteria for a second time. Any discrepancies regarding eligibility for included studies were resolved through discussion between authors S.S.J. and R.R. If discrepancies remained unresolved, a third author (S.R.P.) was consulted.

2.5 | Data collection process

Data extraction was independently conducted by one author (S.S.J.) and validated for accuracy by another author (S.W.).

2.6 | Data items

The following data were extracted: first author details, study setting, study aims, study design, time of study, target population, and sample characteristics including sample size, age and gender of participants, and income level of participants. To address the main research questions, the following were extracted: (i) outcomes and measures used to assess change in use of online food retail, (ii) findings relating the use of online food retail to diet-related chronic disease risk factors, and (iii) themes from lived experiences of sourcing food from online platforms during COVID-19.

2.7 | Synthesis methods

The convergent segregated approach of the Joanna Briggs Institute (JBI) methodology for mixed-methods systematic reviews was used for data synthesis.[28] Quantitative findings were narratively summarized from the data extraction table, which gathered data on study characteristics and results for the outcomes of interest including the use of online food retail and its association with diet-related chronic disease risk factors. The use of online food retail platforms was measured by the change in frequency during the pandemic compared to before the pandemic. A content analysis approach was used to synthesize findings from qualitative studies on participants' use of online food retail during COVID-19—including their reasons for use and experiences. Concepts were formed based on the frequency of terms. Data on the use of online food retail during COVID-19 were further synthesized by the COVID-19 time period.

Diet-related chronic disease risk factors associated with the use of online food retail platforms were evaluated for their potential impact on health as either negative or positive. Evidence of dietary behaviors that could have a positive impact on health would involve orders of foods from the five food groups[29] such as vegetables and legumes, fruits, dairy products and alternatives, grains and cereals, and meat and alternatives. Conversely, orders of "discretionary foods"[29] such as fried and salty foods, sweets, and other foods high in energy and low in nutrients would be deemed to have a "negative" impact on health.

2.8 | Study risk of bias assessment

The JBI critical appraisal checklists were used to assess the quality of the included studies based on their study design. Cross-sectional studies were appraised using the relevant checklist, which encompassed 8 items[30] and 11 items for cohort studies.[31] Qualitative studies were assessed against the relevant 10-item questionnaire.[32] For mixed-methods studies, the JBI checklists were used to assess the quantitative and qualitative components separately. An overall "risk of bias" judgment was assigned based on the total points the studies had accumulated from their quality appraisal checklist. An answer resulting in "yes" scored 3 points, "no" scored 0 points, and "unclear" scored 1 point.[33] The overall quality of the study was based on the percentage of points earned under each quality appraisal tool. A study that was of "poor quality" attained only 33% of the maximum number of points, "moderate quality" scored between 33% and 67%, and "high quality" was given to studies that scored above 67%. Two authors (S.S.J. and E.S.) independently assessed each study, and any disagreements were resolved by a third reviewer (S.R.P.).

2.9 | Deviations from PROSPERO protocol

In this review, some terminology varied from the protocol to ensure alignment with the published literature on digital food environments, which is rapidly emerging. That is, instead of online food purchasing platforms, online food retail was used as an umbrella term to describe the main categories of online food delivery. In addition, given the diverse age groups captured in each individual study, an analysis of online food retail use by age was not conducted.

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3 | RESULTS

3.1 | Study selection

In total, 53 studies were included in the review following full-text screening as displayed in the PRISMA flow diagram (Figure 1).

3.2 | Study characteristics

The characteristics of the included studies are summarized in Table 2. There were 46 cross-sectional studies, 4 qualitative studies, 2 longitudinal cohort studies, and 1 mixed-methods study. For cross-sectional and cohort studies, 34% (21/62) had a sample size between 1000 and 4000 participants. Sample sizes for qualitative studies ranged between 12[81] and 34.[82] The COVID-19 time periods for when studies were conducted were documented and categorized into quarterly periods starting from 2020. Nearly 40% of outcomes (21/53, 39.6%) were from studies conducted during the second quarter of 2020 from April to June.

3.2.1 | Geographical region and countries

Of the 53 included studies, six studies were multi-country[34–38] and reported outcomes for each individual country, thus resulting in a total of 64 outcomes. As shown in Table 2, study outcomes from East Asia and the Pacific comprised 27% of the total (17/64), North America comprised 22%, and Europe and Central Asia made up 20.6%, followed by the Middle East and North Africa, Latin America, and South Asia. None of the included studies were conducted in sub-Saharan Africa. More than half (55.6%) of the included studies were conducted in high-income countries according to the World Bank classification, and no studies were conducted in low-income countries.

3.2.2 | Participant characteristics

Of the 52 studies, three studies reported participant characteristics for the different countries sampled,[34,37,76] three studies each reported results for two groups of participants,[35,36,78] while two studies[54,58] shared the same group of participants. As such, there were a total of 62 outcomes based on participant characteristics. Most studies had

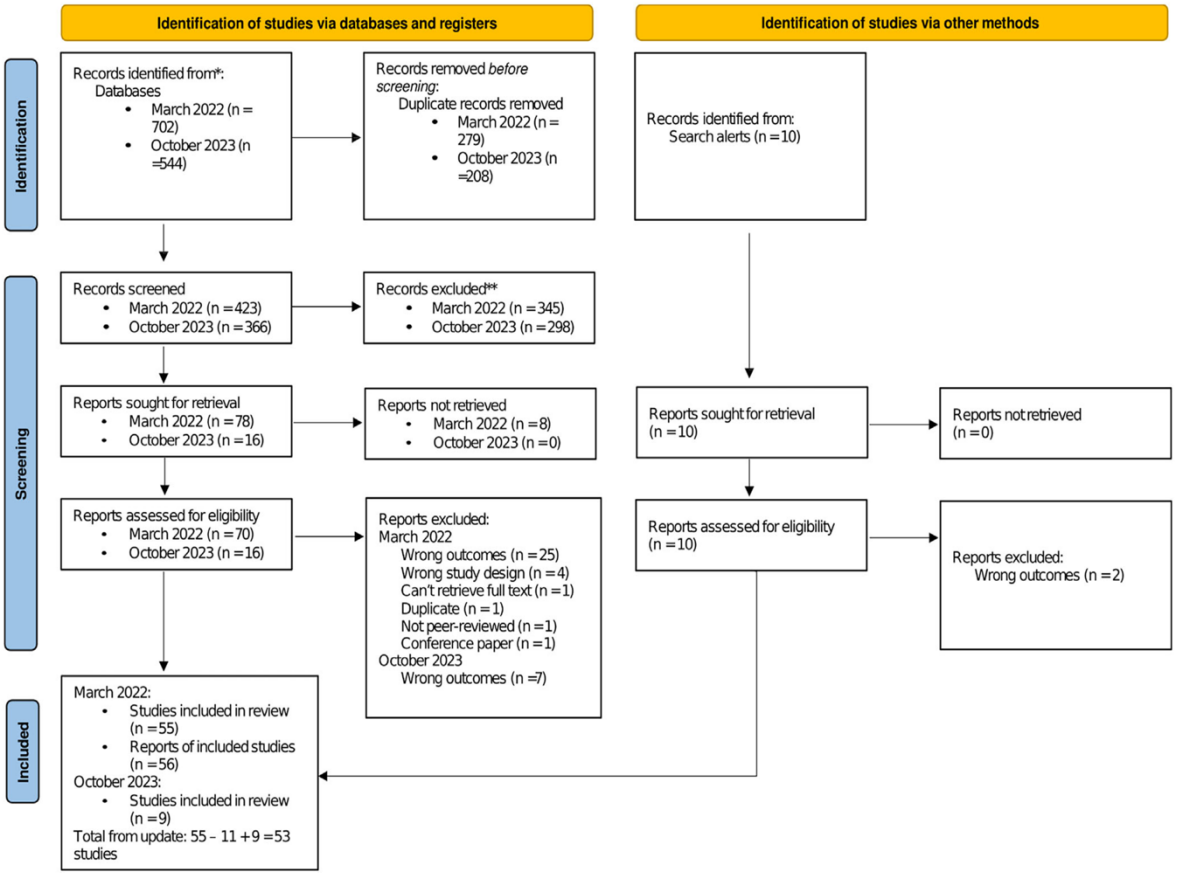

FIGURE 1 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram using the PRISMA 2020 statement.[27]

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TABLE 2 Study characteristics of the included studies ($n = 53$).

Study characteristics	Sub-category of study characteristics	Number of results (%)	References
Study design	Cross-sectional	46 (87%)	34–80
	Qualitative	4 (8%)	81–84
	Longitudinal cohort	2 (4%)	85,86
	Mixed-methods	1 (2%)	87
Sample size	Qualitative studies with <20 participants	2 (3%)	81,83
	Qualitative studies with 20–50 participants	2 (3%)	82,84
	Cross-sectional/cohort studies with 100–500 participants	17 (27%)	45,47,48
	Cross-sectional/cohort studies with 500–1000 participants	14 (23%)	35,44,52,53,59,61,64,67–69,77–80
	Cross-sectional/cohort studies with 1000–4000 participants	21 (34%)	34,36,39–43,46,51,54,56–58,62,63,65,70,72,73,86
	Cross-sectional/cohort studies with >4000 participants	6 (10%)	34,66,75
COVID-19 period	2020 first quarter (Jan–Mar)	2 (4%)	61,62
	2020 second quarter (Apr–Jun)	21 (40%)	35–37,40,43,44,50–52,54,56,59,62,66,68,69,71,75,78,80,81
	2020 third quarter (Jul–Sep)	11 (21%)	39,42,45,47,63–65,70,74,84,86
	2020 fourth quarter (Oct–Dec)	8 (15%)	34,38,46,48,49,55,57,67
	2021 first quarter (Jan–Mar)	4 (8%)	53,77,85,87
	2021 second quarter (Apr–Jun)	4 (8%)	41,79,82,83
	2021 third quarter (Jul–Sep)	1 (2%)	72
	2022 second quarter (Apr–Jun)	1 (2%)	60
	2022 fourth quarter (Oct–Dec)	1 (2%)	76
Geographical region	East Asia and the Pacific	17 (27%)	34–36,49–51,54,58,60–63,66,84,86,87
	North America	14 (22%)	34,36,39,43,52,56,57,68,74,78,79,83,85
	Europe and Central Asia	13 (21%)	34,38,46,59,67,69,71,72,75,76,80,81
	Middle East and North Africa	12 (19%)	37,40–42,44,45,47,48,55,70
	Latin America	5 (8%)	34,53,64,65,77
	South Asia	2 (3%)	73,82
	Sub-Saharan Africa	0 (0%)	
Countries in studies by World Bank classification	High-income	35 (56%)	34–36,38–45,52,54,56,57,59,60,67–69,71,74–76,78,79,81,83–85,87
	Upper middle-income	23 (37%)	34–37,46,47,49–51,53,61–66,72,77,80,86
	Lower middle-income	5 (8%)	48,55,70,73,82
	Low-income	0 (0%)	
Gender of participants	Majority female (>50%)	44 (71%)	34–40,43,44,46,47,50–55,57,59,60,63–70,72,74,76,77,80,81,84–87
	Majority male (>50%)	11 (18%)	35,45,48,56,61,63,73,75,76,78
	Mixed (almost equal proportions)	1 (2%)	36
	All female	4 (7%)	41,42,82,83
	All male	0 (0%)	
	Not reported	2 (3%)	71,79
Age of participants	Majority youth <18 years	1 (2%)	70
	Majority young adults 18–30 years	24 (39%)	35–37,41,42,46,48–51,55,63,64,66,67,74,76,80,86,87
	Majority adults 30–40 years	18 (29%)	34,37,38,40,44,45,48,53,57,61,63,65,72,73,77,81,84
	Majority adults 40–50 years	8 (13%)	36,43,54,68,75,78,82,85
	Majority adults 50–60 years	4 (7%)	39,52,71,83
	Majority adults >60 years	5 (8%)	34,56
	Not reported	2 (3%)	69,79

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TABLE 2 (Continued)

Study characteristics	Sub-category of study characteristics	Number of results (%)	References
Household income level of participant	Majority high-income	14 (23%)	34,36,50,53–55,57,63,74,80,82
	Majority middle-income	19 (31%)	36,44–49,52,56,61,63–65,68,72,75,78,85,86
	Majority low-income	9 (15%)	34,41–43,59,66,70,73,81
	Mixed level of incomes (roughly equal mix of low/middle/high)	2 (3%)	71,77
	Not reported	18 (29%)	35,37–40,51,60,67,69,76,79,83,84,87

Abbreviation: COVID-19, coronavirus disease 2019.

TABLE 3 Changes in the frequency of use of online food retail platforms before and during COVID-19.

	Online groceries		Meal delivery apps		Meal-kit services	
Sub-category	*N*	References	*N*	References	*N*	References
Increased usage overall	43	36,38,42–48,50–52,55–59,61–63,67–74,77–84,86	18	35,38,39,41,45,49,52,55,60,65,76,78,81,83–85,87	2	54,84
Varied usage overall	1	34	0		0	
Decreased usage overall	1	85	22	34,36,37,40,42,44,46–48,53,54,57,64,66,70,75	0	

Note: *N* indicates the number of individual outcomes supporting the change in use; outcomes may outnumber the referenced studies as studies may have reported more than one relevant outcome.

participant populations comprised mainly of females (44/62, 71%), a larger proportion of young adults aged between 18 and 30 years (24/62, 39%), and participants who were mostly classified as middle-income (19/62, 31%), although it was noted that a large number of studies did not report the income level of participants (18/62, 29%).

3.3 | Change in frequency of use of online food retail platforms during COVID-19

The use of online food retail platforms was measured by the change in frequency during the pandemic compared to before the pandemic. The results are summarized in Table 3 and described below. Collectively, there were 45 reported outcomes on the usage of online groceries, 40 outcomes on the use of meal delivery apps, and only 2 outcomes on meal-kit delivery services. As each study may have reported multiple outcomes on the use of online food retail platforms, the number of outcomes outnumbers the referenced studies in Table 3.

Of the 45 total outcomes that noted a change in frequency of online grocery use during COVID-19, 43 outcomes suggested an increase in usage compared to before COVID-19, 1 outcome implied varied use, and 1 outcome showed a decrease in usage during COVID-19 (Table 3). Varied use indicated that among the participants sampled for the study, there were both similar proportions of participants reporting a decrease and an increase in use. For meal delivery applications, there were 22 outcomes that found a decrease in use compared to 18 outcomes that demonstrated an increase in use. The two outcomes on meal-kit delivery services both indicated that the impacts of COVID-19 lockdowns led to an increase in use.

3.4 | Changes in the use of online food retail platforms throughout different time periods of the COVID-19 pandemic

This review showed that online groceries and meal delivery apps varied in use across different time periods of the COVID-19 pandemic. During the initial outbreak in the first quarter of 2020 (Q1 2020), two studies from China found that there was an increase in use of online groceries.[61,62] Further into the pandemic in the second quarter (Q2 2020), many more studies reported an increase in use of online groceries.[36,43,47,50–52,56,59,62,68,69,71,78,80,81] While four studies reported an overall increase in the use of meal delivery apps,[35,52,78,81] more studies saw a decrease in use.[36,37,40,47,54,66,75] In the third quarter of 2020 (Q3 2020), the pattern of increased online grocery shopping was maintained[42,44,45,63,70,74,84,86] with only one study that noted a decrease.[85] Meal delivery apps during this period saw more mixed results with a similar number of studies, which reported decreased usage[42,45,64,70] compared to an overall increase in use.[44,65,84,85] The same trends were observed in the fourth quarter of 2020 (Q4 2020). The studies conducted during this COVID-19 period all observed an increase in online groceries.[34,38,46,48,55,57,67] More studies saw decreased use of meal delivery apps[34,38,46,48,57] compared to an increase in use.[38,49,55] From the second half of 2021 to the last quarter of 2022, all study outcomes showed an increase in use of online groceries and meal delivery apps.[41,60,72,76,79,82,83]

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3.5 | Themes from qualitative studies relating to the use of online food retail platforms

Findings from the four qualitative studies included in this review suggest that online platforms offered an alternate way to source food during the COVID-19 lockdowns. These platforms were important in rural communities and areas where it was challenging to venture outdoors according to two studies conducted in India and the United States.[82,83] Two qualitative studies also suggest that ordering takeaway meals via meal delivery apps was often a treat or "reward" for families during lockdown.[81,84] One study mentioned the benefits of meal delivery applications in alleviating cooking duties for female gatekeepers who had already experienced high levels of stress from working from home and caring duties.[88] Some negatives of online grocery shopping were highlighted in another study. Interviews revealed that participants thought online grocery shopping was cumbersome as orders needed to be prepared ahead of time and, at times, were incorrect with items missing in the delivered package.[81]

3.6 | Associations between the use of online food retail platforms and diet-related chronic disease risk factors

Nine of the 52 included studies reported on diet-related outcomes associated with meal delivery app use (Table 4). The potential impacts on health were categorized as either positive or negative. Eight outcomes were associated with negative diet-related chronic disease risk factors,[38,41,49,53,64,66,76,87] and only one outcome was perceived as promoting health.[86] Negative impacts on health relating to use of meal delivery apps included associations with perceived obesity status,[41] weight gain,[38,49] emotional eating,[53,65] snacking behavior,[66] and a shift to unhealthier food orders.[66,76] One study showed that more frequent users of meal delivery apps had lower vegetable intake and higher sugar-sweetened beverage consumption compared to less frequent users.[87] Another study that appeared to associate online food ordering with increased dietary diversity and higher dietary quality was considered to positively influence health.[86]

3.7 | Risk of bias

The risk of bias for 46 of the 53 studies was assessed using the JBI critical appraisal checklists for cross-sectional studies. The JBI checklists for qualitative studies were used to assess 4 of the 53 studies, and the JBI checklists for cohort studies were used for 2 of the 53 studies. The JBI checklists for qualitative studies and cross-sectional studies were used to assess the quality of the one mixed-methods study. A total of 33 of the 46 cross-sectional studies received a "high" score, 12 of the 46 were given a "moderate" score, and a "low" score was determined for one study.[69] All results from the critical appraisal for cross-sectional studies are presented in Figure S1.

TABLE 4 Diet-related chronic disease risk factors associated with the use of online food retail platforms and potential impacts on health.

Study	Diet-related chronic disease risk factors associated with online food retail use	Potential impacts on health (positive, negative, or mixed)
Algheshairy 2022[41]	Significant association between use of food delivery apps during COVID-19 and perceived obesity status ($p < 0.05$)	Negative
Chen 2021[49]	Significant positive association between weight gain after 1-month lockdown and increased online food ordering through meal delivery applications ($\chi^2 = 7.806$, $p = 0.005$)	Negative
Costa 2021[53]	Highest means of emotional eating were found among inactive individuals who reported increased purchase of meal delivery (42.96, 95% CI [38.51, 47.41]). Increased purchase of meal delivery (beta coefficient = 5.89) was associated with emotional eating in the physically inactive group	Negative
Liboredo 2022[64]	Factors that independently increased the probability of being in the highest quartile of uncontrolled eating score were increased food delivery (OR: 1.498, 95% CI: 1.105, 2.031)	Negative
Luo 2022[66]	An increasing number of participants ordered breakfast and midnight snacks. After lockdown, more participants were ordering fried food or hamburgers, hot pot decreased from 58.1% to 50.8% of orders, and Chinese dishes with rice decreased from 46.3% to 35.8%	Negative
Skotnicka 2021[38]	Ordering ready-made meals at restaurants appeared to increase the odds of gaining body mass (OR: 1.19, 95% CI: 1.05, 1.5, $p = 0.005$)	Negative
Tham 2023[87]	Frequent users of meal delivery apps—those that used it at least twice per week reported a 12% lower frequency of consuming two servings of vegetables per day compared to those who used meal delivery apps less than once a week (aPR: 0.88, 95% CI: 0.63, 1.24). Compared to infrequent meal delivery app users (less than once a week), those who used meal delivery apps at least twice a week and those who used meal delivery apps once a week were 11% and 38%, respectively, more likely to drink sugar-sweetened beverages	Negative
Varese 2023[76]	Before the pandemic, meals such as pizza, fruits, and vegetables were ordered more in Poland. After COVID-19, hamburgers were more often ordered in Poland	Negative
Zhang 2020[86]	Participants who depended mostly on online food ordering and delivery had significantly higher Household Dietary Diversity Score than those who only did in-person grocery shopping or relied on a combination of in-person shopping and in-house storage supplies	Positive

Abbreviations: aPR, adjusted prevalence ratio; CI, confidence interval; COVID-19, coronavirus disease 2019; OR, odds ratio.

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Of the four qualitative studies, two were rated as "high" quality and two as "moderate." The two studies that were given a moderate rating lacked a statement locating the researcher culturally or theoretically, and the influence of the researcher on the research, or vice versa, was not adequately addressed (Figure S2). Both longitudinal cohort studies were given a "moderate" score (Figure S3). The one mixed-methods study included in this review received a "high" score as a cross-sectional study and as a qualitative study, which reflected a good integration of both methods.

4 | DISCUSSION

Key findings from this systematic review demonstrate a strong shift to using online platforms to purchase food across many countries during COVID-19 restrictions. There was widespread uptake of online grocery shopping across the majority of studies included in this review, with 43 of the 45 (96%) outcomes supporting an increase in use. Unexpectedly, 22 of the 40 (55%) study outcomes reported that many participants decreased their use of meal delivery apps for takeaway meals. These outcomes, however, were counteracted by other studies that reported a high proportion of participants who had increased their use of meal delivery apps. Compared to positive dietary behaviors, more studies reported that the use of online food retail was associated with negative dietary chronic disease risk factors such as weight gain and emotional eating. Taken together, the emerging evidence suggests that while there was considerable uptake of online food retail platforms as a source of food throughout the pandemic, these platforms may promote unhealthy behaviors that contribute to overweight and obesity.

Studies in this review consistently reported an increase in use of online grocery delivery services throughout the COVID-19 pandemic. A potential reason for using online grocery delivery may have been linked to participants' fear of contracting COVID-19, as outlined in a study included in this review.[59] Moreover, a recent meta-analysis conducted by Tyrväinen and Karjaluoto further investigated the purchase intentions behind online grocery shopping during the pandemic.[89] The analysis found that consumers did not make online grocery purchases because of their perceived usefulness or positive attitude towards these services, but rather because the abrupt changes instigated by COVID-19 restrictions "forced" their shopping to move online.[89]

There are several potential implications of increased online grocery shopping on food choices, nutrition, and health. Recent research from the United Kingdom during COVID-19 suggests that while online shopping was an alternative way to purchase fruit and vegetables during the pandemic, the expenditure for processed products surpassed the expenditure for fresh products.[90] This is potentially concerning as a growing body of evidence has linked the consumption of ultra-processed foods to increased risk of chronic diseases.[91,92] A study from the United States has shown that consumers from low-income households may be buying less fresh fruits and vegetables online compared to in-store.[93] In addition, a virtual supermarket program implemented in the United States in another study also found that although nearly half of participants increased their purchases of healthier products, an equally large proportion reported buying more juices and sugar-sweetened beverages.[94] It is evident that online grocery purchases may have a substantial impact on diet quality, and while there is room to nudge consumers towards healthier choices, there is a matched capacity for the purchase of unhealthier choices.

Many studies included in this review reported a decrease in participants' use of meal delivery apps throughout the COVID-19 pandemic. These results, while unexpected, were similar to the findings from a rapid assessment online survey of over 2000 individuals from 119 countries during April 2020, the second month of the COVID-19 pandemic. The study conducted by O'Meara et al. demonstrated that a larger proportion of participants decreased their delivery of takeaway foods (47%) compared to 23% of participants who reported an increase in meal delivery.[95] Despite this, these results differ from market research, which reported that meal delivery apps experienced an overall surge in use.[96,97] A report from Accenture also found that after lockdown, customers of Uber Eats had spent three times more compared to pre-pandemic levels.[98] Timing may have also impacted the results. In this review, it was shown that, compared to the first half of 2020 in the early stages of the pandemic, more studies in the fourth quarter of 2020 observed a decrease in use of meal delivery apps. Research from the United States showed that spending at full-service restaurants returned slowly in 2021,[99] suggesting that some individuals and households returned to dining in at restaurants once restrictions were eased.

Concerningly, of the nine diet-related outcomes associated with online food ordering during COVID-19, eight outcomes linked the use of these services to weight gain, emotional eating, snacking behavior, and a shift to unhealthier food orders. Another cross-sectional study from Australia echoes these results, as respondents who engaged in meal delivery applications were more likely to be of higher BMI and have higher levels of sugary drink consumption and fast-food restaurant patronage.[100] Alternatively, one study noted that ordering groceries online was associated with improvements to dietary quality and dietary diversity. In spite of this, the benefits of dietary diversity greatly depend on the constituents and proportions of the foods that make up the diet. Higher intakes of processed foods, refined grains, and sugar-sweetened beverages negate lower intakes of minimally processed foods, and this has been observed in the literature.[101] Moreover, a study revealed that youth in China were ordering spicy hot pot meals, fried foods or hamburgers, and cakes/pastries the most via meal delivery applications during COVID-19.[102] This again highlights that while there is a great potential for healthy choices to be made through online food retail platforms, there is a greater propensity towards unhealthier choices.

During crises, food acquisition can be challenging amidst food production and supply chain issues. Qualitative studies included in this systematic review indicate that online food retail platforms were an important alternative to sourcing food during the pandemic. Participants in rural communities and areas particularly valued the option of getting food delivered. A study from Nanjing, China, has similarly demonstrated the crucial role of online food access for food acquisition during COVID-19 lockdowns.[103] Researchers from this study suggested that food insecurity issues were avoided by most survey

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participants due to the high integration of physical and digital food outlets in Chinese urban communities. The accessibility of foods from physical food outlets was supplemented by digital food outlets, which offered a delivery service for foods.[103] Despite the promising prospects of online food retail in easing food security concerns, the extra delivery costs for online forms of food retail may be a disadvantage for some households,[104] and during the pandemic, online food delivery was often unavailable due to high demands.[52] To ensure all individuals have safe and secure access to food during future emergencies and crises, it is imperative that online food retail settings improve and promote more healthful options and become more affordable and available, especially in rural areas.

4.1 | Strengths and limitations

To our knowledge, this systematic review is the first to comprehensively synthesize published peer-reviewed studies to encapsulate the use of online food retail platforms during the COVID-19 pandemic and associated chronic disease risk factors. Using nine electronic databases, a comprehensive search was conducted. In addition, this review has also captured data from both quantitative and qualitative studies, which is important for illuminating the experiences of individuals during the pandemic.

Several limitations are, however, noted. It was not possible to assess the change in usage as nearly 90% of the included studies were cross-sectional, across different countries and time points, and used different survey tools. Cross-sectional studies have inherent biases due to self-reported measures and reliance on retrospective recall of participants' behaviors during COVID-19. Despite this, the COVID-19 pandemic was an unexpected event, and as such, collecting objective in-person data amid restrictions was often unachievable and limited the research conducted during this time.

Finally, it was likely that many households supplemented their in-store shopping with online grocery delivery, and this dual modality of food shopping must be considered when interpreting the results from this review. It is also an indication that future policies should promote healthy food choices in both physical and digital food settings, given the likelihood of consumers mixing their modes of food shopping.

The lack of studies from low-income countries is an important research gap to address in future studies. The digital food environment must be assessed and monitored in low-income as well as higher income countries. Current online food retail behaviors and associated diet-related chronic disease risk factors following the pandemic should also be further investigated to examine the extent of the COVID-19 pandemic's impact on population diets and health.

5 | CONCLUSION

Restrictions resulting from the COVID-19 pandemic have threatened food accessibility, and online food retail platforms have provided an alternate option for sourcing food. Understanding how populations across the world have used these online food retail platforms and their associated diet-related chronic disease risk factors may provide more clarity on their risks to population health. This review demonstrates a surge in the adoption of online food retail platforms. Importantly, the small body of evidence presented in this review indicates that the use of online food retail is associated with negative impacts on diet-related chronic disease risk factors. It is critical to further investigate policies and measures that will help improve the healthfulness of online food retail settings. Given the rapid adoption of digital technology and its largely unmeasured impacts on behaviors and health outcomes, the digital food environment requires further investigation and monitoring.

AUTHOR CONTRIBUTIONS

S.S.J., A.A.G., and S.R.P. formulated the research question. S.S.J. performed the systematic literature search, extracted the data from the included studies, and wrote the manuscript. S.S.J. and R.R. conducted the title, abstract, and full-text screening and identified the studies that met the inclusion criteria. S.S.J. and E.S. critically appraised all the included studies. S.W. validated the extracted data. S.R.P. and A.A.G. provided supervision and guidance. R.R., E.S., S.W., P.P., J.R., M.A.-F., M.A.F., A.A.G., and S.R.P. assisted in the revision of the manuscript. All authors have read and approved the final manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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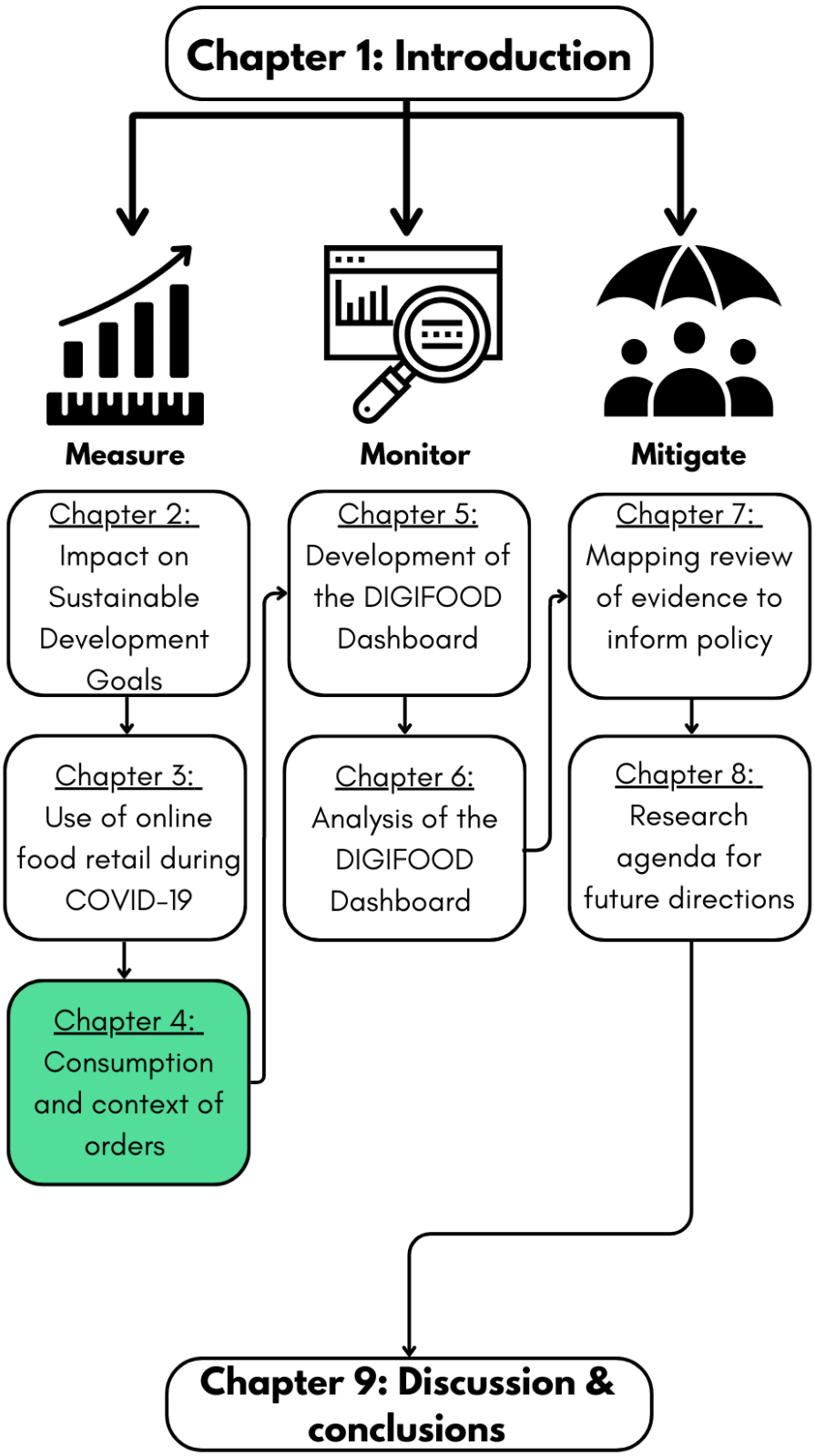
Chapter 1: Introduction
Measure
Monitor
Mitigate
Chapter 2: Impact on Sustainable Development Goals
Chapter 3: Use of online food retail during COVID-19
Chapter 4: Consumption and context of orders
Chapter 5: Development of the DIGIFOOD Dashboard
Chapter 6: Analysis of the DIGIFOOD Dashboard
Chapter 7: Mapping review of evidence to inform policy
Chapter 8: Research agenda for future directions
Chapter 9: Discussion & conclusions

CHAPTER 4 | CONSUMPTION AND CONTEXT OF MEAL DELIVERY APP ORDERS

Preface to the chapter

Chapter 4 has investigated what foods and beverages are ordered from meal delivery applications and the contextual factors surrounding an online food ordering event using mobile Ecological Momentary Assessment. This chapter thereby addresses Aim 3 of the thesis and contributes to the first sub-theme of 'measuring risks which meal delivery applications pose to population diets and health'. This study has been peer-reviewed (submitted 22nd May 2023, revised 18th October 2023) and published (29th November 2023) in *JMIR mHealth and uHealth*. Author contributions to this paper are outlined in the authorship attribution statement. Supplementary material can be found in Appendix B including B.1 CREMAS checklist, B.2 Acceptability outcomes, B.3 Online food delivery behaviours and contextual data, B.4 R Script for data analysis. Ethical approval from the Human Research Ethics Committee at the University of Sydney was obtained for this study and all related documents are attached in Appendix B (B.5-B.9).

Published peer reviewed manuscript

I am the first author for this article which was published in *JMIR mHealth and uHealth* in November 2023.

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Author attribution statement

This statement is to specify the contribution made by Si Si Jia in the preparation and submission of the following manuscript included in this chapter: “Using Mobile Ecological Momentary Assessment to Understand Consumption and Context Around Online Food Delivery Use: Pilot Feasibility and Acceptability Study”.

As first author, Si Si Jia was primarily responsible for formulating the research question, conceptualising the study design, obtaining ethics approval, participant recruitment, data analyses, writing the draft manuscript and subsequent revisions.

The individual roles of all co-authors are listed below:

Task	**Role of co-authors**
Conceptualisation of research question	SJ, SRP, AAG
Conceptualisation of study design	SJ
Obtaining ethics approval	SJ
Participant recruitment	SJ
Data analyses	SJ
Writing – Original Draft	SJ
Writing – Revision	SJ, RR, PP, KH, MAF, AAG, SRP
Supervision	SRP, AAG

Si Si Jia 25 March 2025

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

Dr Stephanie Partridge 25 March 2025

Original Paper

Using Mobile Ecological Momentary Assessment to Understand Consumption and Context Around Online Food Delivery Use: Pilot Feasibility and Acceptability Study

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Abstract

Background: Mobile ecological momentary assessment (EMA) is a powerful tool for collecting real-time and contextual data from individuals. As our reliance on online technologies to increase convenience accelerates, the way we access food is changing. Online food delivery (OFD) services may further encourage unhealthy food consumption habits, given the high availability of energy-dense, nutrient-poor foods. We used EMA to understand the real-time effects of OFD on individuals' food choices and consumption behaviors.

Objective: The primary aims of this pilot study were to assess the feasibility and acceptability of using EMA in young users of OFD and compare 2 different EMA sampling methods. The secondary aims were to gather data on OFD events and their context and examine any correlations between demographics, lifestyle chronic disease risk factors, and OFD use.

Methods: This study used EMA methods via a mobile app (mEMASense, ilumivu Inc). Existing users of OFD services aged 16 to 35 years in Australia who had access to a smartphone were recruited. Participants were randomly assigned to 1 of 2 groups: signal-contingent or event-contingent. The signal-contingent group was monitored over 3 days between 7 AM and 10 PM. They received 5 prompts each day to complete EMA surveys via the smartphone app. In contrast, the event-contingent group was monitored over 7 days and was asked to self-report any instance of OFD.

Results: A total of 102 participants were analyzed, with 53 participants in the signal-contingent group and 49 participants in the event-contingent group. Compliance rates, indicating the feasibility of signal-contingent and event-contingent protocols, were similar at 72.5% (574/792) and 73.2% (251/343), respectively. Feedback from the participants suggested that the EMA app was not easy to use, which affected their acceptability of the study. Participants in the event-contingent group were 3.53 (95% CI 1.52-8.17) times more likely to have had an OFD event captured during the study. Pizza (23/124, 18.5%) and fried chicken (18/124, 14.5%) comprised a bulk of the 124 OFD orders captured. Most orders were placed at home (98/124, 79%) for 1 person (68/124, 54.8%). Age (incidence rate ratio 0.95, 95% CI 0.91-0.99; *P*=.03) and dependents (incidence rate ratio 2.01, 95% CI

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1.16-3.49; *P*=.01) were significantly associated with the number of OFD events in a week after adjusting for gender, socioeconomic status, diet quality score, and perceived stress levels.

Conclusions: This pilot study showed that EMA using an event-contingent sampling approach may be a better method to capture OFD events and context than signal-contingent sampling. The compliance rates showed that both sampling methods were feasible and acceptable. Although the findings from this study have gathered some insight on the consumption and context of OFD in young people, further studies are required to develop targeted interventions.

(JMIR Mhealth Uhealth 2023;11:e49135) doi: 10.2196/49135

KEYWORDS

ecological momentary assessment; mobile applications; mobile apps; feasibility studies; online food delivery; smartphone; young adult; adolescent; food environment; consumer behavior; mobile phone

Introduction

Background

Unhealthy diets are a leading contributor to the global burden of disease [1]. Globally, there is an increasing trend toward the consumption of "out-of-home" foods, potentially exacerbating suboptimal diets. These foods include fast foods and takeaway or "take-out" foods from a variety of sources including restaurants, fast-food chains, convenience stores, coffee shops, and takeaway food outlets. An analysis of the UK National Diet and Nutrition Survey 2008-2012 found that 27% of adults had consumed meals outside the home once per week or more [2], and research from the United States estimated that out-of-home meals comprised 50% of household budgets in 2018 [3]. Results from Australia's National Household Expenditure and Time Use Surveys have shown a steady incline in spending on out-of-home foods—increasing from 22.8% of total food budgets in 1989 to 26.5% in 2010 [4]. Rising consumption of out-of-home foods has been similarly observed in low- and middle-income countries including China [5,6] and Latin American countries [7].

However, these out-of-home meals are often high in fat, salt, and sugar and low in vitamins and minerals [8]. A systematic review of 15 prospective studies found that a high frequency of eating out and consuming out-of-home meals was associated with weight gain and a greater risk of becoming overweight or obese [9]. Moreover, studies have shown associations between frequent consumption of home-cooked meals and greater adherence to the Dietary Approaches to Stop Hypertension diet and Mediterranean diets as well as greater intake of fruits and vegetables [10]. Thus, the replacement of home-cooked meals with out-of-home meals may result in further detriments to dietary health.

In recent years, online food delivery (OFD) services such as Uber Eats, DoorDash, and JustEat have transformed the concept of out-of-home foods by allowing customers to order a variety of food and drink items straight from kitchen to doorstep [11]. With this added convenience, OFD potentially increases access to and consumption of out-of-home food. A study from the United Kingdom found that adults with access to the greatest number of food outlets available to them online had 71% greater odds of OFD use (odds ratio [OR] 1.71, 95% CI 1.09-2.68) compared with those with the lowest access [12].

A growing number of studies have shown that a high proportion of menu offerings on popular OFD platforms are poor in nutritional quality. In Thailand, a majority of the most popular menu items were considered unhealthy against the World Health Organization's recommended daily intake values [13]. Of the 25 most popular menu items, 23 exceeded the recommended sodium intake for adults, and 80% of all sweet items offered were 1.5 times above the recommended daily intake for sugar [13]. Similarly, more than three-quarters of menu items were classified as discretionary "junk foods" in Australia [14] and New Zealand [15]. A cross-sectional study conducted in 3 international cities (Chicago, Melbourne, and Amsterdam) revealed "burgers," "pizza," and "Italian" were in the top 10 most advertised meals on the website or app of the OFD [16].

OFD services are now regularly used by millions of people with heightened use found among young people aged between 16 and 34 years [17,18], who are already experiencing escalating rates of weight gain [19]. Furthermore, in Australia, by the age of 16 years, approximately 80% of young people have a debit card [20] in their name. This is critical considering the ease of digital payment options and tools offered on OFD apps, which amplifies young people's accessibility to takeaway foods. A study in China found that >47.8% of male university students and >30.7% of female university students have used OFD more than once per week [21]. Therefore, there is an urgent need to assess and understand the consumption and behaviors associated with the use of these OFD services.

Traditional dietary assessment methods such as 24-hour recalls, diet history, and food frequency questionnaires are reliant on participants retrospectively recalling their intake, whereas food records involve prospective recording, but both approaches are time-consuming and prone to inherent biases [22,23]. Recent studies have demonstrated that ecological momentary assessments (EMAs) can be a valid measure of dietary intake [24,25]. EMA is a data collection method that gathers real-time information from participants studying behaviors and contexts as they perform regular day-to-day activities in real-world settings [26]. Due to technological advances, researchers now use smartphones or mobile phones to conduct EMA studies, which have improved data collection and added flexibility to study designs [27]. A systematic review of 39 EMA studies conducted in young people aged 16 to 30 years indicated that EMA is an acceptable and feasible methodology to capture dietary intake and food consumption for this population [28].

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Objectives

Although dietary intake generally can be spontaneous and difficult to capture, OFD events are likely to be even more sporadic. Thus, compared with traditional dietary assessment methods, EMA may be an alternate method for capturing OFD events. In addition, unlike traditional dietary assessment methods, the context including social and psychological factors surrounding the real-time OFD event can be obtained using EMA. To the best of our knowledge, no previous study has used EMA to study OFD use. Therefore, this study aimed to determine the feasibility and acceptability of EMA in a sample of young people who are users of OFD. A secondary aim was to investigate associations between the frequency of OFD use and demographic variables such as age, gender, and socioeconomic level as well as other lifestyle chronic disease risk factors including diet quality score, physical activity levels, stress levels, and sleep quality.

Methods

Recruitment

From June to October 2022, participants were recruited via flyers, social media advertising, and word of mouth. Eligible participants were (1) aged between 16 and 35 years; (2) users of OFD, defined as at least once in the past 3 months; (3) living in Australia; and (4) having access to a smartphone. This was to ensure that participants were not first-time users of OFD, as this study aimed to gain a specific understanding of the behaviors and demographics of OFD users. The target sample comprised at least 140 participants accounting for a 30% (42/140) dropout rate. Using quota sampling, the target was 28 participants in the 16 to 18 years age group, 28 participants in the 30 to 35 years age group, and 42 participants each in the 19 to 24 and 25 to 29 years age groups. Previous pilot EMA studies used nonprobability sampling methods to recruit a similar number of participants [25,29].

Ethical Considerations

This study was approved by The University of Sydney Human Research Ethics Committee (2022/006). Reporting followed an adapted Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Checklist for Reporting EMA Studies (CREMAS) guidelines [30] (Multimedia Appendix 1).

Data Collection

After participants joined the study and provided consent, they were directed to a series of baseline surveys on REDCap (Research Electronic Data Capture; Vanderbilt University) to obtain data on participant demographics, usual OFD behaviors, physical activity levels, sleep quality, and perceived stress levels. The questions were adapted from the 7-item International Physical Activity Questionnaire—Short Form [31], Pittsburgh Sleep Quality Index [30], and Perceived Stress Scale [32].

Upon completing the baseline surveys on REDCap, participants were sent a unique mobile code to download and set up the EMA mobile app (mEMASense, ilumivu Inc) on their personal smartphone devices. This app is available for both the Android and Apple operating systems. Using a computer-generated code, participants were randomly allocated 1:1 to 1 of 2 groups, "Prompts" or "No Prompts," which determined the sampling approach used—respectively representative of the signal-contingent or event-contingent approach. A signal-contingent design involves sending prompts to participants randomly over the course of a given hour, day, or week [33]. In contrast, an event-contingent design allows participants to complete a prompt whenever they experience the event of interest [33].

Participants in each group received a separate set of instructions via REDCap to inform them of their group allocation and what was required from them in either the Prompts or No Prompts group. An external link was also sent to participants to complete the Australian Eating Survey [34], a validated food frequency questionnaire developed by researchers from the University of Newcastle, to capture usual dietary intake.

Data were collected over 1 monitoring period (1 wave). Figure 1 depicts a flow diagram of the overall data collection process, and Figure 2 provides an overview of the 2 varying EMA sampling protocols used in the study.

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Figure 1. Flowchart of the data collection processes. mEMA: mobile-based ecological momentary assessment; REDCap: Research Electronic Data Capture.

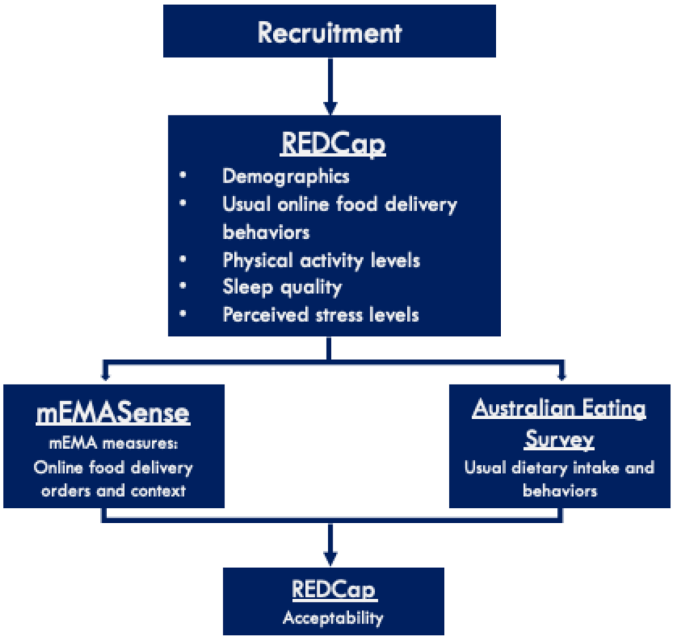
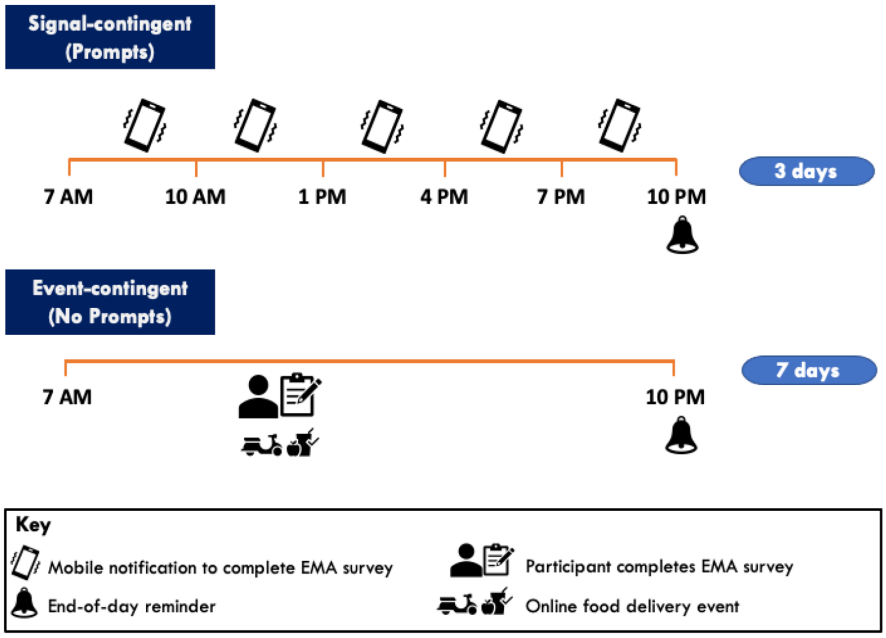


Figure 2. Overview of the 2 varying mobile-based ecological momentary assessment sampling protocols used in the study: signal-contingent (Prompts) group compared with the event-contingent (No Prompts) group. Participants in the No Prompts group were observed over 1 week (7 days), whereas those in the Prompts group were observed over 1 week with prompts sent on 3 separate days. EMA: ecological momentary assessment.



EMA Procedure

Signal-Contingent Sampling (Prompts Group)

Participants in the Prompts group were monitored over 1 week on 3 days, including 2 weekdays (Monday-Friday) and 1 day on the weekend (Saturday or Sunday) between 7 AM and 10 PM. To ensure that at least 1 weekday and 1 weekend day were captured, the EMA prompt days were assigned on the second, fourth, and sixth day from the day participants joined the study. Participants were unaware of this prompting schedule and were only informed that they would be prompted on 3 "random days" over the 7 days from their enrollment into the study. This was implemented to improve the external validity of the study by aiming to capture unanticipated OFD events.

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Participants were prompted by the app via a notification at a randomly assigned time during the 5 predetermined intervals (7 AM-10 AM, 10 AM-1 PM, 1 PM-4 PM, 4 PM-7 PM, and 7 PM-10 PM). An end-of-day prompt was sent at 10 PM on each of the study days to record any OFD ordering event that was not previously captured. When prompted, participants were asked to complete the short survey on the EMA app that started with the question "In the past 10-15 minutes, were you eating or drinking?" If unavailable at the time of the prompt, participants had a 45-minute time window to respond with 2 reminders sent 15 minutes apart after the initial prompt. After this point, the survey became inaccessible until the next prompt and recording opportunity. In total, 6 EMA surveys were prompted on each of the 3 study days, totaling 18 EMA surveys per participant across the data collection period.

Event-Contingent Sampling (No Prompts Group)

Participants in the No Prompts group were instructed to record any online food order they placed over 1 week from their enrollment in the study. An end-of-day prompt was sent at 10 PM on each of the 7 days to remind and allow participants to record any OFD event not previously captured.

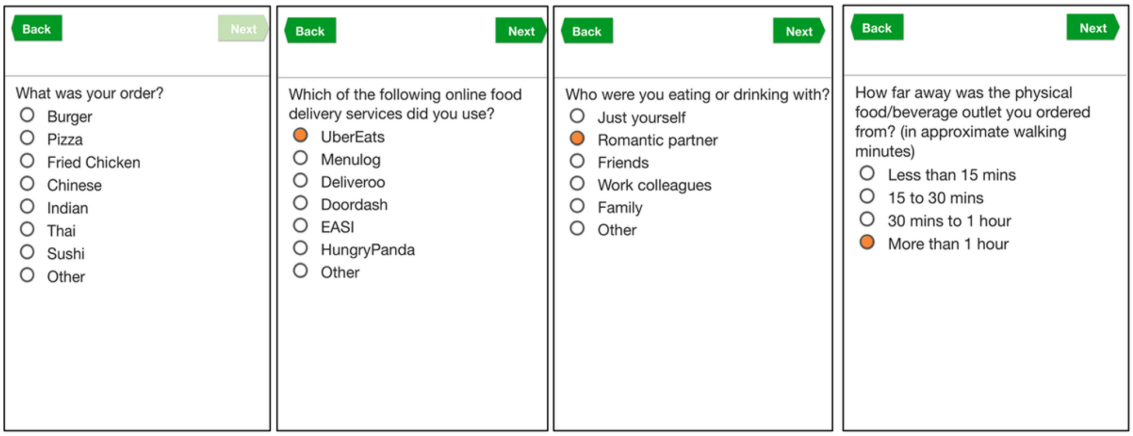
Participants Attending High School

Participants aged between 16 and 18 years who were attending high school in the Prompts group were monitored across 3 days, including 2 weekdays (Monday-Friday) during nonschool hours (4 PM and 10 PM) and 1 day on the weekend (Saturday or Sunday) between 7 AM and 10 PM. This was done to ensure minimal disruption to high school commitments. Individuals attending high school in the No Prompts (the "event-contingent") group were only required to answer the surveys during nonschool hours on weekdays (from 4 PM to 10 PM).

Capturing an OFD Order Event

Participants in both the Prompts and No Prompts groups were asked for the following details and surrounding context of their online food order: how they received their order (whether through pick-up or delivery), what they ordered, who they were with (by themselves, with romantic partner, work colleagues, friends, or family), where they were (home, workplace, or university), how far away they were from the food outlet in walking minutes, if any promotions or discount codes were used, their hunger levels, and cravings and stress levels at the time of ordering. All instances were timestamped to record when they consumed their online food order. Please see Figure 3 for a screenshot of the EMA survey questions delivered through the mEMASense app.

Figure 3. Selection of questions from the survey delivered through the mEMASense app to capture context surrounding an online food delivery event.



Incentives

Participants were offered gift vouchers up to AUD 45 (US $29) for their completion of the entire pilot study. If participants completed one-third of the study, they were awarded 1 AUD 15 (US $9) voucher for their time, and participants who had completed two-thirds were compensated with AUD 30 (US $19) worth of gift vouchers.

Feasibility

The compliance rate was used to measure the feasibility of the study. This was calculated differently for the different sampling approaches. In the Prompts group, the compliance rate per participant was the number of answered prompts divided by 18, which was the total number of expected prompts. The mean compliance rate for the study was calculated to represent the sample in the Prompts group.

Similarly, for the No Prompts group, the compliance rate per participant was the number of answered end-of-day reminders divided by the total number of expected end-of-day reminders. These end-of-day reminders were sent daily over the 1-week study period, resulting in 7 total reminders. Furthermore, the percentage of online food ordering events captured by the end-of-day reminders was also analyzed. This indicated how likely participants were to forget their recording of each online food ordering event using the No Prompts approach.

Acceptability

Participants were administered a final end-of-study questionnaire composed of 5 items to gather insight into their acceptability of the EMA methodology, the mobile app used to send the EMA

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prompts, and the perceived participant burden from the 2 different sampling approaches. These 5-point Likert scale questions were adapted from a previous study [29] with an additional closing open-ended question to gather general qualitative feedback.

Study Measurements and Outcomes

Demographic

Age, gender, ethnicity, education status, working status, number of dependents, residential postcode, and car access were obtained from the demographic survey. Residential postcodes were matched to quintiles on the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD), an area-based socioeconomic measure, where a higher index value reflects an area of greater socioeconomic advantage compared with people residing in other areas [35]. Participants were also asked to report their height (cm) and weight (kg) so that their BMI could be determined.

Lifestyle Chronic Disease Risk Factors

Measures from the Australian Eating Survey generated the Australian Recommended Food Score, a diet quality index that reflects alignment with the Australian Dietary Guidelines [36]. Responses to the International Physical Activity Questionnaire allowed participants to be categorized into low, moderate, or high physical activity levels using scoring guidelines [37]. Similarly, a score was produced to categorize participants' perceived stress levels into low, moderate, or high [38]. Sleep quality was reflected by the number of hours of sleep reported by the participants and compared with recommended sleep guidelines [39].

Data collected from the EMA app were used as the outcome variables of interest, including the number of OFD events, OFD order details, and related contextual data, as shown in Figure 1.

Statistical Analysis

Overview

The study's analytic sample comprised participants who met the minimum requirements outlined in the sampling protocol. This entailed completing at least one-third of the study period, which translated to a minimum of 4 prompts for adults or 2 prompts for adolescents within a single study day for those in the signal-contingent group. For participants in the event-contingent group, it meant answering at least 2 end-of-day reminders. In addition, those who had finished the end-of-study acceptability questionnaire were also included in this sample. Data sets from REDCap surveys, the Australian Eating Survey, and the EMA app were downloaded and linked together via participants' unique mobile code for the EMA app and REDCap ID number. Data were checked and cleaned before analysis. All statistical analyses were performed using R statistical software (version 2023.03.0+386; R Core Team).

Descriptive statistics, including means, SDs, and frequencies, were used to report the baseline characteristics of the sample and the OFD behaviors and context captured via the EMA app. Other statistical analyses were conducted as described below in the Feasibility Analysis, Acceptability Analysis, Comparison of Sampling Approaches, and Exploratory Analysis sections.

Feasibility Analysis

Compliance rates were the main outcome to determine the feasibility of the EMA protocol. In the Prompts group (signal-contingent), this was calculated as the total number of prompts answered over the expected total number of prompts answered. These compliance rate calculations slightly differed for adolescent participants who received fewer prompts per study day. In the No Prompts group, as the event of interest may not have occurred daily, compliance was measured by participant's responses to the end-of-day study reminders. This was similarly measured as the total number of end-of-day reminders answered above the expected total of 7.

To investigate factors associated with compliance, a 2-level multilevel logistic regression analysis was conducted on participant data from the Prompts group. The outcome variable used for analysis was whether the participant had answered the delivered prompt (coded as "TRUE") or had not answered (coded as "FALSE"). Level 1 factors were factors at the observation level such as time of the day (ie, morning, afternoon, or evening) and day of the week (weekday or weekend). Level 2 factors were at the person or participant level such as their demographics including age, gender, and IRSAD decile. The intraclass correlation coefficients were calculated to determine the proportion of variance that is because of between-person differences.

Acceptability Analysis

Median scores and IQRs were reported to summarize responses to the 5-item acceptability questionnaire in both the Prompts and No Prompts groups. Open-ended feedback was analyzed using content analysis methods. Concepts were developed based on the occurrence of terms.

Comparison of Sampling Approaches

A multivariable logistic regression model was used to analyze whether the sampling approach (ie, Prompts vs No Prompts) was associated with capturing OFD events during the study period. The outcome variable was whether an OFD event was recorded during the study period. The model was adjusted for age, gender, and frequency of OFD ordering reported at baseline.

Exploratory Analysis on Demographic and Lifestyle Risk Factors and Their Associations With OFD Use

A zero-inflated negative binomial regression model was built to analyze associations between participant demographic characteristics, lifestyle chronic disease risk factors, and number of OFD events in a week. Incidence rate ratios were the effect size from this model used to indicate how often OFD events occurred over the study period in relation to participants' demographic characteristics and lifestyle chronic disease risk factors. A zero-inflated model was deemed appropriate as our data had an excess of "zeros" for the number of OFD events recorded by the participants. This model was adjusted for age, gender, and socioeconomic status as indicated by the IRSAD quintile. An influential point, which is an outlier that affects the slope of the regression, was identified through a bar plot of the

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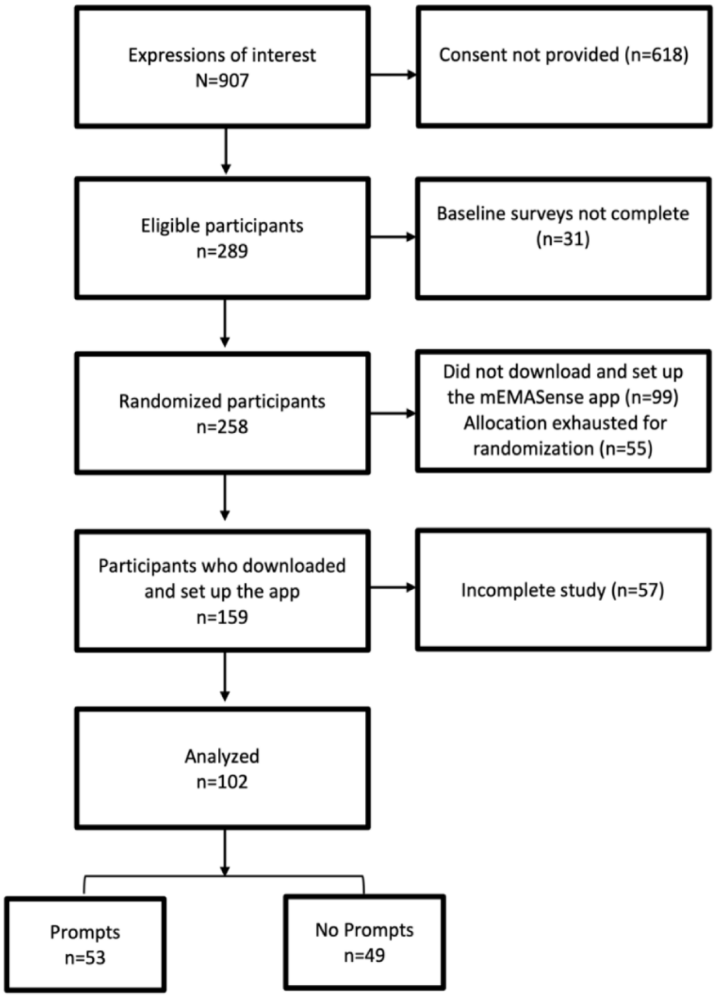
Cook distance and subsequently removed as it had a significant impact on the coefficients.

Results

Participants

As shown in Figure 4, of the 907 expressions of interest received on REDCap, 289 participants provided consent and continued to complete the baseline surveys. However, only 258 (89.2%) of the 289 participants completed all baseline surveys and were subsequently randomized into either the Prompts or No Prompts group. Only 159 (61.6%) of the 258 participants proceeded to the next stage of the study by downloading and setting up the mEMASense app. Of the 159 participants, 102 (64.2%) were part of the final analytical sample, as 57 (35.8%) did not meet the minimum requirements for study completion. Of the 102 participants, there were 53 (52.0%) in the Prompts group and 49 (48.0%) in the No Prompts group.

Figure 4. Participant recruitment process and attrition.



Participant Characteristics

The mean age of all participants was 24.4 (SD 5.4) years. Women comprised 70.6% (72/102) of the study sample, men comprised 28.4% (29/102) of the study sample, and 1.0% (1/102) of the participants identified as nonbinary. In total, 63.7% (65/102) of the participants had a normal BMI range, whereas 28.4% (29/102) were overweight and obese. Approximately half of the sample (48/102, 47%) identified their ethnicity as White, approximately a quarter (24/102, 23.5%) identified as Chinese, and 14.7% (15/102) reported their ethnicity as Asian and South-East Asian (not further specified). Most of the participants (89/102, 87.3%) resided in areas of high socioeconomic advantage in the upper quintiles of the IRSAD, and most participants (58/102, 56.9%) were highly educated (Table 1).

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Table 1. Demographics of participants (N=102).

Demographics	Value
Age (years), mean (SD)	24.4 (5.4)
Age (years), n (%)	
16-18	17 (16.7)
19-24	34 (33.3)
25-29	33 (32.3)
30-35	18 (17.6)
Gender identity, n (%)	
Woman	72 (70.6)
Man	29 (28.4)
Nonbinary	1 (1)
BMI (kg/m^2), n (%)	
Underweight (<18.5)	7 (6.9)
Normal weight (18.5-24.9)	65 (63.7)
Overweight (25.0-29.9)	20 (19.6)
Obese (>30.0)	9 (8.8)
N/A[a]	1 (1)
Ethnicity, n (%)	
Asian (not specified)	11 (10.8)
Bangladeshi	1 (1)
Chinese	24 (23.5)
Indian	3 (2.9)
Japanese	1 (1)
Jewish	1 (1)
Southeast Asian (not further specified)	4 (3.9)
Vietnamese	1 (1)
White	48 (47)
Multiracial[b]	7 (6.9)
N/A[a]	1 (1)
IRSAD[c] quintiles (1 representing most disadvantaged and 5 representing most advantaged), n (%)	
Quintile 1	5 (4.9)
Quintile 2	2 (2)
Quintile 3	6 (5.9)
Quintile 4	17 (16.7)
Quintile 5	72 (70.6)
Education level, n (%)	
Current high school student	13 (12.7)
Completed high school	2 (2)
Currently studying for degree or diploma	28 (27.4)
Completed trade or technical qualification	0 (0)
Completed a degree or diploma	33 (32.3)
Completed a postgraduate degree	25 (24.5)

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Demographics	Value
N/A[a]	1 (1)
Car access, n (%)	
Yes	61 (59.8)
No	41 (40.2)
Number of dependents, n (%)	
0	78 (76.5)
1	8 (7.8)
2	15 (14.7)
3	1 (1)

[a]N/A: not applicable (owing to missing values).

[b]Including White and Chinese, White and Japanese, White and Pacific Islander, White and Asian, and nonspecified.

[c]IRSAD: Index of Relative Socio-Economic Advantage and Disadvantage.

Usual OFD Behaviors and Lifestyle Behavioral Risk Factors

As shown in Table 2, in total, 52% (53/102) of the participants reported using an OFD service 1 to 2 times a month, and 27.5% (28/102) of the participants reported using it once a week at baseline. Approximately 89.2% (91/102) of the sample had used Uber Eats, which was followed by DoorDash as the next highly used service by 59.8% (61/102) of the participants. Only 23.5% (24/102) of the participants had membership with an OFD service, which was commonly a free 6-month trial.

The mean Australian Recommended Food Score for participants was 31 (SD 11.6) out of a maximum score of 73 indicating optimal nutrition. The median percentage of energy intake contributed by discretionary foods was 35% (IQR 26-44) among participants . Analyses from the International Physical Activity Questionnaire indicated that a large proportion of participants (64/102, 62.7%) had high physical activity levels, and 54.9% (56/102) of the sample experienced moderate levels of stress. The mean hours of sleep reported was 6.5 (SD 1.0) in adolescents and 7.2 (SD 1.1) in adults (Table 2).

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Table 2. Online food delivery (OFD) behaviors at baseline and self-reported lifestyle behavioral risk factors (N=102).

Lifestyle risk factor	Value
OFD behaviors	
Frequency of using an OFD service, n (%)	
Rarely or never	0 (0)
1-2 times a month	53 (52)
Once a week	28 (27.4)
A few times a week	13 (12.7)
Once a day	4 (3.9)
More than once a day	4 (3.9)
OFD service (those electing "Yes, I use this delivery service"), n (%)	
Uber Eats	91 (89.2)
MenuLog	58 (56.9)
Deliveroo	60 (58.8)
Doordash	61 (59.8)
EASI	18 (17.6)
Others[a]	12 (11.8)
Fantuan	3 (2.9)
HungryPanda	1 (1)
Panda	3 (2.9)
PandaFresh	2 (2)
Restaurant-specific delivery service	1 (1)
N/A[b]	3 (2.9)
OFD services membership, n (%)	
Yes	24 (23.5)
No	78 (76.5)
OFD membership (those electing "Yes, I have a membership subscription")[a], n (%)	
Dashpass	6 (5.9)
Deliveroo	3 (2.9)
Uber Eats	10 (9.8)
N/A[b]	5 (4.9)
Monthly cost of OFD membership for those with a subscription (US $), n (%)	
Free trial for 6 months	6 (5.9)
Dashpass (9.99)	2 (2)
Uber Eats (9.99)	3 (2.9)
Deliveroo plus (12.99)	3 (2.9)
N/A[b]	10 (9.8)
Usual dietary behaviors[c]	
Australian Recommended Food Score (maximum 73), mean (SD)	31 (11.6)
Percentage of energy from noncore foods, median (IQR)	35% (26-44)
Out-of-home food consumption (general, nonspecific to OFD), n (%)	
<1 per week	20 (19.6)
1-2 per week	51 (50)

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Lifestyle risk factor	Value
3-4 per week	24 (23.5)
5-6 per week	3 (2.9)
Once a day	2 (2)
1 or more per day	2 (2)
Physical activity levels[d] n, (%)	
Low	3 (2.9)
Moderate	35 (34.3)
High	64 (62.7)
Perceived stress levels[e] n, (%)	
Low	30 (29.4)
Moderate	56 (54.9)
High	16 (15.7)
Hours of sleep, mean (SD)	
Adolescents aged 16-18 years (n=17)	6.5 (1.0)
Adults aged 18-35 years (n=85)	7.2 (1.1)

[a]Participants were allowed to enter >1 other food delivery service or membership they used.

[b]N/A: not applicable (owing to invalid online food delivery service).

[c]Obtained from the Australian Eating Survey results.

[d]Physical activity levels were calculated according to the International Physical Activity Questionnaire analysis guidelines [37].

[e]Perceived stress levels were calculated according to guidelines for the Perceived Stress Scale [38].

Feasibility

Compliance rate was used as a measure of feasibility for the EMA study. Among the analytic sample, compliance with the study protocol was compared between the Prompts and No Prompts groups.

Prompts Group

Adolescents Aged 16-18 Years

The compliance rate for the adolescent Prompts group was 70.4% (76/108), with an average of 8 (out of 12) prompts answered per adolescent participant.

Adults Aged 18-35 Years

The compliance rate for the adult Prompts group was 72.5% (574/792), with an average of 13 (out of 18) prompts answered per adult participant.

No Prompts Group

Compliance in the No Prompts group was measured by the response to all end-of-day study reminders. The compliance rate for the No Prompts group was 73.2% (251/343). Furthermore, of 49 participants, 36 (73%) followed the protocol and logged instances of using an OFD service during their study period, unprompted, as per the "event-contingent" sampling protocol.

Factors Influencing Missing Prompt Data

Results from a multilevel logistic regression model showed that compliance or response to a prompt did not vary by age, gender, socioeconomic status, or whether it was a weekday or weekend (Table 3). However, compared with the evening between 6 PM and 12 AM, participants were 1.47 times more likely to answer prompts in the afternoon between 12 PM and 6 PM (95% CI 1.02-2.12). The intraclass correlation coefficients between participants were low (0.27), indicating that multilevel modeling was appropriate.

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Table 3. Results from the multilevel logistic regression model to examine observation level and within-person level factors and their influence on a participant's likelihood to respond to prompts (n=53).

Predictors	Response to prompt (yes or no)	
	Odds ratios (95% CI)	*P* value
Days (weekend)	0.81 (0.59-1.11)	.18
Time of day (afternoon)	1.47 (1.02-2.12)	.04[a]
Time of day (morning)	0.84 (0.58-1.22)	.36
Age (years)	1.02 (0.95-1.08)	.6
Gender (woman)	2.07 (1.00-4.31)	.05
IRSAD[b] decile	1.19 (0.99-1.42)	.06

[a]Intraclass correlation coefficient: 0.27.

[b]IRSAD: Index of Relative Socio-economic Advantage and Disadvantage.

Acceptability

Prompts

Responses from participants in the Prompts group reflected an overall opinion that the number of prompts sent during the study period was an appropriate amount, indicated by a median score of 3. The times of day that the prompts were sent were generally agreed upon by participants as being appropriate and not burdensome, with a high median score of 4 (Multimedia Appendix 2). Participants were ambivalent in their response to the app being easy to use, with a median score of 3 indicating that they neither agreed nor disagreed with the statement. The EMA study did not appear to make a majority of participants more conscious of their diet and eating behaviors, with more responses skewed toward disagreeing with the statement. The length of study for the Prompts group, however, was distributed more toward being *too short* (Multimedia Appendix 2).

No Prompts

In the No Prompts group, participants' responses also showed that the number of prompts sent during the study period was appropriate, with a median score of 3. Many participants agreed that end-of-day reminders were necessary to remember to log an OFD order, as shown by the median score of 4 and with a distribution skewed toward "strongly agree" (Multimedia Appendix 2). However, more participants disagreed that the mobile app was easy to use. This was indicated by a median score of 3, with more scores indicating strong disagreement. Furthermore, responses from participants varied on whether the surveys made them more conscious of their diet and eating behaviors, as shown by the median score of 3. Responses on length of study for the No Prompts group were also distributed more toward being *too short*.

Open Feedback

Open feedback was obtained from 45 participants. Responses from 38% (17/45) of the participants indicated the difficulty of navigating the app, with many stating that it was "clunky," "not user-friendly," and "cumbersome." Moreover, 27% (12/45) of the responses indicated that the timing of the prompts could be improved. Participants in the group that received prompts suggested receiving prompts closer to mealtimes. Some participants in the No Prompts group commented on the timing of the "end of day" reminders as being "too late" and after they had gone to sleep.

Moreover, 4 participants suggested further clarity of the training instructions and to have these instructions available and accessible to them throughout the study period. There were variable open responses on study length, although more participants wrote that a longer study period would be more representative and able to capture their OFD behaviors.

OFD Events

Accuracy of Using EMA to Capture OFD Events

As shown in Table 4, this study captured 124 OFD events from 56.9% (58/102) unique participants. The actual frequency of OFD ordering throughout the study period did not match the reported frequency at baseline in 52% (53/102) of the participants and exactly matched in 48% (49/102) of the participants. For instance, if a participant had reported using an OFD service once a week in the baseline survey and the study did not capture an OFD event during the monitoring period, this would be a case where the reported frequency did not match the actual frequency. In the 53 participants where actual food ordering frequency differed, 26 (49%) had more OFD events during the study compared with 27 (51%) who had ordered less than what was reported at the start of the study.

Table 4. Comparison of the number of online food delivery (OFD) events captured between varying sampling approaches (event-contingent vs signal-contingent; n=58 unique participants).

Sampling approach	OFD events captured, n	OFD orders from end-of-day reminders, n	Total, n
No Prompts (event-contingent)	57	22	79
Prompts (signal-contingent)	41	4	45
Total	98	26	124

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As shown in Table 4, there appeared to be more OFD events (79/124, 63.7%) captured from the event-contingent group compared with the signal-contingent group (45/124, 36.2%). Results from a multivariable logistic regression showed that there was a strong level of evidence to support a significant association between the sampling approach and the capture of an OFD event during the study period after adjusting for age and gender. Compared with the Prompts group, participants in the No Prompts group were 3.53 times more likely (95% CI 1.52-8.17) to have logged an OFD event.

Contextual Data Surrounding Online Food Ordering Events

A total of 124 instances of OFD were captured from 58 unique participants. More than half of all orders (65/124, 52.4%) were placed in the evening (between 6 PM and 12 AM) and were less common at night or morning, comprising 9.7% (12/124) of ordering events each (Multimedia Appendix 3). As shown in Multimedia Appendix 3, most orders were made on a Saturday (25/124, 20.2%), followed by Tuesday (22/124, 17.7%) and Friday (21/124, 16.9%). The most common food delivery orders were pizza (23/124, 18.5%), fried chicken (18/124, 14.5%), Chinese food (18/124, 14.5%), and burgers (17/124, 13.7%). However, 28.2% (35/124) of the orders were from a category other than what was provided, including Mexican; bubble tea; fast-food franchises (Red Rooster, KFC, and McDonald's); cakes, pastries, and bakery items; groceries; and Vietnamese food. The following food categories were mentioned only once from all OFD events: hot chips and Caesar salad, breakfast platter, Malaysian, Nepalese, Afghan, modern Australian, Japanese, fried vegetables, Korean (fried chicken, chips, and seafood pancake), salad bowl, and sandwich.

For 50% (62/124) of the OFD orders captured, participants used Uber Eats, followed by DoorDash (23/124, 18.5% of the orders). In 54.8% (68/124) of the orders, participants ordered for just themselves, 15.3% (19/124) ordered for family, and 13.7% (17/124) ordered for their romantic partner.

The prevailing reason for using an OFD service was convenience, which contributed to 37.1% (46/124) of the responses. Taste and cravings attributed to 20.9% (26/124) of the orders. Most participants (98/124, 79%) ordered when they were at home, and 8.1% (10/124) of the participants ordered when they were at university or technical and further education. In 54.8% (68/124) of the online food ordering events, participants had ordered from a food outlet situated within a 15- to 30-minute walking distance, and 21.8% (27/124) of the participants ordered from an outlet that was between a 30-minute to 1-hour walk away (Multimedia Appendix 3).

A promotional code or offer was used for approximately one-third (37/124, 29.8%) of all orders. A wide variety of promotions and discounts were reported by the participants, from free delivery to receiving 10% or 50% off on their orders. The following discounts and promotions were only mentioned once from all OFD events: first-order discount, free additional food, referral discount, ShopBack, 30% off, AUD $16 off, AUD $20 off, and AUD $30 off (AUD $1 = USD $0.66). For 50.8% (63/124) of recorded OFD events, participants described the hunger levels as "quite hungry" or "really hungry." In 72.6% (90/124) of the OFD orders, participants responded that the order satisfied their cravings. Participants reported neutral to high levels of stress, ranging from not stressed or relaxed to very stressed in 72.6% (90/124) of all the OFD events.

Associations

In a zero-inflated negative binomial regression model adjusted for age, gender, and socioeconomic status, there was evidence that age and dependents were significantly associated with the number of OFD events in a week (Table 5). With every 1-year increase in age, the incidence rate of OFD events in a week decreased by 5% (95% CI 0.91-0.99). Compared with participants with no dependents, those with dependents had an incidence rate of OFD events 2.01 times higher (95% CI 1.16-3.49). Stress levels, age, gender, and socioeconomic status were not statistically significant factors associated with OFD events.

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Table 5. Incidence rate ratios (IRRs) of demographic and lifestyle risk factors in a zero-inflated negative binomial regression model (N=101).

Factors	IRR (95% CI)	*P* value
Dependents		
No dependents (reference)	N/A[a]	N/A
Dependents	2.01 (1.16-3.49)	*.01*
Diet quality score	0.98 (0.96-1.00)	.1
Stress levels		
High stress (reference)	N/A	N/A
Moderate stress	0.60 (0.36-1.00)	.05
Low stress	0.51 (0.26-1.00)	.05
Age (years)	0.95 (0.91-0.99)	.03
Gender		
Man (reference)	N/A	N/A
Woman	0.85 (0.47-1.54)	.59
Socioeconomic status (IRSAD[b])	0.97 (0.84-1.13)	.73

[a]N/A: not applicable.

[b]IRSAD: Index of Relative Socio-Economic Advantage and Disadvantage.

Discussion

Principal Findings

This pilot study tested the feasibility and acceptability of using EMA to capture OFD events and contextual behaviors in young people aged 16 to 35 years. Compliance rates, as an indicator of feasibility, to signal-contingent and event-contingent protocols were similar at 72% and 73%, respectively, in adults. However, participants in the event-contingent group were more likely to have captured an OFD event during the study period. The EMA protocols for both groups were acceptable; however, most participants agreed that the study could be improved by an app that was easier to navigate. Contextual data revealed that OFD orders consisted largely of unhealthy foods. These orders were commonly placed for evening meals, typically after 6 PM, were mostly for a single person, and were ordered at home. Moreover, the orders often originated from an outlet within a 15- to 30-minute walking distance. Analyses showed that there was a significant association between age, number of dependents, and number of OFD events. These formative findings warrant further investigation with refinement of the EMA methodology to increase acceptability and improve the OFD data captured from participants.

High compliance rates indicated a feasible and acceptable EMA protocol for the study population and events captured. In the guidelines proposed by Stone and Shiffman [40] for EMA protocols, compliance rates of ≥80% are considered optimal. This study observed compliance rates between 70% and 73%, which fell short of the recommendations yet aligned with the findings from systematic reviews of similar dietary EMA studies conducted in young people. In a review by Liao et al [30], an average compliance rate of 71% was reported among studies. However, this is in contrast with the review by Battaglia et al [28], where compliance rates were reported to be >80% in more than half of the included studies. Stone et al [41] suggested that noncompliance is mainly attributed to monitoring burden and participants forgetting to record. For this study, the 3 additional reminders set 15 minutes apart and 1 end-of-day prompt included in the protocol aimed to eliminate instances of noncompliance from forgetfulness. Therefore, the monitoring burden may have influenced compliance. Feedback from participants showed that 27% (12/45) of the participants thought that the timing of prompts could have been improved. Data from the multilevel regression analysis supported this as prompts were more likely responded to in the afternoon compared with the evening. Similarly, another feasibility study on a mobile EMA intervention reported that several participants disliked receiving alerts at night, which may have influenced response rates to prompts [42]. These are important considerations for future EMA study designs aiming to collect data from participants during evening hours.

Participants who were assigned to the event-contingent sampling approach were 3 times more likely to have had an OFD event captured during the study compared with the signal-contingent group. This indicates that event-contingent sampling appeared to be the better approach to capturing OFD events. It is likely that event-contingent sampling was more appropriate because of OFD being a specific and sporadic event that, among study participants, varied in the frequency of use. Thus, unprompted records of any instance of OFD over the 1-week monitoring period were more effective than answering prompts delivered on 3 random sampling days. However, an additional end-of-day reminder proved to be critical for the event-contingent group as almost one-third (22/79, 28%) of the OFD orders were captured through this reminder, which otherwise would have been forgotten.

Another possible key factor affecting participants' experience of the EMA study and compliance was the perceived ease of

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use of the mobile app used to capture data. Many participants found that the EMA app was difficult to navigate and not user friendly, which may have negatively affected their experience of this study. Another EMA study also found participants commenting on the "difficult and bothersome" nature of EMA apps, although this was specific to the Visual Analog Slider used for one of the momentary assessments [29]. The Technology Acceptance Model is a highly influential information systems theory that suggests consumer acceptability is largely attributed to the perceived ease of use and usefulness of a given technological tool [43]. Consequently, the layout and technical aspects of EMA app themselves are critical to improving acceptability and compliance by participants.

This study revealed that orders were commonly placed for evening meals, typically after 6 PM, were mostly for a single person, and were ordered at home. Moreover, the orders often originated from an outlet within a 15- to 30-minute walking distance. According to physical activity research, a 1-km distance typically reflects a 15- to 20-minute walk for an average adult [44]. As such, this study revealed that a large proportion of customers are ordering food from potentially >1-2 km away and beyond what is typically considered their walkable neighborhood food environment [45] or the 20-minute neighborhood concept that is growing in popularity [46]. Furthermore, the results from this study are consistent with an annual market report from Uber Eats Canada, which revealed that 6 PM, typically considered "dinner time," was the most popular time of day for orders [47]. An Australian study on the food preparation location context of meals and snacks consumed by young adults showed that dinners prepared from outside of the home are predominately discretionary (20%) compared with the predominately 5-food group (13%) [48]. In addition, pizza was the most popular food category that was ordered, followed by fried chicken, Chinese food, and burgers. These findings also align with the annual report from Uber Eats Australia [49], which indicated that chicken burgers and chicken burritos were in the top 10 most popular orders list from local small businesses. Altogether, this provides preliminary evidence that most foods ordered by OFD services are not healthy and supplements previous studies that have analyzed online menu items and showed that a high proportion of offerings are poor in nutritional quality [13-15,50].

The results from a zero-inflated negative binomial regression model showed that dependents were positively associated with the number of OFD events. This finding is consistent with a previous study conducted by Keeble et al [51], which determined that the odds of any OFD service use were greater for those living with children (OR 2.71, 95% CI 2.44-3.01). Similarly, another study established that the positive relationship between access to the greatest number of food outlets online and use of OFD services in the previous week was specific to those living with children [12]. It is possible that dependents may increase their levels of financial and time stress [52], both of which present barriers to the preparation of healthy home-cooked meals [53]. The use of OFD services may help alleviate time constraints and hence explain the higher frequency of use among those with dependents.

Convenience prevailed as the selected reason for an OFD order (46/124, 37.1%), whereas "being busy" accounted for 12.1% (15/124) of the orders. Price promotions were also used in approximately one-third of all recorded events. These findings align with a qualitative study from the United Kingdom that investigated customer experiences of using OFD services [54]. Keeble et al [54] identified "less effort for more convenience" as a key theme behind customer's use of OFD. In addition, price promotions often influenced and justified the use of these services. Individuals with limited time may be higher consumers of out-of-home food, as research from the United States showed that in a sample of busy young adults, working >40 hours a week was associated with time-related barriers to healthful eating [55]. This perceived lack of time is linked to lower fruit and vegetable intake and greater intake of convenience and fast foods [56]. Of concern, a previous study has shown that ordering meals online for home delivery was significantly associated with higher levels of sugary drinks consumption (P=.003) and fast-food restaurant patronage (P<.001) [57]. A survey conducted in China similarly showed that young adults aged 18 to 30 years often ignored the nutritional value of their OFD orders; however, concerning trends emerged, as these young consumers reported potential physical health changes such as weight gain, elevated blood lipids, and gastrointestinal discomfort as a result of long-term OFD use [58]. However, this study did not find a significant association between diet quality score and the number of OFD events. Despite this, further research is needed to clarify the relationship between unhealthy diets and OFD use.

Strengths and Limitations

To the best of our knowledge, this is the first study to use EMA to capture OFD behaviors and context in near real time. Real-time monitoring is critical to ensuring ecological validity and is a major advantage of the EMA methodology, given the sporadic nature of OFD use. Moreover, this study gathered data on the use of OFD that is independent of market research or company reports and is an important addition to the public health literature that currently lacks evidence on the consumption of OFD.

However, several limitations of this study must also be acknowledged. This was a pilot study where 2 varying EMA protocols were tested for their feasibility and acceptability. Hence, caution is warranted when interpreting the associations found in this study between demographics, lifestyle risk factors, and OFD events. In addition, this study has yet to validate the capture of OFD consumption against gold standard dietary assessment methods such as the 24-hour recall. An important next step would be to examine the percentage match for each occasion of OFD consumption between a 24-hour recall and the EMA protocol.

All data gathered and analyzed in this study were self-reported by the participants, which is inherently prone to response bias. Furthermore, the EMA app used in this study was limited to iOS or Android users and appeared to cause more issues with Android users. Owing to convenience sampling, the study sample was highly educated females residing in areas of high

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socioeconomic advantage, which accordingly may limit the generalizability of the findings.

In addition, it is noted that the monitoring period of 7 days may not have adequately or accurately captured OFD events, as more than half of the study sample reportedly used OFD services 1 to 2 times a month. Future studies could use the event-contingent sampling approach and potentially extend the monitoring period to 14 days instead, alongside incorporating end-of-day reminders.

Moreover, although a training guide was provided online to participants, the study would also benefit from an in-person training day, as recommended by previous EMA studies [59,60]. This would reinforce what is required of the participants for the study, reduce missing data, and improve adherence to the protocol. A training day can also provide an opportunity to obtain objective measurements for weight, height, and waist circumference.

Conclusions

This study showed that mobile EMA is a viable method to capture OFD events and behaviors of its users in near real time, with better results obtained from event-contingent sampling. However, further amendments to the study protocol are necessary to improve compliance and acceptability among participants. In addition, validation of the EMA protocol against gold standard dietary assessment methods such as the 24-hour recall is an important next step. Further research is also essential to support the significant associations found between higher OFD use and those of younger age and those with dependents. This formative work may inform future EMA protocols to capture OFD orders and contextual factors and assist in further understanding OFD use and its impact on diet and health.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Adapted Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Checklist for Reporting EMA Studies (CREMAS).
[PDF File (Adobe PDF File), 150 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Acceptability of the mobile-based ecological momentary assessment protocol comparing the 2 sampling approaches.
[PNG File , 148 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Table of online food delivery (OFD) behaviors and contextual data captured from 58 unique participants.
[DOCX File , 23 KB-Multimedia Appendix 3]

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Abbreviations

EMA: ecological momentary assessment
IRR: incidence rate ratio
IRSAD: Index of Relative Socio-Economic Advantage and Disadvantage
OFD: online food delivery
REDCap: Research Electronic Data Capture

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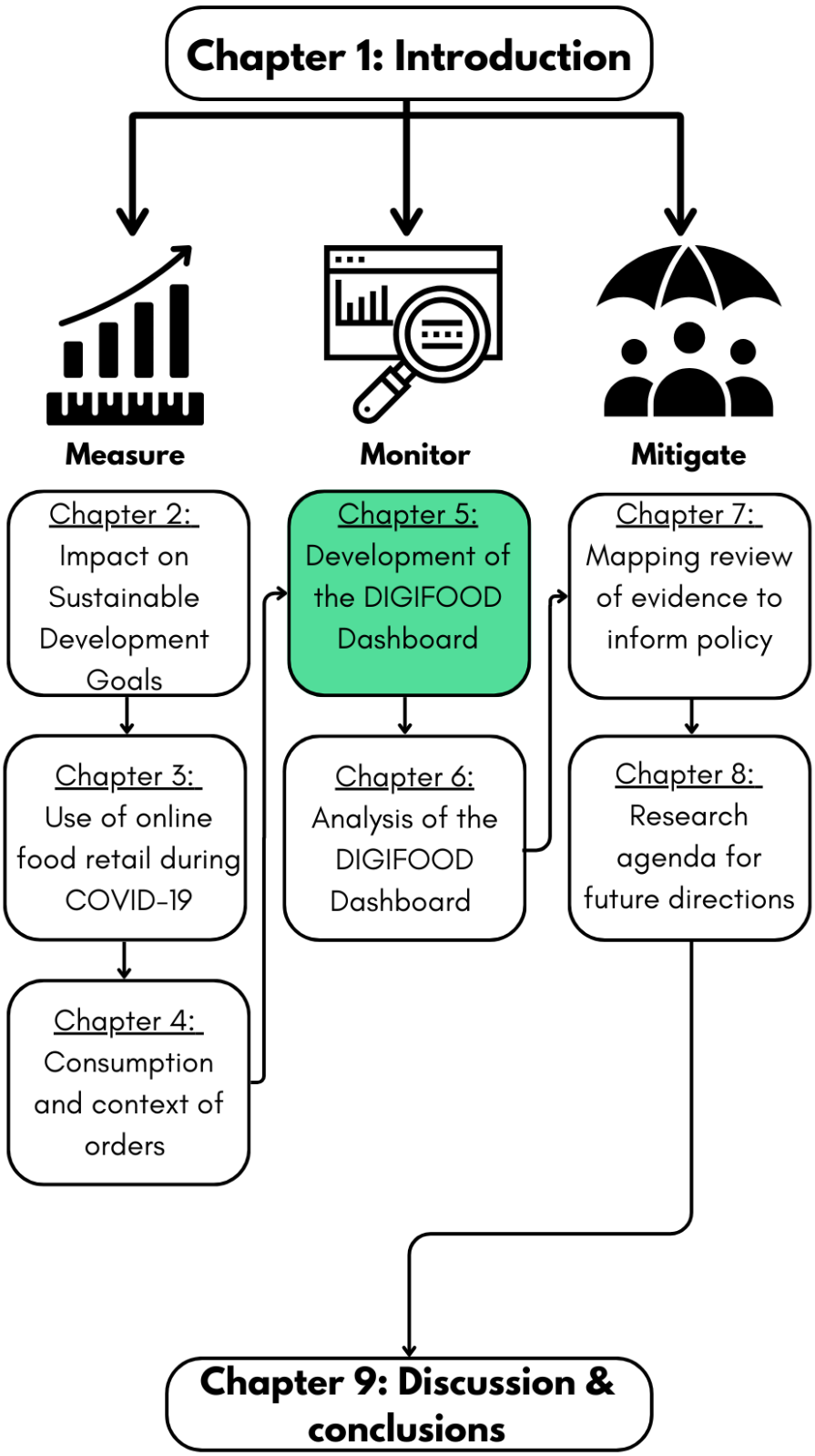
Chapter 1: Introduction
Measure
Monitor
Mitigate
Chapter 2: Impact on Sustainable Development Goals
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CHAPTER 5 | DEVELOPMENT OF THE DIGIFOOD DASHBOARD

Preface to the chapter

Chapter 5 has developed a data-driven dashboard to monitor the impact of the 'digital food environment' on the 'local physical food environment' using an interdisciplinary approach. This chapter thereby addresses Aim 4 of the thesis and contributes to the second sub-theme of 'monitoring risks which meal delivery applications pose to population diets and health'. This study has been peer-reviewed (submitted 26th April 2024, revised 20th June 2024) and published (13th August 2024) in *JMIR Public Health and Surveillance*. Author contributions to this paper are outlined in the authorship attribution statement. Supplementary material is included in Appendix C with a list of search locations used for web scraping on Uber Eats (C.1), dashboard terminology (C.2) and list of Google business categories used as search terms for web scraping on Google Maps (C.3). C.4 is an old version of the DIGIFOOD dashboard which was first developed as a prototype in 2021. C.5 and C.6 are iterations of the DIGIFOOD dashboard in 2024 with additional data web-scraped from Google Maps. C.7 – C.9 presents the final versions of the DIGIFOOD dashboard with comparisons of the online, local and hybrid food environments.

Published peer reviewed manuscript

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Conference presentations

Jia, S et al (2023) Characterising the out-of-home food environment using big data sources. 10-min oral in symposium session. International Society of Behavioural Nutrition and Physical Activity 22nd Annual Meeting, Uppsala, Sweden.

Jia, S et al (2022) How are online food delivery services changing food accessibility? Preliminary analysis using the DIGIFOOD Dashboard. Poster. 24th IUHPE 2022 Conference, Montreal, Canada (VIRTUAL)

Jia, S et al (2021) The development of the DIGIFOOD Dashboard to monitor the impact of online food delivery services on the food environment. 3-min oral. Nutrition Society of Australia 2021 Conference (VIRTUAL).

Author attribution statement

This statement is to specify the contribution made by Si Si Jia in the preparation and submission of the following manuscript included in this chapter: “Developing the DIGIFOOD Dashboard to Monitor the Digitalization of Local Food Environments: Interdisciplinary Approach”.

As first author, Si Si Jia was primarily responsible for formulating the research question, annotating and categorising data, contributing to the data visualisation, writing the draft manuscript and subsequent revisions.

The individual roles of all co-authors are listed below:

Task	**Role of co-authors**
Conceptualisation of research question	SJ, SRP, AAG
Data cleaning and processing	XL
Data annotation and categorisation	SJ, SRP
Data visualisation	XL, SJ
Writing – Original Draft	SJ
Writing – Revision	SJ, XL, SRP, AAG
Supervision	SRP, AAG

Si Si Jia 25 March 2025

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

Dr Stephanie Partridge 25 March 2025

Original Paper

Developing the DIGIFOOD Dashboard to Monitor the Digitalization of Local Food Environments: Interdisciplinary Approach

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Abstract

Background: Online food delivery services (OFDS) enable individuals to conveniently access foods from any deliverable location. The increased accessibility to foods may have implications on the consumption of healthful or unhealthful foods. Concerningly, previous research suggests that OFDS offer an abundance of energy-dense and nutrient-poor foods, which are heavily promoted through deals or discounts.

Objective: In this paper, we describe the development of the DIGIFOOD dashboard to monitor the digitalization of local food environments in New South Wales, Australia, resulting from the proliferation of OFDS.

Methods: Together with a team of data scientists, we designed a purpose-built dashboard using Microsoft Power BI. The development process involved three main stages: (1) data acquisition of food outlets via web scraping, (2) data cleaning and processing, and (3) visualization of food outlets on the dashboard. We also describe the categorization process of food outlets to characterize the healthfulness of local, online, and hybrid food environments. These categories included takeaway franchises, independent takeaways, independent restaurants and cafes, supermarkets or groceries, bakeries, alcohol retailers, convenience stores, and sandwich or salad shops.

Results: To date, the DIGIFOOD dashboard has mapped 36,967 unique local food outlets (locally accessible and scraped from Google Maps) and 16,158 unique online food outlets (accessible online and scraped from Uber Eats) across New South Wales, Australia. In 2023, the market-leading OFDS operated in 1061 unique suburbs or localities in New South Wales. The Sydney-Parramatta region, a major urban area in New South Wales accounting for 28 postcodes, recorded the highest number of online food outlets (n=4221). In contrast, the Far West and Orana region, a rural area in New South Wales with only 2 postcodes, recorded the lowest number of food outlets accessible online (n=7). Urban areas appeared to have the greatest increase in total food outlets accessible via online food delivery. In both local and online food environments, it was evident that independent restaurants and cafes comprised the largest proportion of food outlets at 47.2% (17,437/36,967) and 51.8% (8369/16,158), respectively. However, compared to local food environments, the online food environment has relatively more takeaway franchises (2734/16,158, 16.9% compared to 3273/36,967, 8.9%) and independent takeaway outlets (2416/16,158, 14.9% compared to 4026/36,967, 10.9%).

Conclusions: The DIGIFOOD dashboard leverages the current rich data landscape to display and contrast the availability and healthfulness of food outlets that are locally accessible versus accessible online. The DIGIFOOD dashboard can be a useful monitoring tool for the evolving digital food environment at a regional scale and has the potential to be scaled up at a national level. Future iterations of the dashboard, including data from additional prominent OFDS, can be used by policy makers to identify high-priority areas with limited access to healthful foods both online and locally.

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(JMIR Public Health Surveill 2024;10:e59924) doi: 10.2196/59924

KEYWORDS

online food delivery; food environment; dashboard; web scraping; big data; surveillance; monitoring; prevention; food; food delivery; development study; development; accessibility; Australia; monitoring tool; tool; tools

Introduction

Background

Food environments are shaped by physical, economic, political, and sociocultural factors, which in turn can determine the accessibility, availability, and affordability of foods [1]. Food environments are therefore considered powerful influences of dietary behaviors and health. Two main food environments have been described by Cummins and Macintyre [2]—one in which individuals shop for food intended for home consumption—from grocery stores and supermarkets, and another where foods are purchased for out-of-home food consumption—from restaurants and takeaways.

The World Health Organization (WHO) [3] has reported exponential growth of the out-of-home food sector, and evidence suggests that out-of-home foods are higher in energy, saturated fats, sugar, and salt, which may elevate the risk for obesity and associated diet-related chronic diseases such as type 2 diabetes and cardiovascular disease. Despite this, research on the impact of food environments on dietary and health outcomes remains conflicting. An umbrella review of 32 reviews found evidence of an association between fast-food exposure and greater body weight, although the risk of bias for these studies was high [4]. Another systematic review of 15 studies showed there was no association between availability and distance to healthy food outlets and on dietary intake and BMI in adults [5]. In children aged up to 12 years, however, there was a significant association between healthy food access and better dietary intake and lower BMI [5].

Adding to these complex relationships, in recent years, digital technology has also transformed the accessibility and availability of foods. In the current Information Age, digital technologies are deeply integrated into all areas of life and have transformed the way people work, communicate, and consume services and goods. As a result, rapid digitalization has also transformed out-of-home food environments, leading to the rise of online food delivery services (OFDS). These platforms are central agents in the digitalized food system where individuals interact with information and services from online settings to access and purchase foods [6]. The global OFDS market size is expected to reach over US $1.2 trillion in 2024 and has infiltrated multiple markets worldwide including China, the United States, and the United Kingdom [7].

The resulting disintegration of geographical boundaries of food environments via delivery services may further obfuscate the complex relationship between physical food surroundings and dietary health. Research suggests that OFDS enable individuals to order food from outlets located over 3 km away [8], which is 3 times the distance of what is considered a traditional 1 km "local neighborhood environment" [1]. While increased access to a greater variety of food outlets could be beneficial for individuals and households living in areas that are highly concentrated with fast-food or other unhealthy food outlets, there are also considerable potential harms related to OFDS. Numerous studies have shown a high proportion of popular menu items offered through OFDS are high in fat, salt, and sugar [9-11] and energy dense [12]. Thus, increased access to food outlets enabled by online food delivery has the potential to further exacerbate existing obesogenic food environments. Rising consumption of out-of-home foods contributing to unhealthy diets has been observed in countries including Australia [13], China [14,15], and the United Kingdom [16].

It is therefore critical to examine existing food environments and changes resulting from the digitalization of food environments. A study in China showed that the local neighborhood food environment is a key determinant for using food delivery services [17]. Residents in China who had better access and more choices of healthy foods near their homes were less likely to order food through an OFDS. In contrast, those who worked in suburban areas were more likely to order food through delivery service compared to those working in urban areas, as urban workers had better food accessibility. This highlights an interesting relationship between food environments including both around the workplace and home and the resulting use of OFDS.

The WHO [18] has advocated for monitoring the nutritional quality of meal delivery apps to potentially inform and change policy. Nutrition surveillance is critical to informing policy planning and improving nutrition at the population level. Artificial intelligence tools can be used to collect data and merge with databases to provide a snapshot of the nutritional quality across the food landscape. A systematic review has evaluated 13 publicly available interactive data-driven dashboards as strategies for nutrition surveillance [19], including examples such as John Hopkins University's Food Systems Dashboard [20] and the Global Food and Nutrition Security Dashboard [21]. The goals of these dashboards have focused on sharing global nutrition data, supporting evidence for nutrition programs and policies, and monitoring and tracking nutritional progress and gaps. Moreover, a review on the current landscape of nutrition informatics (nutri-informatics) [22] has recommended greater integration of nutrition into computational biomedical sciences and a need for further representation of public health nutrition investigations. In 2023, the WHO developed a novel digital platform to monitor meal delivery apps across Europe and currently has collected data from Ireland, Italy, Slovakia, Spain, and the United Kingdom [23]. The WHO platform provides important information about the digital food landscape in Europe including the most common restaurants per region, average kilojoule content per meal type, and energy value per monetary unit [23]. There is therefore indication of growing development and use of data visualizations in nutrition and health domains, which may strengthen research relating to the

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determinants of nutritional status to inform future policies and strategies.

Objectives

In this study, we introduce the development of the DIGIFOOD dashboard, a data-driven tool to monitor the emerging impact of OFDS on local food environments in New South Wales, Australia. The dashboard visualizes the geographical accessibility and healthfulness of local versus online food outlets. The primary aim of this study was to describe the development process of the DIGIFOOD dashboard as a collaborative effort between public health nutrition researchers and data scientists. We present three main components to this development process: (1) data acquisition of food outlets via web scraping, (2) data cleaning and processing, and (3) visualization of food outlets on the dashboard.

Methods

Data Acquisition—Uber Eats Data

Web-scraping services (Scraping Solutions, a commercial provider) were used to scrape data from Uber Eats, the market-leading OFDS in Australia, to extract information on all partnering outlets located across New South Wales, which is the most populous state in Australia. Web scraping involves the creation of code or programs to automatically download and extract data from publicly available websites. This method has previously been used by public health researchers in the United Kingdom to obtain a data set of food outlets from Just Eat, a leading OFDS [24]. Data scrapers were not logged in to any personal accounts and set the scrape date and time to Friday between 6 PM and 6:30 PM to simulate when food outlets would operate for dinner. Data were scraped in 2021 for a prototype of the dashboard and again in 2023 for the current larger project.

In phase 1, we obtained data on all possible suburb and locality names that were serviced by Uber Eats across New South Wales, Australia, including suburb or locality name, state or territory, postcode, longitude, and latitude. Using the geographical coordinates, we obtained the midpoint of the search suburb or rural locality name. In January 2023, the Uber Eats Australia website listed 52 locations across New South Wales where delivery was available (see Table S1 in Multimedia Appendix 1). We matched all locations listed on the Uber Eats website to a possible total of 1828 suburb and locality names (out of a total of 4524 individual names across New South Wales using data from Australia Post). The 1828 suburb and locality names and postcodes were provided to web scraping as input to search all Uber Eats food outlets in New South Wales. Of these suburb and locality names, 1061 returned search results from Uber Eats, and publicly available data were subsequently obtained in 3 phases. In phase 2, all suburbs from phase 1 were searched in Uber Eats, and data were extracted from all resulting food outlets that delivered to the searched suburb or locality name. Food outlet data included the name of the food outlet, street address, suburb, state, postcode, opening and closing hours, rating of food outlet, categories, delivery fee, latitude and longitude, and restaurant ID. In phase 3, geographical distances from food outlets to the midpoint of the suburb or locality name identified from phase 1 were obtained (n=66,948). Table S2 in Multimedia Appendix 1 presents an explanation of these terms.

Data Acquisition—Google Maps Data

Google Maps was used as a source of data to represent the local food environment (labeled as "local" food outlets). These food outlets may be inclusive of those that are on Uber Eats and represent the brick-and-mortar location. According to market research, 93% of consumers use Google Maps to search for local stores and businesses [25]. Google consumer insights also revealed that 89% of dining research is done by mobile before visiting a restaurant [26]. Moreover, several public health studies have found Google data to be a reliable source for identifying food retailers [27-30] comparable to in-person ground-truthing audits. Thus, it is likely that most food outlets have a Google Maps business listing and can be representative of the local food environment.

Relevant search terms (n=120) representative of the food environment were obtained from a list of over 4000 Google My Business categories, publicly available online [31]. These were search terms containing keywords that study investigators considered had aligned with predominant food outlets described in the food environment literature including cafes, convenience stores, restaurants, supermarkets, and takeaway [32,33]. Table S3 in Multimedia Appendix 1 present the full list of Google search terms.

Next, each of these 30 terms was searched in all suburb and locality names serviced by Uber Eats as obtained in phase 2 of the Uber Eats data scrape (n=1061). Using a Google application programming interface (API) key, relevant data from food outlets on Google Cloud platform services were scraped. Briefly, an API is an intermediary between websites and software where data and information are exchanged when requests are sent [34]. The Google Places API responds to HTTP queries with information about locations. This API defines places as establishments, geographic locations, and notable points of interest [35]. The Google Places API's nearby search function delivers a list of all instances of the specified keyword within a fixed radius (eg, "Italian Restaurant in Leichhardt NSW 2040, Australia"). The following data were collected: input query, name, review rating, number of reviews, price category, category, service options, address 1, suburb, state, postcode, opening hours, latitude, longitude, food outlet, URL, RefURL, and scrape date.

The Local, Online, and Hybrid Food Environments

Data from Uber Eats were used as measures of the online or digital food environment, while data from Google Maps were used as measures of the local or physical food environment. The hybrid food environment was defined as the collective online and local food environment to account for the impact of OFDS. Figures 1 and 2 provide a conceptual diagram of how we have defined these food environments using the data we have scraped.

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Figure 1. Conceptual diagram of the online food environment versus local food environment. Food outlets of the local food environment are geographically bound by a physical distance—in our study, this was defined using postcode. To observe the impact of online food delivery services on local food environments, we conceptualized the "hybrid food environment" as the combination of local and online food outlets minus the overlapping outlets. In this figure, the hybrid food environment would be the local food environment with the extra food outlets from the online food environment that can deliver in. FE: food environment.

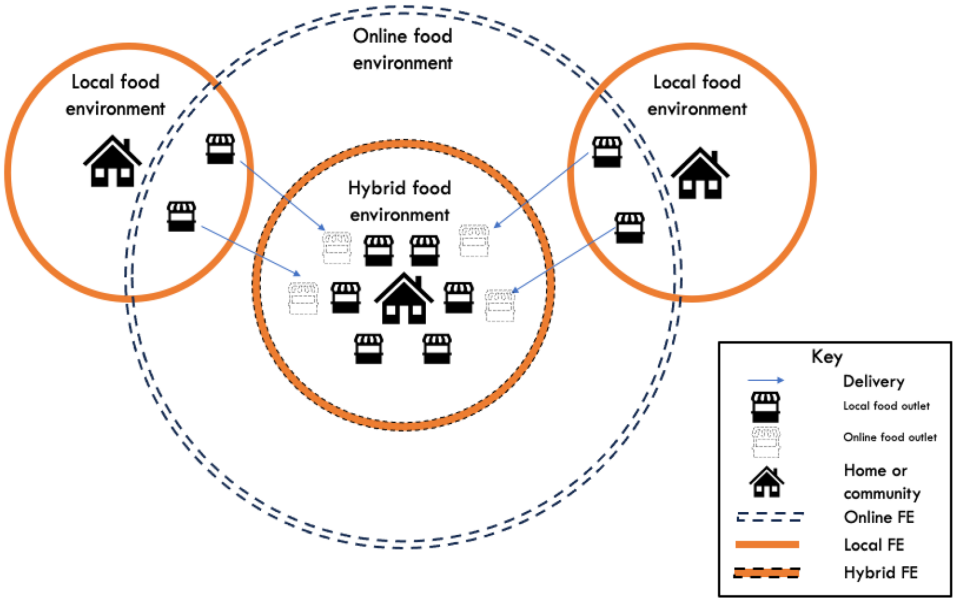
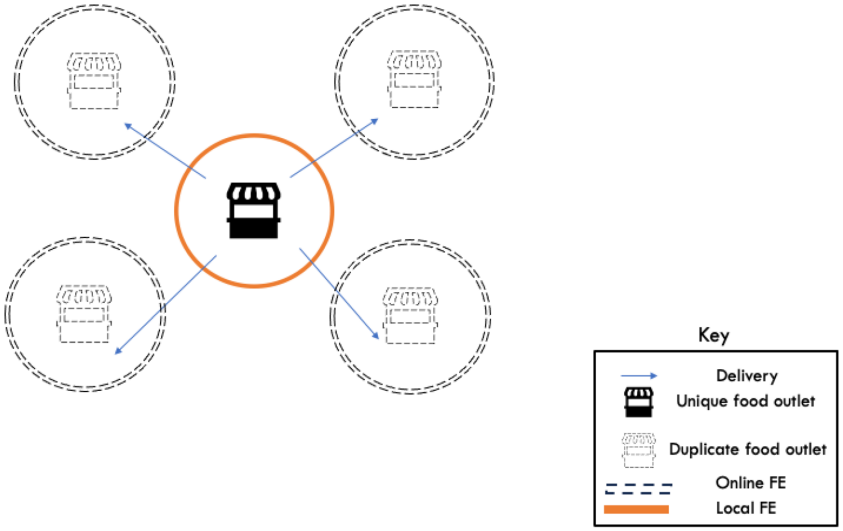


Figure 2. Unique food outlets on Uber Eats were counted as those that had a physical brick-and-mortar store location that offered delivery to neighboring postcodes. Duplicate outlets were counted as all the various locations where the unique food outlet delivered to via online food delivery services. FE: food environment.



Data Cleaning

Identifying Unique Outlets on Uber Eats (Online Food Environment)

Following the 3 phases of data scraping from Uber Eats, a full set of data was obtained. After removing duplicate food outlets (ie, food outlets that appeared more than once in a delivery suburb where the outlet delivered to), as opposed to the physical suburb (where the outlet was located), this resulted in 16,158 unique food outlets. These were identified using the unique ID linked to each food outlet on Uber Eats.

Identifying Unique Outlets on Google Maps (Local Food Environment)

A full data set of 64,239 food outlets from Google Maps was obtained on July 18, 2023. Irrelevant nonfood businesses, for example, appliance store, corporate office, and jewelry store, were filtered out. In addition, outlets that were tagged as "permanently closed" were also filtered out. As such, this was

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further refined to 36,967 unique food outlets. Unique Google Maps outlets were identified using their Google Customer ID, which Google assigns to an individual business entity.

Matching Outlets From Uber Eats and Google Maps Data

Overview

It was anticipated that the Uber Eats data would be a subset of the Google Maps data since most online food outlets on Uber Eats would have a physical store location typically listed on Google Maps as a business. Thus, we expected to see nearly all Uber Eats outlets (n=16,158) to have matched to an outlet in the Google Maps data set (n=36,967). To avoid duplication of food outlets from the 2 data sets, common food outlets (ie, outlets that were both listed on Google Maps and offered delivery service via Uber Eats) were matched by names and addresses. Only relevant columns from both the Google Maps data set and the Uber Eats data were kept for matching including suburb, street address, postcode, state, name, CID, and category.

Processing Data for Matching

Suburb

In the "suburb" column, all string data were converted into lowercase, special characters such as a dash or quote were removed, and spaces were kept in. Any suburbs that were not part of New South Wales were removed, for example, suburbs in the Australian Capital Territory were excluded.

Street Address

Similarly, in the "address 1" column, all string data were converted into lowercase. If the street address also contained the suburb name, postcode, and state, these were removed such that only the address component was kept. If food outlets were located in shopping centers, multilevel buildings, central areas, or plazas, this part of the name was removed. Multimedia Appendix 1 presents the list of manually identified food courts, centers, and buildings.

Name of Outlet

All string data of food outlet names were converted into lowercase, and all special characters such as apostrophes and nonalphanumerical characters were removed. If the name of the food outlet had included the name of food centers, petrol station, suburb, city (Sydney), or state (New South Wales), this would be subsequently removed from the name.

Missing Information

Mandatory fields were required for the parsing process, which converts the data from one format into another format. In cases where there were postcodes available and suburb names were missing, a suburb name that was linked most to the same postcode from other food outlets would be used instead. For example, the postcode "2000" most commonly had the suburb name "Sydney," although a small proportion could also be "Haymarket"—as an assumption, Sydney would be used instead of Haymarket to fill in the empty suburb name. If both the suburb name and postcode were missing, then the fields would be filled in with "empty" and "0000," respectively. If the street address had no street number, it would be filled in with "12345" in front.

Matching Criteria

Food outlets were matched using the processed names and addresses of food outlets in both Uber Eats and Google data sets. A combination of the following various matches was used. With each step, fewer restrictions were placed on the matching criteria. Table 1 provides the sequence in which food outlets were matched based on differing criteria.

Table 1. Sequence of criteria for matching food outlets between Uber Eats and Google Maps data sets.

Step	Criteria for matching
1	Same name, street name, suburb, postcode
2	Same name, street name, suburb
3	Same name, street name, postcode
4	Same name, postcode
5	Same name, suburb
6	Same name, street name, street type
7	Same name, suburb, postcode
8	Same name, street number, street name
9	Same name, street number, suburb, postcode
10	Same street number, street name, suburb, postcode
11	Same street name, suburb, postcode
12	Same postcode
13	Same suburb
14	Same street name
15	Same street type

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For steps 10 and 11, outlets were considered a match if they had fulfilled the criteria and if the names met the 83% similarity threshold. This threshold level was chosen from observation after trial and error. Food outlets were matched using "jelly" (similarity scale from 0 to 1) and "fuzzy" (similarity scale from 0 to 100) matching algorithms if their similarity scores for both name and address were above 90%.

The resulting 2000 unmatched outlets were manually verified. Reasons for errors in matching included inconsistencies in addresses when food outlets were located within multilevel buildings (eg, shopping centers such as Westfield and Central Park) or central food areas (eg, Spice Alley), incorrectly formatted addresses (eg, state is in the postcode column or postcode is in the state column), naming inconsistencies for suburbs (eg, "Brighton Le Sands" and "Brightonlesands"), naming inconsistencies for food outlet names, and incomplete scrape of food outlet data from Google Maps. After accounting for the reasons, 66% (10,708/16,158) of outlets were matched between the 2 data sets (Uber Eats and Google).

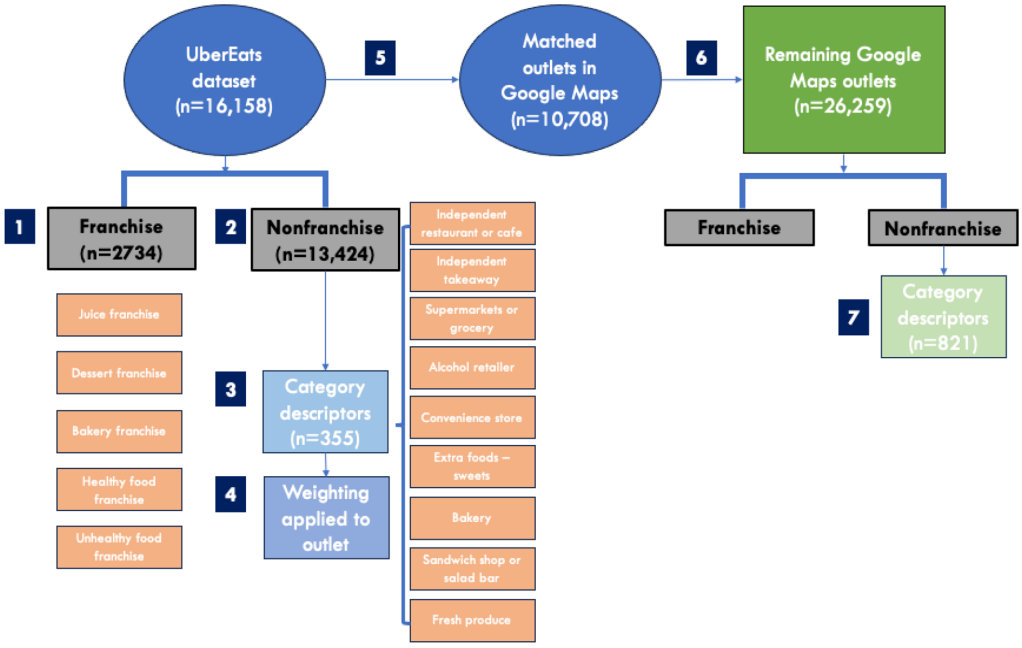
Categorization of Food Outlets

Overview

To descriptively analyze the healthfulness of local and online food environments, we assigned food outlets 1 of 9 categories based on the Food Environment Score, which was developed by a group of Australian public health and nutrition experts in a modified Delphi survey [36]. The 9 main categories included takeaway franchises, independent takeaways, independent restaurants or cafes, supermarkets, fresh produce, sandwich shops or salad bars, sweets or extra foods, bakeries, and convenience stores or service stations. Table S2 in Multimedia Appendix 1 presents the definitions of these categories.

Initially, outlets were labeled either as a franchise or nonfranchise outlet (step 1 in Figure 3). We defined a franchise as a brand that has more than 10 different locations in the data sets. Under menu labeling legislation in the state of New South Wales, franchises or "standard food outlets" are defined as having greater than 20 locations in the state or over 50 nationally. We used a more generous definition for franchise, to be inclusive rather than exclusive, accounting for any potential missing data that would result in a true franchise store incorrectly assigned to the nonfranchise category.

Figure 3. Categorization process of food outlets. Step 1: Outlets were first assigned as franchise or nonfranchise. Steps 2-3: 1 of 9 main categories was assigned to each category descriptor. Step 4: The predominant main category for each food outlet was based on the weighting of various category descriptors. Steps 5-7: The same process was repeated for food outlets from the Google Maps data set.



Nonfranchise Outlets

For nonfranchise outlets, we first manually assigned a main category to all category descriptors in the Uber Eats data set (n=355). For example, a category descriptor of "Asian" would be assigned a main category of independent restaurant or cafe. Some category descriptors were relevant to more than 1 main category. These cases included "Grocer," which was assigned both supermarkets and fresh produce; "Hotel," which was assigned alcohol retailer and independent restaurant or cafe; and "Restaurant," which was relevant for independent restaurant or cafe and independent takeaway. If there were any irrelevant non–food-related category descriptors that could not be assigned a main category, they were assigned "N/A" (steps 2 and 3 in Figure 3).

All these category descriptors and their assigned main category received a base score of 2. Using the previous example, "Asian"

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received a score of 2 for independent restaurant or cafe, while "Chicken" received a score of 2 for independent takeaway. Weightings for certain categories were tweaked to adjust for the prominence; for example, "Fast food" would receive a score of 4 for independent takeaway, while specific and more niche category descriptors such as "Japanese set item" would receive a score of 1 for independent restaurant or cafe (step 4 in Figure 3).

In majority of cases where food outlets had more than 1 category descriptor, the main category would be assigned based on the highest cumulative score. Using "Shawarma Today" as an example, the associated category descriptors were comfort food, burger, and salad. Comfort food received a score of 2 for independent takeaway, burger received a score of 2 for independent takeaway, and salad received a score of 2 for sandwich shop or salad bar. Tallying up the scores, independent takeaway received a total score of 4, while sandwich shop or salad bar only received a score of 2. Hence overall, "Shawarma Today" was assigned independent takeaway as its main category. When the score for main categories was a tie, the main category that appeared less frequently in the total food outlet data set was assigned higher priority. This was to adjust for overrepresentation of food outlet categories and increase the diversity of different food outlet types in the data set.

The main category was transferred from the outlet in Uber Eats data set to the same matching outlet in the Google Maps data set (step 5 in Figure 3). For the remaining outlets in the Google Maps data set, a similar process was conducted using category tags extracted from Google Maps (n=821; steps 6 and 7 in Figure 3).

Franchise Outlets

Franchise outlets were further categorized into dessert franchise, bakery franchise, juice franchise, healthy food franchise, or unhealthy food franchise (step 1 in Figure 3). These were manually determined based on the predominant offerings of menu items. For example, franchise stores that were mainly offering sweets, cakes, ice cream, or sugar-sweetened beverages were categorized as dessert franchise. Bakery franchises were those that offered breads, pastries, and other baked goods. Juice franchises sold mainly juices and smoothies from fruits and vegetables. Healthy food franchises were assigned to stores that mostly offered salads, sushi, or sandwiches. Unhealthy food franchises were renowned fast-food chains predominantly selling burgers, pizza, and fried chicken.

Implementation of Data Inputs Into DIGIFOOD Dashboard

Microsoft Power BI was used to geographically map and visualize local and online food outlets across New South Wales, Australia. Data files on postcodes, regions, and suburbs and localities were downloaded from the Australian Bureau of Statistics—Australian Statistical Geography Standard Edition 3 (Postal Areas 2021, Suburbs and Localities 2021, Statistical Area Level 4 2021). These files were linked by Mesh Blocks, which are the smallest geographic areas and form the building blocks for the larger regions of the Australian Statistical Geography Standard. Suburbs and localities are an Australian Bureau of Statistics Mesh Block approximation of the officially recognized boundaries of suburbs—in cities and larger towns, and localities—outside cities and larger towns, as defined by the state and territory governments of Australia. Rural or urban definitions depend on the density or urban infrastructure criteria. Population numbers for each region in New South Wales were obtained from the 2021 census data [37]. Table S2 in Multimedia Appendix 1 presents further details.

The 3 main components of the dashboard included a geographical map of online, local, and hybrid food outlets; a pie chart of the main categories of food outlets; and a word cloud that visualizes the frequency of cuisines across a specified area.

Statistical Analysis

Descriptive statistics were used to analyze data in the DIGIFOOD dashboard, and the results are presented in this manuscript.

Ethical Considerations

Ethics approval was not required. This work does not contain any data involving human participants. Data on food outlets obtained via web scraping were publicly available and used for noncommercial research purposes.

Results

Data Overview

Of the 4524 suburb and locality names across New South Wales, 1061 were serviced by Uber Eats at the time of data acquisition. To date, 36,967 unique food outlets representing the local food environment and 16,158 unique food outlets representing the online food environment in New South Wales, Australia, have been mapped on the DIGIFOOD dashboard. These figures potentially suggest that 43.7% (16,158/36,967) of all available food outlets are accessible via the market-leading OFDS in Australia.

The highest number of online food outlets (n=4221) and locally accessible food outlets were found in the Sydney-Parramatta region (n=10,069), which encompasses 28 postcodes in the scraped data set. In contrast, the Far West and Orana region, which covers 2 postcodes, had the lowest number of locally accessible food outlets (n=7; Table 2).

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Table 2. Number of local, online, and hybrid outlets by regions in New South Wales, Australia, ordered by ascending number of local outlets.

New South Wales region	Postcodes, n	2021 census population, n	Local outlets, n	Online outlets, n	Hybrid outlets[a], n	Change in local food outlets resulting from OFDS[b,c], n/N (%)
Far West and Orana	2	115,566	299	7	300	299/300 (100)
Coffs Harbour-Grafton	4	146,127	667	7	667	667/667 (100)
New England and North West	4	185,560	893	25	905	893/905 (101)
Southern Highlands and Shoalhaven	2	161,006	1031	3	1031	1031/1031 (100)
Murray	3	123,552	1175	159	1219	1175/1219 (104)
Richmond-Tweed	8	257,061	1317	97	1352	1317/1352 (103)
Capital Region	5	238,810	1345	57	1374	1345/1374 (102)
Mid North Coast	7	229,035	1559	20	1564	1559/1564 (100)
Riverina	10	161,349	1562	164	1634	1562/1634 (105)
Central West	6	212,962	1776	16	1778	1776/1778 (100)
Central Coast	10	346,596	4860	339	5059	4860/5059 (104)
Newcastle and Lake Macquarie	21	390,519	5232	297	5350	5232/5350 (111)
Hunter Valley exc Newcastle	12	291,946	5036	686	5569	5036/5569 (102)
Sydney-Sutherland	11	229,604	5611	514	6022	5611/6022 (107)
Illawarra	16	313,842	5626	824	6081	5626/6081 (108)
Sydney-Ryde	11	202,038	6179	1309	7302	6179/7302 (118)
Sydney-Northern Beaches	20	263,554	6190	839	6930	6190/6930 (112)
Sydney-Outer South West	14	297,292	6319	1077	7148	6319/7148 (113)
Sydney-Eastern Suburbs	16	261,410	6618	2170	8604	6618/8604 (130)
Sydney-Blacktown	16	396,776	7029	2035	8683	7029/8683 (124)
Sydney-North Sydney and Hornsby	26	424,045	7046	1728	8633	7046/8633 (123)
Sydney-Baulkham Hills and Hawkesbury	14	264,371	7515	1592	8709	7515/8709 (116)
Sydney-Inner West	25	304,771	8070	3562	11,228	8070/11,228 (139)
Sydney-Outer West and Blue Mountains	24	332,056	8130	1609	9128	8130/9128 (112)
Sydney-City and Inner South	26	331,340	8684	3850	12,282	8684/12,282 (141)
Sydney-South West	21	474,430	8978	2462	10,808	8978/10,808 (120)
Sydney-Inner South West	31	605,118	9464	3231	12,335	9464/12,335 (130)
Sydney-Parramatta	28	493,515	10,069	4221	13,758	10,069/13,758 (137)
Total			36,967	16,158	51,470	36,967/51,470 (139)

[a]Hybrid food outlets represent the combined local and online food outlets within the region. Figure 1 and Table S2 in Multimedia Appendix 1 provides further information.

[b]OFDS: online food delivery services.

[c]Percentage change in food outlets resulting from OFDS was calculated as the number of hybrid outlets divided by the number of local outlets, multiplied by 100.

Regions where OFDS had the most significant impact were Sydney-City and Inner South, Sydney-Inner West, Sydney-Parramatta, Sydney-Eastern Suburbs, and Sydney-Inner South West in descending order. These regions all observed a greater than 130% increase in total food outlets by comparing hybrid outlets to local outlets (Table 2).

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In contrast, OFDS appeared to have the least significant impact in Far West and Orana, Coffs Harbour-Grafton, Southern Highlands and Shoalhaven, Mid North Coast, and Central West regions (Table 2). These regions did not observe an overall change in total food outlets, as the number of hybrid food outlets reflected 100% of the number of local food outlets (Table 2).

In both local food environments and online food environments, it was evident that independent restaurants and cafes comprised the largest proportion of food outlets at 47.2% (17,437/36,967) and 51.8% (8369/16,158), respectively (Table 3). However, compared to local food environments, the online food environment has relatively more takeaway franchises (2734/16,158, 16.9% compared to 3273/36,967, 8.9%) and independent takeaway outlets (2416/16,158, 14.9% compared to 4026/36,967, 10.9%). Noticeably, there were relatively more unhealthy food franchises (1612/16,158, 10% compared to 1961/36,967, 5.3%) and dessert franchises (706/16,158, 4.4% compared to 800/36,967, 2.2%).

Table 3. Categorization of food outlets accessible locally and online across New South Wales, Australia.

Categories	Local (n=36,967), n (%)[a]	Online (n=16,158), n (%)[a]	Hybrid (n=51,470), n (%)	Local outlets that are accessible online by category, n/N (%)
Independent restaurants or cafes	17,437 (47.2)	8369 (51.8)	25,566 (49.7)	8369/17,437 (48)
Independent takeaway	4026 (10.9)	2416 (14.9)	6393 (12.4)	2416/4026 (60)
Takeaway franchise	3273 (8.9)	2734 (16.9)	5510 (10.7)	2734/3273 (83.5)
Unhealthy food franchise	1961 (5.3)	1612 (10)	3200 (6.2)	1612/1961 (82.2)
Healthy food franchise	213 (0.6)	188 (1.2)	387 (0.8)	188/213 (88.2)
Bakery franchise	254 (0.7)	131 (0.8)	373 (0.7)	131/254 (51.6)
Dessert franchise	800 (2.2)	706 (4.4)	1411 (2.7)	706/800 (88.3)
Juice franchise	45 (0.1)	97 (0.6)	139 (0.3)	97/45 (216)
Supermarkets or grocers	2441 (6.6)	217 (1.3)	2646 (5.1)	217/2441 (8.9)
Alcohol retailer	2242 (6.1)	590 (3.6)	2824 (5.5)	590/2242 (26.3)
Convenience stores or petrol station	2117 (5.7)	541 (3.3)	2632 (5.1)	541/2117 (25.6)
Fresh produce (excluding groceries)	2106 (5.7)	44 (0.3)	2149 (4.2)	44/2106 (2.1)
Extra foods—sweets	1613 (4.4)	678 (4.2)	2260 (4.4)	678/1613 (42)
Bakery	1200 (3.2)	115 (0.7)	1307 (2.5)	115/1200 (9.6)
Sandwich shops or salad bars	512 (1.4)	454 (2.8)	950 (1.8)	454/512 (88.7)
Total	36,967	16,158	51,470	16,158/36,967 (43.7)

[a]Local and online contain duplicates between the 2 data sets.

Furthermore, Table 3 shows that most takeaway food franchises, including unhealthy food franchises, healthy food franchises, dessert franchises, and juice franchises, in addition to sandwich shops and salad bars, are offered and accessible online via the market-leading meal delivery app, as these represented close to or more than 80% of locally available food outlets. In contrast, supermarkets and grocers, fresh produce, and bakeries are the least accessible online via Uber Eats, as these represented less than 10% of the total local food outlets.

Case Study for Application of the DIGIFOOD Dashboard: Sydney-Parramatta Metropolitan Region

Overview

Policy makers, especially those in local governments, could use the DIGIFOOD dashboard tool to gain insight into the local, online, and hybrid food environments in their areas of interest. This could help inform planning decisions and approval of development proposals to optimize the health and well-being of communities.

For example, the Sydney-Parramatta region of New South Wales is a major metropolitan area with a population of over 493,515 (2021 census) [38]. The dashboard also allows users to navigate between the displays of data to observe (1) local food environments, (2) online food environments, and (3) hybrid food environments. These displays are shown in Figures 4-6 using the example of the Sydney-Parramatta region. Features of the DIGIFOOD dashboard are explained in Table 4.

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Figure 4. Local food environment display for the Sydney-Parramatta region.

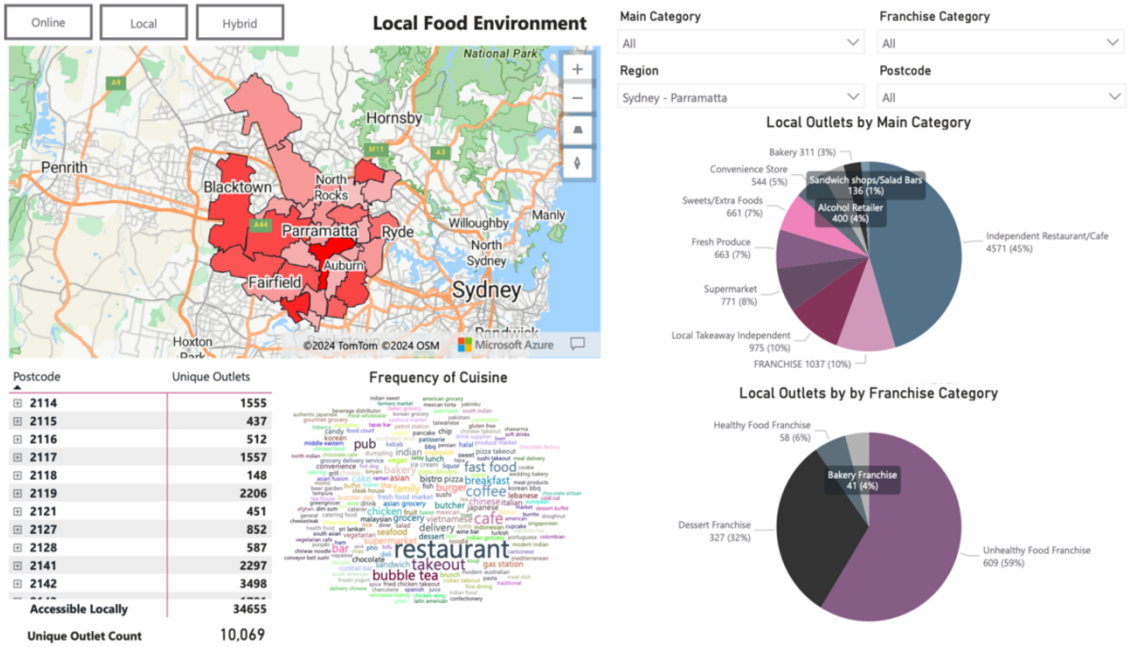

Figure 5. Online food environment display for the Sydney-Parramatta region.

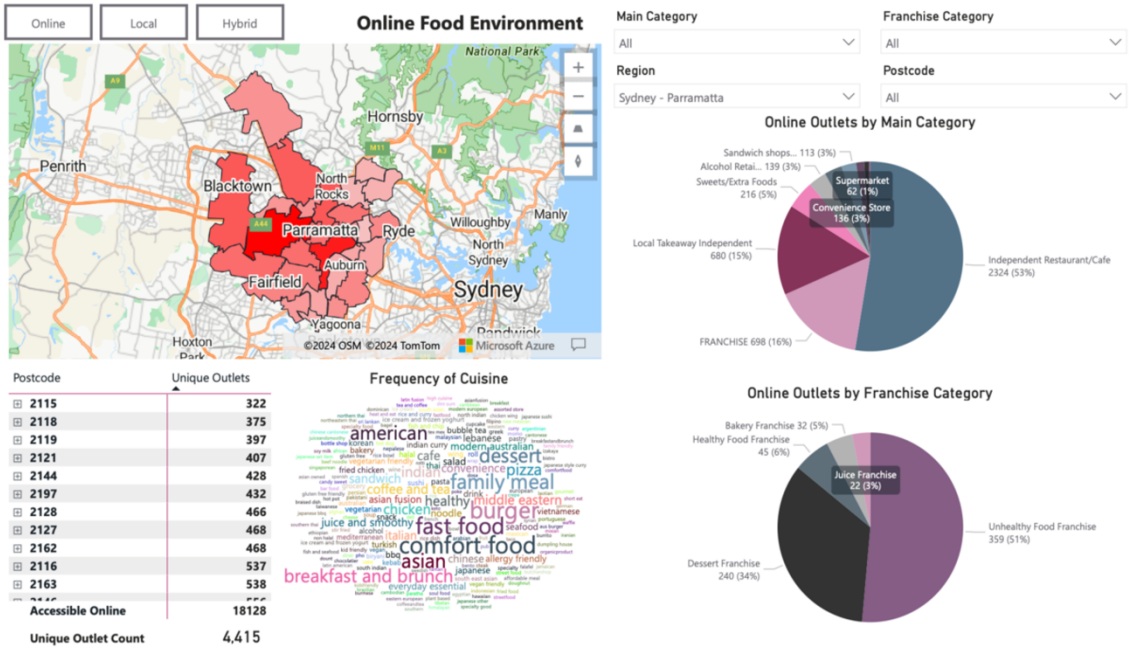

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Figure 6. Hybrid food environment display for the Sydney-Parramatta region.

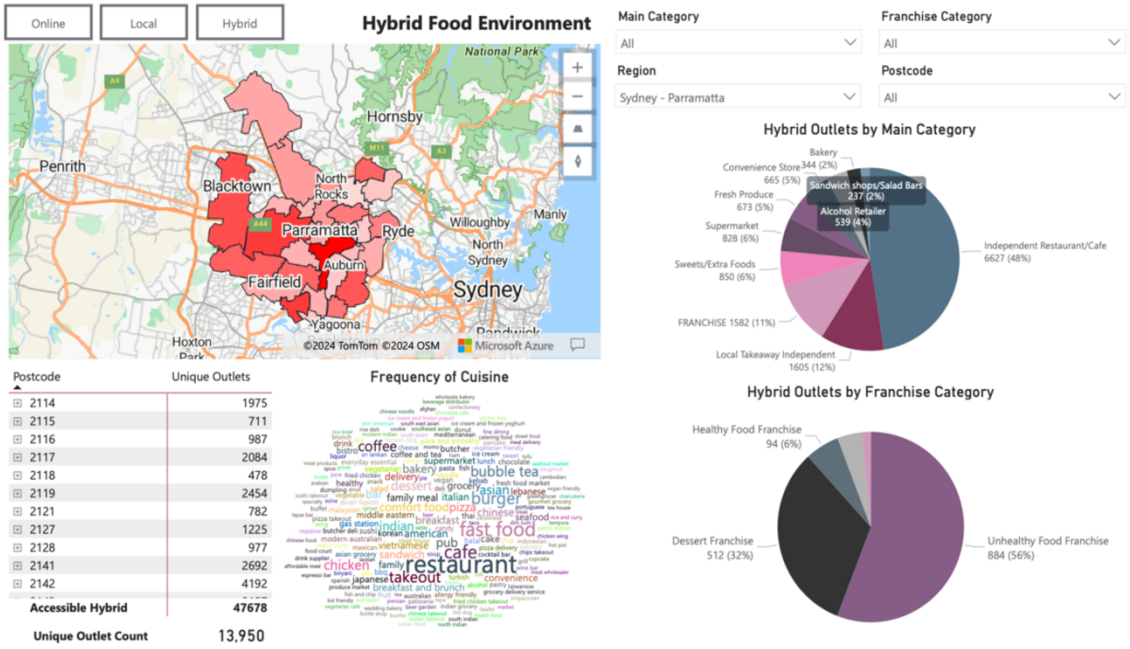

Table 4. Features of the DIGIFOOD dashboard.

Feature	Explanation	Case study example
Pie chart of food outlet categories	The pie chart represents the composition of food outlets by main categories and franchises.	In Figure 5, the pie chart shows that online food outlets were mostly comprised of unhealthy food franchises, followed by dessert franchises, healthy food franchises, and bakery franchises.
Frequency of cuisine word cloud	The word cloud displays the frequency of "cuisines," also known as category descriptors for food outlets. Larger words represent a higher frequency of the cuisine.	In Figure 6, the word cloud shows a large variety of cuisines available in the hybrid food environment. Cuisines that were more prominent included restaurants, fast food, burgers, and bubble tea.
Map density	In the map section, areas that were of a darker red color indicated a higher relative density of food outlets sorted by postcode.	In Figures 4-6, the postcode 2148 for Blacktown in the Sydney-Parramatta region appears to have a high density of local, online, and hybrid food outlets as determined by the darker red color.
Search by postcode	In addition to searching food environments by region, the dashboard enables a search by postcodes of interest. This will then provide data specific to the postcode, including frequency of cuisine word cloud and pie charts of the categorization of food outlets.	For instance, users can obtain a closer look at postcode 2148 to observe changes in the frequency of cuisine, composition of categories, and number of food outlets.

Comparison of the 3 Different Food Environments

At the regional level, it was clear that compared to the local food environment, the online food environment was offering more franchise stores—with a higher proportion of juice and bakery franchises available, as shown in the pie charts (Figure 4). From the word cloud display in Figure 5, it was clear that the online food outlets were comprised mainly of fast food, comfort food, family meals, and American food. Figure 6 shows the significant increase in a number of food outlets in the hybrid food environment compared to the local food environment. The pie charts in Figure 6 compared to Figure 4 also demonstrated substantial growth in unhealthy food franchises.

Discussion

Principal Findings

Nutrition surveillance is fundamental to informing healthy policy planning at the population level [6,39]. OFDS are expanding food environments and increasing food accessibility within local neighborhoods or communities. The changing access to more healthful or unhealthful food outlets has important implications on population health and nutrition. Monitoring the digitalization of food environments is therefore essential for guiding policy development to ultimately enhance nutritional outcomes across the population.

This study presents the development of the DIGIFOOD dashboard to monitor changes in the local food environments

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of New South Wales in Australia. We explain our multidisciplinary approach to developing the DIGIFOOD dashboard to monitor the availability and accessibility of both local and online food outlets. This tool can also identify areas most affected by adverse changes resulting from the digitalization of food environments, where healthy food options are outnumbered by unhealthy food options.

The WHO Europe has similarly developed a dashboard to monitor the out-of-home food environment [23]. The platform currently collects data from 2 major food delivery platforms in Europe and provides information on available restaurants, their geographical location and delivery reach, as well as menu items if available [23]. Where the energy information of menu items is provided, the WHO dashboard developed by Hetz et al [23] can provide a comparative analysis of average calories per restaurant or restaurant type. However, it was noted by Hetz et al [23] that a lack of data on menu items with energy labeling can limit such analyses. Furthermore, recent studies have shown that menu labeling is largely absent and inconsistent on OFDS [40-42], and only franchise restaurants are mandated to provide nutritional labeling. The DIGIFOOD dashboard shows that nearly 50% of food outlets on OFDS are smaller independent takeaways and independent restaurants and cafes. These outlets therefore may not have the resources to calculate or provide nutritional information of menu items.

Digitalization Is Changing the Geographical Boundaries of Food Environments

The DIGIFOOD dashboard provides unique insight into the impact of digitalization on the geographical boundaries of traditional local food environments. We demonstrate that in New South Wales, the overall hybrid food environment that accounts for the collective impact of online and local food outlets is largely comprised of independent restaurants or cafes (25,566/51,470, 49.7%), followed by independent takeaway outlets (6393/51,470, 12.4%) and franchise takeaway outlets (5510/51,470, 10.7%). These findings suggest that indeed local food environments are becoming further saturated by additional food outlets accessible online and can get delivered in.

This study also showed that the leading OFDS in Australia appeared to have the greatest impact in metropolitan urban areas compared to the outer regional and rural areas. While regions close to the central business district in Sydney were observed to have a greater than 130% increase in total food outlets from food outlets accessible via delivery, regions in rural areas with a population size 3 to 4 times smaller observed little to no change to total food outlets. It is important to note that, however, these observations have been derived from only 1 OFDS, and it is likely that other competitors may have more prominence in these regional areas.

Another study conducted in China showed that the density of takeaway food facilities offering OFDS was also more concentrated in urban central areas [43]. In contrast, compared to more central urban areas, peripheral areas observed a decreasing trend in the density of these online food outlets. Moreover, researchers in Nanjing, China, established a spatial correlation between online-to-offline food delivery restaurants and fast-food restaurants that provide meals high in fat, oil, and salt [44]. This finding suggests that compared to conventional restaurants that only offer dine-in service restaurants offering online food delivery are more geographically connected to fast-food restaurants (Pearson coefficient of 0.42 and q value of 0.79; P<.001). Hence, online food delivery may further promote accessibility to fast-food restaurants and increase consumption of fast food.

Janatabadi et al [45] have also investigated the social and spatial inequalities of contemporary food desserts in the United Kingdom. A positive association between physical and online access to groceries and health conditions was found [45]. Among individuals with poor health conditions, roughly 550,000 had relatively higher access to online grocery services accompanied by a relatively low level of physical store access [45]. As health conditions improved, the reliance on online food shopping was shown to decrease, and those individuals had higher access to physical grocery stores [45]. This finding potentially suggests that increasing access to OFDS for groceries may be an important consideration for those living in more deprived areas who may face more health challenges or poorer health conditions. Altogether, it is evident that digitalization may be changing the geographical or spatial boundaries of food outlet access. Thus, it is of key interest to continue examining the potential impacts of digital food environments on population health.

Web Scraping

Similar to this study, research from Great Britain used scraped data from food outlets available on Just Eat, the market-leading OFDS in the United Kingdom, as the training material. Web scraping enables easy access to large volumes of data and can help overcome knowledge gaps [46]. In recent years, public health researchers have increasingly used web-scraping techniques to obtain data for analyses; for example, in Canada, researchers obtained food price data from the websites of the largest food retailer corporation, Loblaws [47], to perform food cost analyses. Online food delivery platforms uniquely offer a wealth of publicly available data that can be used to investigate out-of-home food consumption as demonstrated in previous studies [48,49]. Collaboration between data scientists and public health nutrition researchers to use and analyze big data is essential for further research in the field of digital food environments.

Limitations

While web scraping is generally a more efficient way to obtain large volumes of data from online sources, there were several limitations with the quality of data we scraped. We obtained Google Maps data by searching for various food categories of restaurants in a specified suburb within New South Wales using 30 relevant Google Business categories that were identified from a list with over 4000 categories. This therefore may not have completely captured the food environment and, moreover, was a time-intensive step, which required up to 3 months to complete due to the limits on API requests in 1 scrape [50].

In addition, we based our categorization of food outlets to characterize local, online, and hybrid food environments from a small list of food outlet categories in the Food Environment

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Score. These categories or outlet types were broad and resulted in nearly 50% of total food outlets categorized as independent restaurants or cafes. We attempted to adjust this overrepresentation by assigning the category that appeared less frequently whenever there was a tie between categories. We also note that there may be potential inaccuracies, as the food outlet data are often provided by business owners of food outlets. For example, it was noted that Oporto, a fast-food franchise store selling predominantly burgers and chips, had the following categories on Uber Eats: Burgers, Vegan, Desserts, Fast food, Chicken, Family Meals, and Healthy. This limitation, however, is likely to have minimal impact overall, as the main category has factored for the variety of different associated category descriptors or cuisine tags for varying outlets.

Furthermore, we only scraped data from 1 OFDS, Uber Eats, which is the market-leading platform in Australia. This may have underestimated the spread or accessibility of the "digital food environment," as we did not account for restaurants that may have partnered with other popular food delivery services such as Menulog or DoorDash.

We also acknowledge that the data presented in the current version of the DIGIFOOD dashboard are subject to rapid changes in the opening and closing of new food outlets, in addition to growing numbers of partnering outlets with Uber Eats, especially in more rural and remote regions. This indicates that the dashboard must be continuously updated with the latest data to remain relevant and reflective of both local and online food environments.

Future Directions

The immediate next steps for this research will be to generate a healthfulness score to conduct analyses and compare the healthfulness of local and online food environments across the socioeconomic gradient. Local governments and policy makers will also be engaged to tailor aspects or displays of the dashboard that would be most useful to them for decision-making. For example, policy makers may seek further information to guide development plans regarding access to healthy food retail for their communities. In future iterations, the dashboard can also incorporate population data such as population density, infrastructure, amenities in local communities, and walkability measures.

Conclusions

The DIGIFOOD dashboard provides visualization of the current digital food environment driven by the proliferation of OFDS. As such, the dashboard may be a useful tool for policy makers, allowing for monitoring of the digital food environment to devise strategies that may improve accessibility to healthful foods. Further research will be conducted to analyze differences in the healthfulness of the hybrid food environments across geographical areas of varying incomes and resources, in addition to trends between regional and remote areas compared to more urbanized areas.

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Data Availability

The data sets generated during this study are available from the corresponding author on request.

Conflicts of Interest

None declared.

Multimedia Appendix 1

DIGIFOOD dashboard data inputs and terminology.
[DOCX File , 34 KB-Multimedia Appendix 1]

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Abbreviations

API: application programming interface
OFDS: online food delivery services
WHO: World Health Organization

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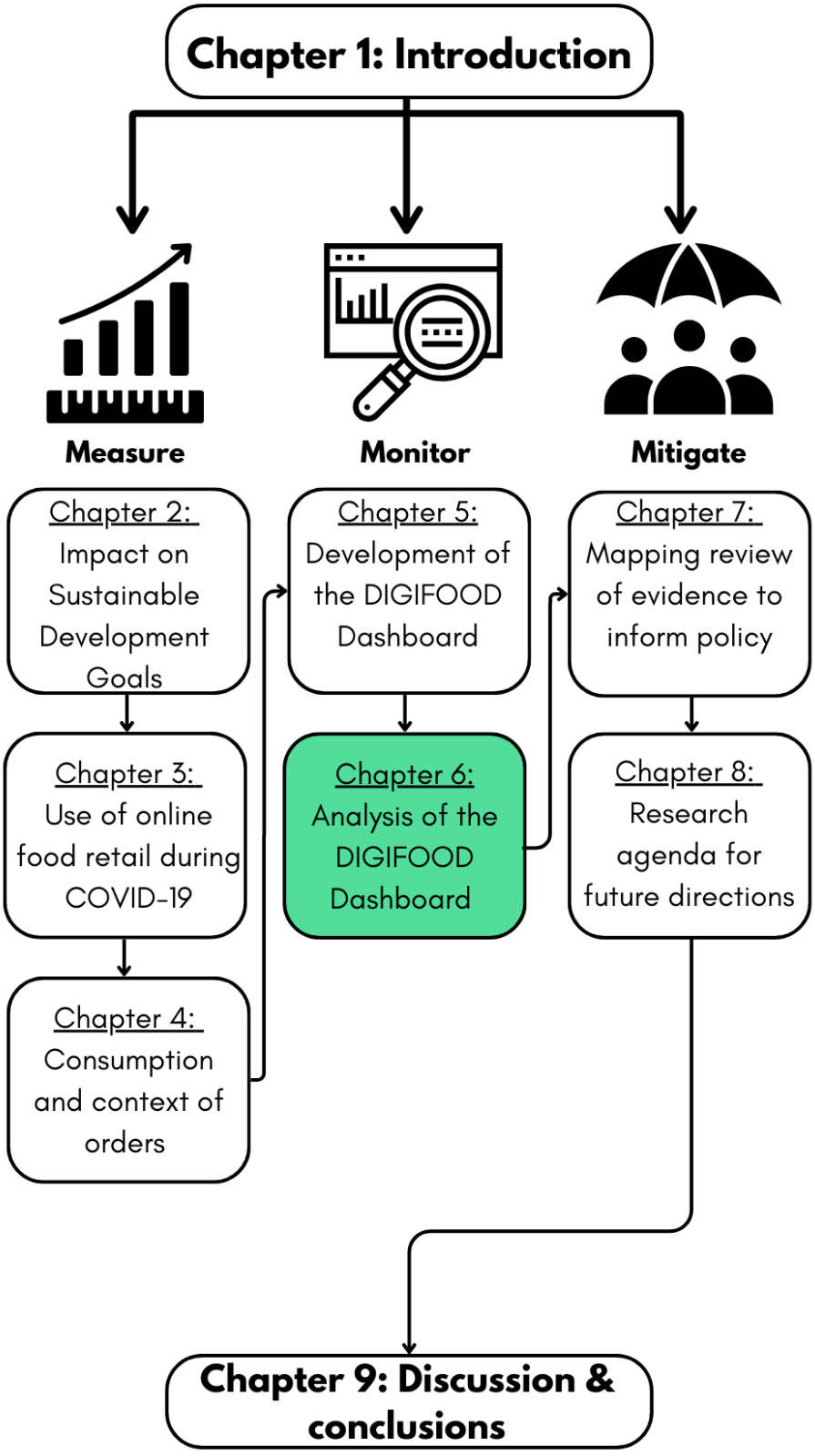
Chapter 1: Introduction
Measure
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Mitigate
Chapter 2: Impact on Sustainable Development Goals
Chapter 3: Use of online food retail during COVID-19
Chapter 4: Consumption and context of orders
Chapter 5: Development of the DIGIFOOD Dashboard
Chapter 6: Analysis of the DIGIFOOD Dashboard
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CHAPTER 6 | ANALYSIS OF THE DIGIFOOD DASHBOARD

Preface to the chapter

Chapter 6 has analysed the data from the DIGIFOOD dashboard to investigate how meal delivery apps are changing food environments across the socioeconomic gradient. This chapter thereby addresses Aim 5 of the thesis and contributes to the second sub-theme of 'monitoring risks which meal delivery applications pose to population diets and health'. This study has been peer-reviewed (submitted 12th November 2024, revised 15h January 2025) and published 27th February 2025 in *The Lancet Regional Health - Western Pacific*. Author contributions to this paper are outlined in the authorship attribution statement. Supplementary material including further details on the methods, results and R script for data analysis can be found in Appendix D as D.1, D.2 and D.3 respectively.

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Author attribution statement

This statement is to specify the contribution made by Si Si Jia in the preparation and submission of the following manuscript included in this chapter: “Assessing socioeconomic disparities in emerging hybrid food environments: a cross-sectional analysis of the DIGIFOOD dashboard”.

As first author, Si Si Jia was primarily responsible for formulating the research question, data analyses, data visualisation, writing of the draft manuscript and subsequent revisions. The individual roles of all co-authors are listed below:

Task	**Role of co-authors**
Conceptualisation of research questions	SJ, SRP, AAG
Data analyses	SJ, KO
Data visualisation	SJ
Writing – Original Draft	SJ
Writing – Revision	SJ, KO, PP, MAF, AAG, SRP
Supervision	SRP, AAG
Funding acquisition to obtain data	SRP, AAG

Si Si Jia 25 March 2025

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

Dr Stephanie Partridge 25 March 2025

Assessing socioeconomic disparities in emerging hybrid food environments: a cross-sectional analysis of the DIGIFOOD dashboard

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Socio-economic conditions in which people are born, live, and age, have profound impacts on health. Evidence suggests that disparities in health outcomes of individuals living in disadvantaged neighbourhoods may be attributed to their food environment—defined as the consumer interface with the food system that encompasses the availability, affordability and desirability of foods.[1]

Meal delivery applications ('apps') are online systems which facilitate the delivery of food or drinks, for consumption.[2] These platforms are a $400-billion global industry and are an emerging disruptor to existing food environments. In England, research revealed that access to online food outlets offering ready-made takeaway meals was greatest in the most disadvantaged areas.[3] Additionally, while meal delivery apps have been shown to improve equity of food accessibility in general, they may also exacerbate disparities between urban and rural communities.[4,5] This study aimed to examine the associations between socioeconomic disadvantage and the 'hybrid food environment'[6] which is defined as the collective environment of online and local (physical) food outlets in a postcode.

We studied 506/597 total unique postcodes that were serviced by UberEats—the market-leading meal delivery app in New South Wales, Australia. Postcodes are a four-digit number used to assist with mail delivery and can be linked to a geographic area for spatial analysis. Data were extracted via web-scraping methods in January 2023 from UberEats to represent food outlets accessible online and Google Maps for food outlets that were locally accessible at the postcode level. The data extraction process has been described in detail in the development of the DIGIFOOD dashboard.[6]

Socioeconomic disadvantage at the postcode level was the main exposure variable (quintiles 1 to 5 with 1 the most disadvantaged). The outcome variable was the count of online and local outlets in a postcode, across nine different food outlet categories adapted from a previous food environment typology.[7] The food outlet categories studied included: i) alcohol retailers, ii) fast-food franchises, iii) independent takeaways, iv) independent restaurants and cafes, v) sweets and desserts, vi) healthy food franchises, vii) sandwich and salad shops, viii) supermarkets and ix) fresh produce. These categories were further labelled as 'unhealthy' (i–v) and 'healthy' (vi–ix) to indicate their potential impact on population health. This aligns with the 'DIGIASSESS' tool which employed the Delphi method to obtain healthfulness ratings of online food outlets from a panel of Australian nutrition and public health experts.[8]

We used quasi-Poisson regression models, adjusting for population size and remoteness. Nine models were conducted, one for each food outlet category. Robust standard errors were used which account for certain violations of model assumptions (e.g., heteroscedasticity).[9]

Additional models included interaction terms between socioeconomic disadvantage quintiles and food environment type to investigate whether there were differences between count of online and local food outlets across the socioeconomic disadvantage gradient. All analyses were performed in R Statistical Software (Version 4.4.1, R Core Team 2021).

Areas experiencing less socioeconomic disadvantage such as those in Quintiles 3, 4 and 5, have greater access to alcohol retailers and healthy food franchises, in the 'hybrid food environment' (Table 1). There were significantly more food outlets accessible online compared to those accessible locally across eight of nine food outlet categories. The only food outlet category where local food outlets outnumbered online food outlets was 'fresh produce'. The rate of fresh produce outlets accessible online was 49% lower (IRR: 0.51, 95% CI:

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[f]Equal contribution.

Food outlet category	Model 1: IRR (95% CI)	Model 2: IRR (95% CI) –	Model 3: IRR (95% CI)
Alcohol			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.98 (0.60, 1.62)	1.27 (0.77, 2.07)	1.51 (0.92, 2.46)
Disadvantage quintile 3	1.23 (0.94, 1.60)	1.36* (1.07, 1.74)	1.33* (1.06, 1.66)
Disadvantage quintile 4	1.21 (0.94, 1.55)	1.67** (1.31, 2.11)	1.43** (1.15, 1.79)
Disadvantage quintile 5—Least disadvantaged	1.23 (0.98, 1.55)	1.73*** (1.39, 2.13)	1.40*** (1.15, 1.72)
Food environment—Local (Ref)	–	–	–
Food environment—Online	2.22*** (1.88, 2.62)	1.93*** (1.64, 2.27)	1.65*** (1.39, 1.96)
Remoteness (Ref)—Major city	–	–	–
Remoteness—Inner regional	–	–	0.47*** (0.33, 0.67)
Remoteness—Outer regional and remote	–	–	0.10*** (0.05, 0.19)
Fast food franchise			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.74* (0.54, 1.02)	0.92 (0.68, 1.26)	1.14 (0.87, 1.49)
Disadvantage quintile 3	0.96 (0.76, 1.25)	1.09 (0.85, 1.40)	1.13 (0.90, 1.40)
Disadvantage quintile 4	0.94 (0.75, 1.18)	1.30* (1.04, 1.62)	1.17 (0.95, 1.43)
Disadvantage quintile 5—Least disadvantaged	0.82 (0.66, 1.02)	1.16 (0.94, 1.43)	0.99 (0.82, 1.21)
Food environment—Local (Ref)	–	–	–
Food environment—Online	5.22*** (4.46, 6.12)	4.54*** (3.95, 5.22)	3.65*** (3.22, 4.14)
Remoteness (Ref)—Major city	–	–	–
Remoteness—Inner regional	–	–	0.31*** (0.22, 0.42)
Remoteness—Outer regional and remote	–	–	0.08*** (0.04, 0.20)
Healthy food franchise			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.97 (0.56, 1.66)	1.16 (0.67, 2.01)	1.52 (0.89, 2.58)
Disadvantage quintile 3	1.00 (0.70, 1.44)	1.11 (0.78, 1.58)	1.22 (0.88, 1.69)
Disadvantage quintile 4	1.18 (0.83, 1.69)	1.57* (1.10, 2.24)	1.44* (1.02, 2.02)
Disadvantage quintile 5—Least disadvantaged	1.17 (0.86, 1.60)	1.59* (1.16, 2.17)	1.38* (1.02, 1.86)
Food environment—Local (Ref)	–	–	–
Food environment—Online	9.15*** (6.65, 12.61)	8.14*** (5.90, 11.24)	6.03*** (4.37, 8.34)
Remoteness (Ref)—Major city	–	–	–
Remoteness—Inner regional	–	–	0.04*** (0.02, 0.10)
Remoteness—Outer regional and remote	–	–	0.04** (0.01, 0.27)
Fresh produce			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.64** (0.44, 0.94)	0.88 (0.64, 1.19)	1.00 (0.76, 1.31)
Disadvantage quintile 3	0.83 (0.59, 1.16)	0.92 (0.69, 1.22)	0.84 (0.65, 1.10)
Disadvantage quintile 4	0.82 (0.60, 1.11)	1.13 (0.87, 1.47)	0.93 (0.72, 1.19)
Disadvantage quintile 5—Least disadvantaged	0.82 (0.62, 1.09)	1.14 (0.89, 1.46)	0.87 (0.69, 1.11)
Food environment—Local (Ref)	–	–	–
Food environment—Online	0.67*** (0.56, 0.80)	0.57*** (0.47, 0.69)	0.51*** (0.42, 0.61)
Remoteness (Ref)—Major city	–	–	–
Remoteness—Inner regional	–	–	0.62 (0.49, 0.80)
Remoteness—Outer regional and remote	–	–	0.13* (0.08, 0.21)
Supermarkets			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.65* (0.44, 0.99)	0.87 (0.60, 1.25)	1.08 (0.78, 1.50)
Disadvantage quintile 3	0.86 (0.64, 1.17)	0.97 (0.73, 1.27)	0.94 (0.74, 1.20)
Disadvantage quintile 4	0.81 (0.61, 1.08)	1.14 (0.89, 1.47)	0.94 (0.74, 1.18)
Disadvantage quintile 5—Least disadvantaged	0.81 (0.62, 1.05)	1.15 (0.91, 1.46)	0.87 (0.70, 1.09)
Food environment—Local (Ref)	–	–	–
Food environment - Online	1.62*** (1.39, 1.89)	1.38*** (1.19, 1.60)	1.14 (0.99, 1.31)
Remoteness (Ref)—Major city	–	–	–

(Table 1 continues on next page)

Food outlet category	Model 1: IRR (95% CI)	Model 2: IRR (95% CI) –	Model 3: IRR (95% CI)
(Continued from previous page)			
Remoteness—Inner regional	–	–	0.31*** (0.23, 0.41)
Remoteness—Outer regional and remote	–	–	0.10*** (0.04, 0.22)
Independent restaurants/Cafes			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.81 (0.53, 1.22)	0.93 (0.61, 1.42)	1.17 (0.79, 1.73)
Disadvantage quintile 3	0.94 (0.71, 1.23)	1.00 (0.76, 1.32)	1.04 (0.81, 1.34)
Disadvantage quintile 4	1.06 (0.82, 1.36)	1.31* (1.02, 1.69)	1.17 (0.92, 1.48)
Disadvantage quintile 5—Least disadvantaged	1.06 (0.84, 1.34)	1.33* (1.05, 1.69)	1.13 (0.91, 1.41)
Food environment—Local (Ref)	–	–	–
Food environment—Online	5.54*** (4.66, 6.58)	5.02*** (4.23, 5.95)	3.91*** (3.31, 4.63)
Remoteness (Ref)—Major City	–	–	–
Remoteness—Inner regional	–	–	0.25*** (0.18, 0.35)
Remoteness—Outer regional and remote	–	–	0.06*** (0.04, 0.11)
Sandwich shops and salad bars			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.77 (0.48, 1.21)	0.87 (0.54, 1.39)	1.12 (0.72, 1.74)
Disadvantage quintile 3	0.91 (0.66, 1.26)	0.98 (0.71, 1.35)	1.05 (0.78, 1.42)
Disadvantage quintile 4	1.00 (0.75, 1.32)	1.22 (0.91, 1.64)	1.11 (0.84, 1.48)
Disadvantage quintile 5—Least disadvantaged	1.09 (0.84, 1.43)	1.36* (1.03, 1.80)	1.18 (0.90, 1.55)
Food environment—Local (Ref)	–	–	–
Food environment—Online	8.77*** (6.96, 11.05)	8.01*** (6.37, 10.09)	5.98*** (4.76, 7.51)
Remoteness (Ref)—Major city	–	–	–
Remoteness—Inner regional	–	–	0.13*** (0.09, 0.19)
Remoteness—Outer regional and remote	–	–	0.02*** (0.01, 0.07)
Sweets and desserts			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.67* (0.43, 1.05)	0.79 (0.50, 1.25)	1.01 (0.66, 1.56)
Disadvantage quintile 3	0.75 (0.56, 1.00)	0.82 (0.61, 1.10)	0.85 (0.65, 1.10)
Disadvantage quintile 4	0.85 (0.66, 1.10)	1.09 (0.84, 1.43)	0.96 (0.75, 1.24)
Disadvantage quintile 5—Least disadvantaged	0.76* (0.59, 0.97)	0.99 (0.77, 1.28)	0.83 (0.65, 1.06)
Food environment—Local (Ref)	–	–	–
Food environment—Online	5.28*** (4.38, 6.38)	4.69*** (3.90, 5.64)	3.58*** (2.99, 4.29)
Remoteness (Ref)—Major city	–	–	–
Remoteness—Inner regional	–	–	0.21*** (0.14, 0.30)
Remoteness—Outer regional and remote	–	–	0.03*** (0.02, 0.07)
Independent takeaways			
Disadvantage quintile 1 (Ref)—Most disadvantaged	–	–	–
Disadvantage quintile 2	0.66** (0.48, 0.91)	0.77* (0.56, 1.07)	0.96 (0.72, 1.26)
Disadvantage quintile 3	0.79* (0.61, 1.01)	0.85 (0.66, 1.09)	0.89 (0.72, 1.11)
Disadvantage quintile 4	0.76** (0.61, 0.95)	0.97 (0.77, 1.21)	0.88 (0.71, 1.09)
Disadvantage quintile 5—Least disadvantaged	0.77** (0.62, 0.96)	1.00 (0.80, 1.24)	0.87 (0.71, 1.06)
Food environment—Local (Ref)	–	–	–
Food environment—Online	6.85*** (5.95, 7.89)	6.12*** (5.38, 6.95)	4.76*** (4.26, 5.31)
Remoteness (Ref)—Major city	–	–	–
Remoteness—Inner regional	–	–	0.27*** (0.20, 0.37)
Remoteness—Outer regional and remote	–	–	0.08*** (0.05, 0.13)

Note: *p < 0.05; **p < 0.01; ***p < 0.001. IRR, Incidence Rate Ratio. Model 1 was unadjusted. Model 2 adjusted for population size. Model 3 additionally adjusted for remoteness.

Table 1: **Results from Quasi-Poisson regression models examining the associations between socioeconomic disadvantage, food environment type, population size, remoteness and number of food outlets in nine different categories.**

0.42, 0.61) than the rate of fresh produce outlets accessible locally ($p < 0.001$).

Significant interactions between socioeconomic disadvantage and food environment type ($p < 0.01$) were observed for unhealthy food retailers including alcohol, fast-food franchises, and independent takeaways (Fig. 1A, B and H). Significant interactions ($p < 0.05$) were also observed for healthy food retailers such as healthy food franchises, fresh produce, supermarkets (Fig. 1C, D and E). Altogether, these findings suggest that compared to areas experiencing the most disadvantage, areas with the least disadvantage have greater access to online, than local food outlets. However, for fresh produce outlets (Fig. 1D), there was no difference between online and local outlets in Quintile 5, but there was a higher number of local fresh produce outlets compared to online outlets in Quintile 1.

We note that online grocery apps or websites which offer specific delivery of fresh produce, were not considered and is a study limitation. This has likely contributed to the observation of fresh produce outlets having more presence physically, than online. Despite this, meal delivery apps are much more popular amongst young people[10] and offer a wider variety of foods and meals.[11] As such, improving online offerings of fresh produce and healthy food retail outlets on popular meal delivery apps, may yield greater benefits to population health.

Meal delivery apps appear to be expanding access to both unhealthy food retail and healthy food retail, with more impact in affluent areas. This could be further widening health inequalities as affluent areas have increased online access to healthier options such as fresh produce and supermarkets, compared to more disadvantaged areas. The role of the local, physical food environment remains to be of high importance for communities in disadvantaged areas as this study showed fresh produce outlets are more accessible in-person, than online via meal delivery apps. As cities expand and meal delivery app use becomes more prevalent, urgent attention is needed to ensure healthy food retail remains to be easily accessible physically in underserved areas, in addition to having increased healthy options available online. Affluent areas face the opposite challenge with a need to reduce access to unhealthy food outlets such as alcohol retailers, online.

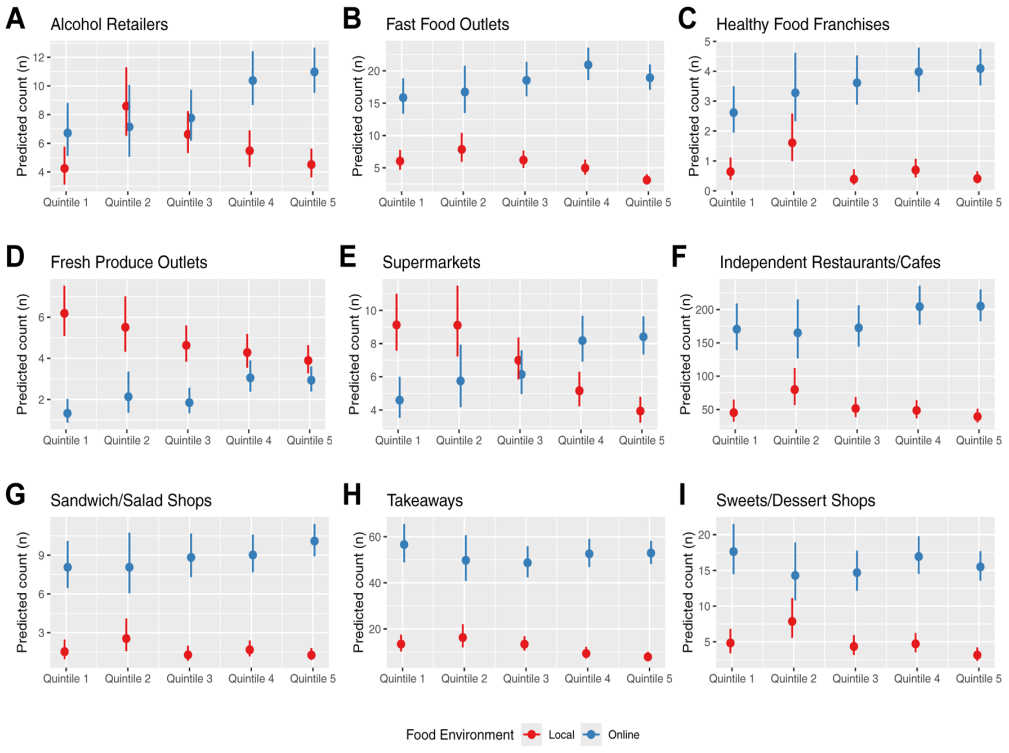

Fig. 1: Interactions between socioeconomic disadvantage and food environment type for each food outlet category. Row 1 (A–C): Alcohol, Fast-food franchises and Healthy food franchises. Row 2 (D–F): Fresh produce, Supermarkets, Independent Restaurants, Row 3 (G–I): Sandwich or salad shops, Takeaways, Sweets or dessert shops.

Contributors

SJ: Conceptualization, Methodology, Data Analysis, Visualization, Writing—Original draft preparation, Writing—Review & Editing. AAG & SRP: Funding Acquisition, Conceptualization, Supervision, Writing—Review & Editing. KO: Data Analysis, Writing–Review & Editing. MAF, PP: Writing–Review & Editing.

SJ verified the data, had access to the raw data and had final responsibility for the decision to submit for publication.

Data sharing statement

The data sets generated during this study are available from the corresponding author on request.

Declaration of interests

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.lanwpc.2025.101504.

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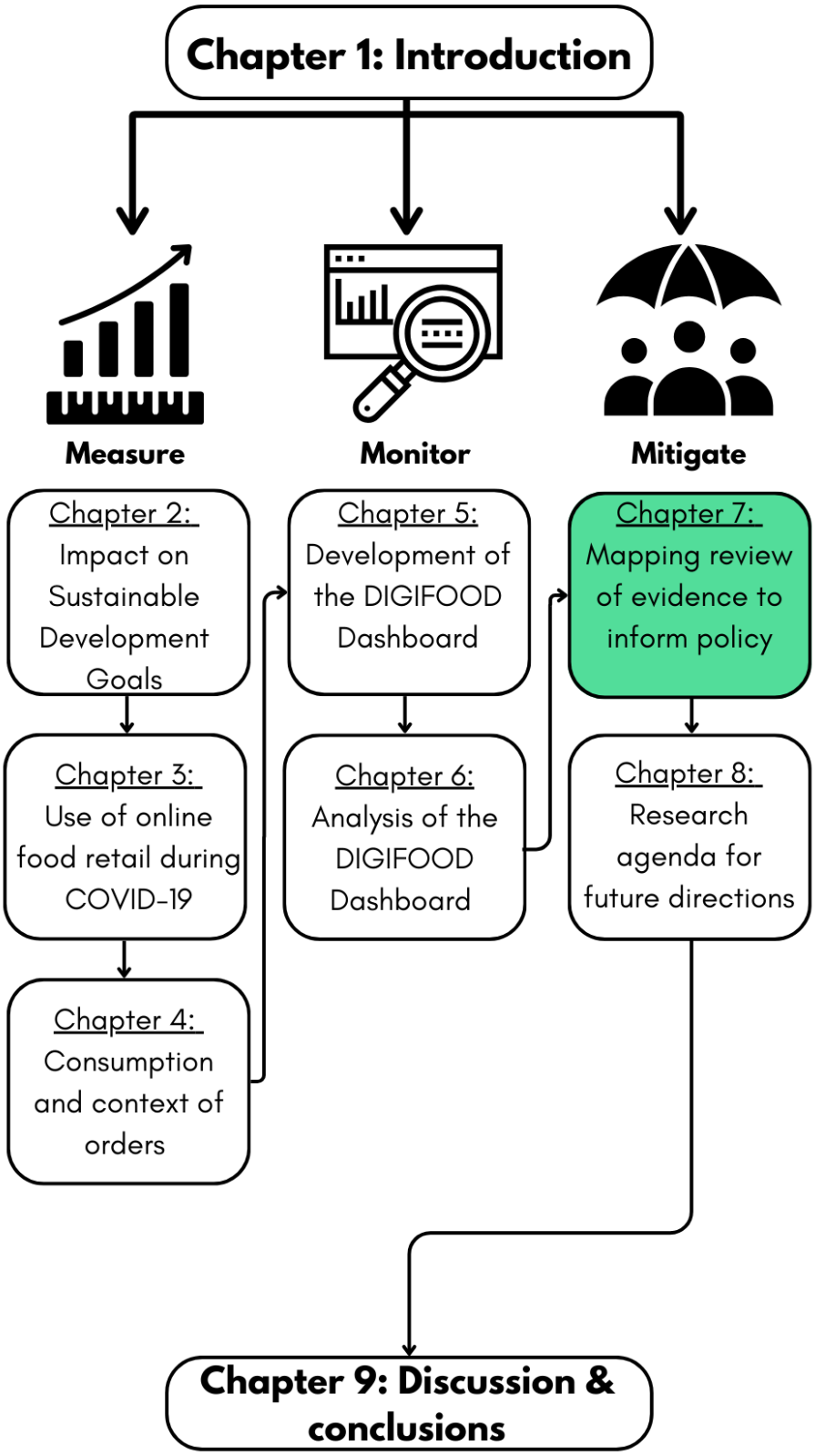
Chapter 1: Introduction
Measure
Monitor
Mitigate
Chapter 2: Impact on Sustainable Development Goals
Chapter 3: Use of online food retail during COVID-19
Chapter 4: Consumption and context of orders
Chapter 5: Development of the DIGIFOOD Dashboard
Chapter 6: Analysis of the DIGIFOOD Dashboard
Chapter 7: Mapping review of evidence to inform policy
Chapter 8: Research agenda for future directions
Chapter 9: Discussion & conclusions

CHAPTER 7 | MAPPING REVIEW OF EVIDENCE TO INFORM POLICY

Preface to the chapter

Chapter 7 has reviewed the emerging evidence and nutrition-related policy options to regulate meal delivery apps. This chapter thereby addresses Aim 6 of the thesis and contributes to the second sub-theme of 'mitigating risks which meal delivery applications pose to population diets and health'. This study has been peer-reviewed (submitted 16th August 2024, revised 31st October 2024) and published (18th November 2024) in *BMC Medicine*. Author contributions to this paper are outlined in the authorship attribution statement. Supplementary material can be found in Appendix E including the full Medline search strategy (E.1) and the PRISMA-ScR checklist (E.2). An additional published study to this thesis chapter which examined the adherence to menu labelling policies on meal delivery apps has been included in Appendix E as E.3.

Published peer reviewed manuscript

I am the first author for this article which was published in *BMC Medicine* in November 2024.

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Conference presentations

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Jia, S et al (2024). Synthesising evidence to regulate online food delivery platforms for population health and wellbeing. 10-min oral. 2024 World Public Health Nutrition Congress, London, England.

Author attribution statement

This statement is to specify the contribution made by Si Si Jia in the preparation and submission of the following manuscript included in this chapter: “Offline to Online: A systematic mapping review of evidence to inform nutrition-related policies applicable to online food delivery platforms”.

As first author, Si Si Jia was primarily responsible for formulating the research question, conducting the literature search of peer-reviewed publications and grey literature for policy examples, writing of the draft manuscript and subsequent revisions.

The individual roles of all co-authors are listed below:

Task	**Role of co-authors**
Conceptualisation of research question	SJ

Literature search	SJ
Screening – title and abstract, full-text	SJ, ART
Writing – Original Draft	SJ
Writing – Revision	SJ, PF, MAF, LV, GS, AAG, SRP
Supervision	SRP, AAG

Si Si Jia 25 March 2025

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

Dr Stephanie Partridge 25 March 2025

Jia et al. BMC Medicine (2024) 22:542
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BMC Medicine

REVIEW Open Access

Offline to online: a systematic mapping review of evidence to inform nutrition-related policies applicable to online food delivery platforms

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Abstract

Background Online food delivery (OFD) platforms offer easy access to an abundance of energy-dense and nutrient-poor takeaway foods and may exacerbate existing unhealthy food environments. Efforts to improve population diets include a range of policy recommendations focused on improving the healthiness of food environments; however, the way in which such policies may apply to OFD platforms is not clear. This paper aimed to synthesise the existing evidence to inform nutrition-related policies applicable to OFD platforms for population health and well-being. A secondary aim was to scan existing nutrition-related policies in Australia and internationally, which have the potential to be applicable to OFD platforms.

Methods Seven electronic databases including Medline, Embase, CINAHL, Business Source Ultimate, Scopus, Web of Science, and Proquest were searched from January 2010 to October 2023. Evidence from studies was mapped to five existing policy domains outlined by the Healthy Food Environment Policy Index (Food-EPI) including (i) food labelling; (ii) food promotion; (iii) food composition and nutritional quality; (iv) food retail; and (v) food pricing. Relevant data sources were searched for currently implemented nutrition-related government policies that may have relevance to OFD platforms.

Results A total of 2012 records were screened, and 43 studies were included. There were 70 relevant study outcomes across the included studies, which addressed one or more of the 5 domains. Of these, 21 were relevant to 'Food Promotion' (30%), 18 to 'Food Retail' (26%), 15 to 'Food Composition (21%), 11 to 'Food Prices' (16%), and six to 'Food Labelling' (9%). Three existing policies from international jurisdictions (England, Singapore, EU) included OFD platforms, of which one was a voluntary measure. Several existing policies under food labelling have the potential to be amended to include OFD platforms under regulatory definitions.

Conclusion OFD platforms have emerged as a disruptor to how people acquire their food and have yet to be widely included in existing nutrition-related policies. Advancing the evidence base to support the design of effective policy

†Alice A. Gibson and Stephanie R. Partridge contributed equally to this work.

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actions and mitigate the potential negative health impacts of OFD platforms will support efforts to improve population diets.

Keywords Digital food environment, Online food delivery, OFD, Public policy, Nutrition policy, Food away from home

Background

Between 1990 and 2019, dietary risk-related non-communicable diseases (NCDs) accounted for 18.9% to 22.7% of all-cause deaths globally [1]. Worldwide, the top five dietary risks for deaths attributable to NCDs were diets high in sodium, low in whole grains, low in legumes, low in fruits, and high in meats [1]. In addition, since 1990, global obesity rates have quadrupled amongst children and adolescents aged 5 to 19 years [2] and more than doubled amongst adults [3]. Now, one in eight people are living with obesity globally [3]. Whilst diets are a known modifiable risk factor for NCDs such as obesity, diabetes, cardiovascular disease, and some types of cancer, shifting populations towards more positive dietary behaviours has proven to be challenging. Globally, almost 40% of populations in both high and low-middle-income countries do not adhere to their national dietary guidelines with overconsumption of red meats and underconsumption of vegetables [4]. Dietary guidelines are crucial reference standards for optimal nutrition and health, and prevention of NCDs [5].

Food environments are defined by the collective physical, economic, policy, and sociocultural surroundings, opportunities, and conditions that influence people's food choices and nutritional status [6]. Unhealthy food environments can be defined as food settings and conditions that are dominated by energy-dense and nutrient-poor foods that are widely available, relatively inexpensive, and heavily marketed [7]. Current food environments are considered predominantly unhealthy [7] and are increasingly undergoing digital transformation that may influence the accessibility and availability of healthy and unhealthy foods. There has been an evident expansion of food accessibility through the use of online food retail platforms, which may have been accelerated by the COVID-19 pandemic [8]. A review has classified online food retail into three distinct categories [9] consisting of online food delivery (OFD), including platforms offering ready-made takeaway meals from restaurants and food service outlets via third-party couriers [10], such as Uber Eats or Just Eat; online groceries for supermarket items such as, but not limited to, fresh produce and packaged foods; and meal kits with ingredients for cook-at-home meals. A systematic scoping review of 22 articles on OFD platforms, the first category of online food retail previously defined, suggested that the majority of these platforms are likely to promote unhealthy food purchasing through extensive use of marketing practices such as price discounts and images and the dominance of unhealthy food offerings [11]. Globally, OFD platforms are dominated by large corporations forecasted to reach US$1.22 trillion in 2024 and estimated to reach 2.8 billion users by 2029 [10].

Given the potential public health challenges, there is an opportunity for governments to explore how nutrition-related policies, such as food labelling and restrictions on marketing unhealthy foods, apply to digital food environments. Additionally, targeted policies tailored for these digital contexts may be required. Drawing from other areas of nutrition research, several nutrition-related practices that OFD companies could take to create healthier food environments have been identified [12]. For example, it has been proposed that OFD companies could include public commitments to nutrition and health as part of their corporate strategies, ensure nutrition information on their platforms meet government regulations, restrict exposure of children to marketing of unhealthy foods and brands, increase visibility and accessibility of healthier products on platforms, and encourage restaurants to increase healthfulness of their offerings [12]. Despite these recommendations, it is recognised that voluntary actions from industry are often inadequate to sufficiently improve food environments and government regulation is often warranted to establish a 'level playing field' [12].

Nutrition policies targeting food environments have the potential to substantially improve population diets and may be effective [13] and cost-effective [14] initiatives to prevent the burden of obesity and related NCDs. Nutrition-related policy options available for the government include 'harder' policy instruments, such as laws, regulations, and economic instruments (e.g. tax and incentives), and 'softer' instruments such as community education (e.g. guidelines or mass media campaigns) [15, 16]. In Australia, nutrition-related policies have mostly focused on developing national strategies and aspects of food labelling including regulation of ingredient lists, nutrition information panels, and health claims [17, 18]. Worldwide, 'harder' policy instruments, such as taxes on sugar-sweetened beverages, have been successfully implemented in more than 50 jurisdictions, with evidence of positive impact on a range of outcomes, including reductions in sales of taxed beverages [19].

To assist in the monitoring of policies and actions for progress towards better nutritional health, the International Network for Food and Obesity and Non-communicable Disease Research, Monitoring and Action Support (INFORMAS) developed the Healthy Food Environment Policy Index (Food-EPI) [20]. The Food-EPI framework includes seven key policy areas specific to food environments, including food composition, labelling, promotion, prices, provision, retail, trade, and investment [20]. These policy areas have been shown to have an important impact on population diets and obesity as they affect the accessibility, availability, and affordability of foods and beverages.

Whilst there are a wide range of nutrition-related policies that are likely to be effective in preventing diet-related NCDs, there are often challenges with implementation [21, 22]. These challenges include maintaining momentum and support for policies over time through changing political agendas and require cross-sectoral and multi-level cooperation between key stakeholders including civil society and businesses [23]. Furthermore, the regulation of OFD may face unique challenges [24]. For example, in an Australian context, OFD platforms operate in a policy and legal 'grey' zone where it is unclear if they are a retailer, manufacturer, food service outlet, or third-party courier [24]. Without this clear definition, OFD platforms are likely to resist regulation [25] under nutrition policies which would otherwise apply to a food retailer or manufacturer. Moreover, it is unclear whether existing regulations which apply to tangible in-person contexts like nutrition labelling on menu boards and product packaging can be directly transferred to online contexts.

As such, the regulation of OFD platforms will likely require careful navigation of existing nutrition policies or consideration of new policies which specifically apply to OFD and the online environment. The primary aim of this study was to synthesise the existing evidence on OFD platforms under relevant food policy areas to inform nutrition-related policies. A secondary aim was to scan and identify existing nutrition-related policies in Australia and internationally, which have the potential to be applied to OFD platforms.

Methods

A systematic mapping review was conducted to map existing evidence to inform the development and implementation of policies to improve the healthiness of online food delivery services under the key policy areas of Food-EPI. Mapping reviews are similar to scoping reviews as they both address a broad research question to guide future research priorities and decision-making [26]. However, unlike a scoping review which catalogues the evidence in response to what is found in the literature, a mapping review has pre-defined coding categories [26]. Food composition, labelling, promotion, retail, and prices were the pre-defined coding categories for this review as they were considered relevant policy domains for the context of OFD platforms. A mapping review also highlights the areas of uncertainty in the evidence base and summarises the existing evidence base in a visual or tabular way [27]. The review methodology was conducted in a systematic way by developing a review protocol, searching relevant databases, screening, coding, and data synthesis [28]. This review also adhered to the PRISMA-ScR checklist—please see Additional file 1: Table S1.

The review protocol was registered on Open Science Framework on 19 September 2023 (https://doi.org/10.17605/OSF.IO/2SWKQ).

Inclusion and exclusion criteria

The inclusion and exclusion criteria used for the systematic mapping review are outlined in Table 1. Briefly, studies were included if they related to OFD platforms and provided evidence on the Food-EPI domains of interest. Whilst the focus of this review was OFD platforms offering ready-made takeaway meals from restaurants and food service outlets, our search terms were designed to also identify evidence that may apply for other categories of online food retail in the digital food environment such as online groceries and meal-kit subscription services.

Search strategy

For our primary research question, a systematic search of Medline (via Ovid), Embase (via Ovid), CINAHL Complete (via Ovid), Scopus, Web of Science (Web of Science Core Collection (1965–present)), ProQuest Central, Business Source Ultimate was conducted from January 2010 to October 2023, using the following search term categories, combinations, truncations, and synonyms: 'food marketing' OR 'food accessibility' OR 'food labelling' OR 'nutritional quality' OR 'price' AND 'digital platforms' OR 'mobile applications' OR 'internet' AND 'online food delivery' OR 'online food shopping' OR 'online food ordering' OR 'meal delivery'. The full Medline search strategy is provided in Additional file 1: Table S2.

For our second research question, a systematic search of relevant policies was conducted firstly using the Benchmarking Food-EPI in Australia progress report by Sacks & Mann, 2023 [18] and the Food Policy Index resources as a starting point. All of these resources are considered the most up-to-date documentation of the Australian government's progress on nutrition-related policies and are authored by members of INFORMAS—a team of food policy experts with deep knowledge of international best-practice standards [17, 18, 20].

Table 1 PICO with inclusion and exclusion criteria for the mapping review component

PICO	Inclusion	Exclusion
Population	People from all countries, ages, and genders	N/A
Intervention/Exposure	Studies on OFD platforms that relate to one or more areas of Food-EPI including food composition, food labelling, food marketing, food retail, and food prices	Studies that observed food safety/hygiene, consumer behaviours or intention, health or conditions of delivery workers, environmental impacts of OFD, non-commercial food delivery platforms (e.g. for school canteens). Food provision and food trade and investment were considered the least relevant Food-EPI areas that would be applicable to OFD platforms and were excluded
Context	Studies focusing on OFD platforms only. No restrictions on the country of where research was conducted	Clinical settings, online groceries, or supermarkets
Outcomes	Primary outcomes related to each policy area of the Food-EPI and relevant to diet, nutrition, and public health including: • Outcomes on diet, dietary intake, and nutritional status • Food retail: availability and/or accessibility of food outlets • Food composition: nutritional composition or portion sizes or choices of menu/food/beverage items • Food promotion: prevalence and/or analysis of marketing techniques • Food labelling: prevalence of nutrition information including energy/calorie labelling of menu/food/beverage items • Food prices: any outcomes related to pricing, affordability, food purchases, expenditure, spending, and associated behaviours	N/A
Study design	Peer-reviewed journal articles were included such as: cross-sectional studies, cohort studies, qualitative studies, quasi-experimental studies, randomised controlled trials, narrative reviews, and systematic reviews	Study protocols, conference abstracts, theses or dissertations, news articles, market reports, commentaries/editorials/opinions
Other features	Publications from any country; however, in English language only. Studies from 2010 to present were included, as OFD platforms only began to grow in popularity around this time [29]	

Additional searches for international policies were manually conducted in the following databases: NOURISHING framework [30], GINA database (WHO) [31], and Google Scholar. In the NOURISHING and GINA databases, all the listed policies were checked for its relevance to OFD platforms. Key search terms relating to (i) 'policy' or 'guideline' and (ii) 'online food delivery' were used in Google Scholar. All results in Google Scholar were checked. Policies were included if they (i) related to one or more Food-EPI policy area, (ii) had potential to cover OFD settings, and (iii) were relevant to diet and diet-related health outcomes.

Study selection

Records identified from the database searches were collated and uploaded to Covidence—a web-based collaboration software platform that streamlines the production of systematic and other literature reviews [32]. After removing any duplicates, four reviewers (SJ, ART, AAG, SRP) screened titles and abstracts. Each record was reviewed by two independent reviewers. Any discrepancies were resolved with a third reviewer. Following this, two independent reviewers, SJ and ART, screened full texts and checked against inclusion criteria. The remaining discrepancies were discussed and resolved through consensus.

Data extraction

The following relevant information were extracted from the full texts of included studies into a standardised form developed by investigator SJ: study information (author, year, country of origin, study design), participant information (number of participants, baseline characteristics, retention rate), primary outcomes, and relevant results.

Data synthesis

Findings were synthesised narratively and informed by the data extraction table. Relevant study outcomes for each of the five FOOD-EPI areas were extracted from studies. This may have resulted in the number of outcomes being greater than the number of included studies. Descriptions of study outcomes used the original wording and classification systems in each original article for precision.

Results

Study selection

After screening 2012 records, a total of 43 studies were included. Please see Fig. 1 for the PRISMA flow diagram.

Study characteristics

Most studies were cross-sectional in study design. All included studies were published between 2020 to 2023. Thirteen study outcomes were from Europe or United Kingdom (UK) region (28%) with the majority conducted in England. This was closely followed by 11 study outcomes from Asia (23%)—mainly in China. Eight outcomes were from studies conducted in Oceania (17%). UberEats™ was the leading OFD platform investigated amongst the included studies ($n=13$), Menulog™ or JustEat™ was investigated eight times, and Meituan™ was studied four times. See Table 2 for further details on study characteristics.

Study outcomes

Overall, there were 70 relevant outcomes mapped to Food-EPI areas across the 43 included studies (Table 3). Studies may have reported more than one relevant outcome. Most outcomes were relevant policies mapped under 'Food Promotion' (20/70, 29%), followed closely followed by 'Food Retail' (18/70, 26%), and 'Food Composition' (15/70, 21%). Fewer studies reported outcomes relevant to 'Food Prices' (11/70, 16%) and 'Food Labelling' (6/70, 9%).

Food composition

Methodological approaches

Ten studies that examined the food composition or nutritional quality of food outlets and menu items on OFD applications used classification systems. Three studies based their evaluation on national dietary guidelines [33–35], dietary indices [36, 37] or health rating scores [38–40], nutrition calculators [41], or chemical analyses [72]. Two studies used more descriptive methods such as identifying cuisine or food type [42] and subjective measures from participants' perceptions [43].

Ratio of unhealthy to healthy options available on OFD

Across all 15 relevant study outcomes to 'Food Composition', it was evident that unhealthy options outnumber healthy options on OFD platforms. At the outlet level, in Australia and New Zealand, nearly three-quarters of food outlets available were classified as 'unhealthy' [33]. At the menu item level, over 70–80% of total menu items across OFD platforms in various studies were objectively classified as unhealthy [33–35, 40, 44]. In Brazil, beverages offered on the leading OFD platform were mostly ultra-processed (78%), followed by water (49%) and natural juices or smoothies (27%) [44]. A study conducted in Malaysia also observed participants subjectively perceived more than 78% of menu items as unhealthy [43].

Identifying unhealthy vs healthy options

Menu items available on OFD that were analysed or scored to be the least healthy, tended to be set meals [36, 45], 'combos' (a type of meal that typically includes

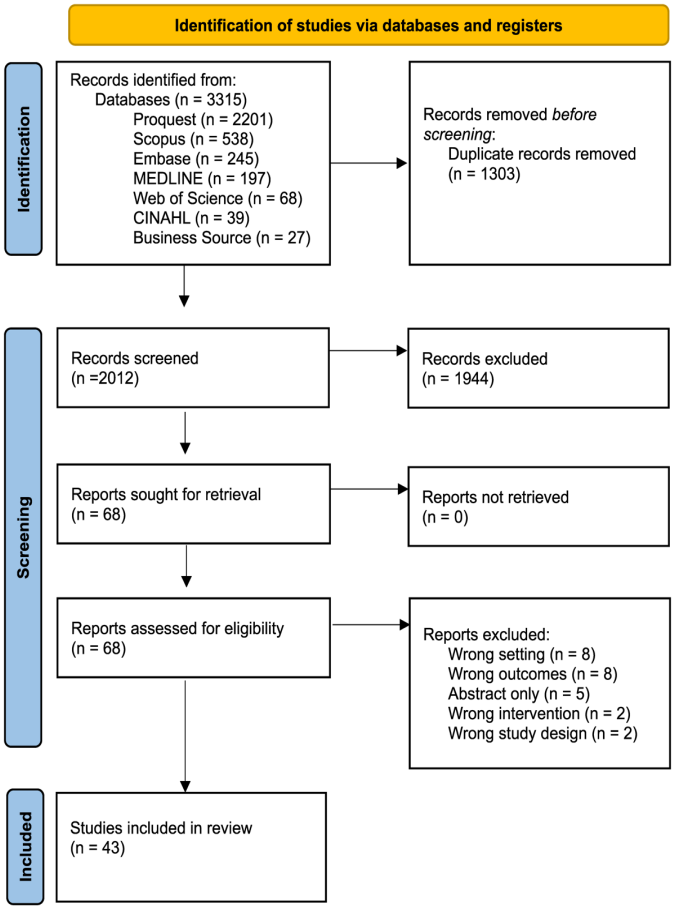

Fig. 1 PRISMA flow diagram using the PRISMA 2020 statement

food items and a beverage) [41], or cakes or desserts [41, 45]. A study from China analysed the healthiness of various food types including noodles and dumplings, set meals, seafood, pot meals, fried and BBQ foods, and healthy and light recipes. Amongst these food types, staple foods and Western fast food comprised the highest proportion of unhealthy meals included [38]. A study from the UK found that the following cuisine tags: pizza, halal, kebab, Italian, American food, Chinese food, desserts, cakes, fish, and chips frequently scored a low health rating of 0 or 1 out of 5 (with 5 being the healthiest) [39]. Indian food, curry, and Bangladeshi food scored slightly higher with a rating of 2 [39].

In contrast, OFD menu options that scored higher for healthiness included: beef and chicken breast salad set meals [36]. The study from the UK observed that Lebanese food scored more positively with a rating of 3 [39].

Nutrients of concern

High saturated fat [41, 42, 72], high sodium [45, 72], and low dietary fibre [72] were flagged as nutrients of concern and were typical of most fast-foods offered on OFD platforms.

Food labelling

Methods

Two studies assessed the prevalence of energy labelling or calorie disclosures on the online menus of third-party OFD platforms [46, 47]. One cross-sectional study observed the impact of energy labelling in a real-world OFD setting [48]. The other three remaining studies were experimental designs on simulated food delivery applications or interfaces, which examined the impact of labelling on food choices in a virtual setting [65–67].

Table 2 Study characteristics ($n=43$)

Study characteristics	Count (%)	References
Study design		
Cross-sectional	26/43 (60.5%)	[33–58]
Longitudinal	4/43 (9.3%)	[59–62]
Content analysis	3/43 (7.0%)	[44, 63, 64]
Experimental	4/43 (9.3%)	[65–68]
Spatial analysis	2/43 (4.7%)	[69, 70]
Randomised controlled trial	1/43 (2.3%)	[71]
Chemical analysis	1/43 (2.3%)	[72]
Desktop review	1/43 (2.3%)	[73]
Qualitative study	1/43 (2.3%)	[74]
Geographical region[a]		
Europe/UK	13/47 (28%)	[39, 42, 53, 54, 60–62, 65, 68, 71, 74]
Asia	11/47 (23%)	[36, 38, 41, 43, 45, 52, 55, 57, 58, 70, 72]
Oceania	8/47 (17%)	[33–35, 40, 50, 56, 64, 73]
North America	7/47 (15%)	[37, 46, 47, 50, 51, 67]
Latin America	6/47 (13%)	[44, 49, 59, 63, 66, 75]
Middle East and North Africa	2/47 (4%)	[48, 69]
Online food delivery platform investigated[b]		
Uber Eats™	13/67 (19.4%)	[33–35, 37, 40, 42, 46, 47, 51, 60, 63, 64, 73]
Menulog™ or Just Eat™	8/67 (11.9%)	[39, 40, 53, 54, 60, 61, 64, 73]
Meituan™	4/67 (6.0%)	[36, 38, 57, 70]
DoorDash™	4/67 (6.0%)	[37, 46, 47, 51]
Deliveroo™	3/67 (4.5%)	[42, 60, 64]
GrubHub™	3/67 (4.5%)	[46, 51, 64]
Virtual/mock delivery app	5/67 (7.5%)	[65–68, 71]
Other (fewer than 3 counts each)	16/67 (23.9%)	[37, 40, 41, 45, 47, 49, 58, 59, 63, 73, 75]
Not specified	11/67 (16.4%)	[43, 44, 48, 50, 52, 55, 56, 62, 69, 72, 74]

[a] Total count is greater than the number of included studies as two studies reported outcomes from more than one geographical region

[b] Total count is greater than the number of included studies as a few studies reported outcomes for more than one OFD platform

Warning labels

In a virtual experiment conducted by Gugliucci and colleagues, participants who were provided with nutritional warnings on OFD websites were less likely to have selected a dish or beverage with excessive content of at least one deleterious nutrient such as saturated fat, sugar, or sodium [66].

Compliance with menu labelling laws

Despite mandatory requirements for menu labelling laws, calorie disclosures were not properly implemented on online menus in Canada [47] and the USA [46]. Moreover, it was identified that there were variations in prevalence of menu labelling across different third-party platforms in both studies.

Impacts on food choices

In a real-world setting in Saudi Arabia, 42% of participants who noticed calorie labelling on menu items indicated that they would change their order by ordering less food, eating less food, or choosing another restaurant [48]. In virtual settings, these impacts on food choices were more mixed. Whilst two experimental studies showed labelling was effective in dissuading consumers from unhealthier choices through nutritional warning labels [66] and calorie labelling [65], one experimental study showed there was no significant impact on consumers' intention to purchase through OFD [67].

Food promotion

Methods

Ten outcomes were obtained from cross-sectional studies that have analysed the content on OFD platforms during a specified time—for example from 6 pm on a Friday [33–35, 42, 45, 49, 50, 59, 73, 75]. Two studies that have examined how foods and beverages are promoted on OFD platforms have used frameworks to code marketing strategies [63, 64]. Nudging trials [71] and experimental

Table 3 Map of study outcomes to food environment domain ($n = 70$)

Study author, year	Food composition	Food labelling	Food promotion	Food prices	Food retail
Abdulkader R, 2022 [41]	X			X	
Alkhaldy A, 2023 [48]		X			
Bianchi F, 2023 [71]		X	X	X	
Botelho L, 2023 [63]			X		
Brar K, 2021 [37]	X				X
Cong N, 2022 [38]	X				X
Dai X, 2022 [36]	X				
De Paula Matos J, 2023 [49]	X		X		
Eu E, 2021 [43]	X			X	
Feizizadeh B, 2023 [69]					X
Finlay A, 2023 [65]		X	X	X	
Goffe L, 2020 [39]	X				
Greenthal E, 2023 [46]			X		
Gugliucci V, 2021 [66]		X			
Gunden N, 2020 [67]		X	X		
Horta P, 2021 [75]	X		X	X	
Horta P, 2021 [44]			X		
Horta P, 2022 [59]			X		
Jia S, 2021 [64]			X		
Jitsoonthornchaikul M, 2022 [45]	X		X		
Kalbus A, 2023 [60]					X
Keeble M, 2021 [53]					X
Keeble M, 2021 [54]					X
Keeble M, 2022 [74]			X	X	
Keeble M, 2023 [61]					X
Li L, 2023 [58]					X
Mahawar N, 2022 [35]	X		X	X	
Maimaiti M, 2020 [55]					X
Miles H, 2022 [73]			X		X
Norriss D, 2022 [40]	X				X
Oostenbach L, 2022 [56]					X
Partridge S, 2020 [33]	X		X	X	X
Pinho M, 2020 [62]					X
Poelman M, 2020 [50]			X		X
Ratilla M, 2022 [68]			X		
Ren J, 2020 [72]	X				
Rinaldi C, 2022 [42]	X		X		X
Shi Y, 2021 [57]					X
Talamini G, 2022 [70]					X
Thompson H, 2022 [51]			X	X	
Vanderlee L, 2023 [47]		X			
Wang C, 2021 [34]	X		X	X	
Wu Y, 2022 [52]				X	
Total per food-EPI area	15	6	20	11	18
Total outcomes	70				

studies [66–68] have assessed the impact of different promotion or marketing strategies in a virtual setting.

Marketing strategies

Images Use of images was found to be a common marketing strategy in six studies [34, 35, 44, 49, 59, 75]. In three of these studies, images were found to be more frequently used on unhealthful menu items such as ultra-processed beverages, ice cream, candies, and salty-packaged snacks [44] or discretionary meals that are high in energy, sugars, salts, and saturated fats [34, 35]. In one experimental study using a virtual OFD platform, researchers found a positive effect of image type on consumers' intentions to purchase [67]. The display of consumers eating food items, compared to food item only, was associated with purchasing through the virtual OFD platform [67].

Price promotion Price promotions were another common marketing strategy used by OFD platforms [34, 35, 42, 49, 73, 74]. These included the offer of free delivery [49, 73], price discounts [42, 49, 73], value bundles [34, 35] and loyalty points [73]. Price promotions were also more generally used on menu items that were high in sugars, fats, or salt [42, 44, 59, 75].

Digital salience nudges

Nudging interventions refer to deliberate changes to and designs of people's choice environments—the ways in which options are presented or framed—which can influence behaviours [76]. Digital nudging refers to nudges implemented in digital environments and present multiple advantages for influencing user behaviour compared to analogue settings [77]. In digital settings, user interfaces can be highly adaptable to increase the salience of items and may be more likely to be purchased [77]. For example, studies showed that menu items labelled as 'most popular' were commonly presented at a prominent position on OFD platforms. Three studies which investigated the most popular menu items found that these foods and beverages did not meet dietary guidelines in their respective countries [33–35, 45].

A five-armed randomised controlled trial from the UK established that repositioning of both foods and food outlets in order of lowest energy content to highest energy content on a virtual mock food delivery app had the greatest effect in lowering the energy content of baskets at checkouts [71]. Similarly, another virtual experimental study from the Czech Republic showed that when healthier restaurants were displayed on the ordering page, the odds of a healthier choice were nearly four times higher than in the low availability condition [68].

Content—what is being promoted?

One study conducted on restaurants in Amsterdam, Melbourne and Chicago, highlighted the use of keywords or category tags associated with a food outlet, as a way to advertise meal options on OFD platforms [50]. In all three cities, burgers, pizza, and Italian were in the top 10 most advertised meals. Keywords such as 'healthy' were advertised less often.

Food prices

Methods

Relevant study outcomes for food prices on OFD platforms were extracted from eight cross-sectional studies [33–35, 41, 43, 51, 52, 59], two 'nudging' experimental studies [65, 71], and one qualitative study [74].

Food prices in relation to healthiness

Two studies found that menu items on OFD platforms that were the least expensive were often poor in nutritional quality [35, 41]. In India, items from fast-food restaurants that were available on the OFD platform had the highest median calorie content (194 kcal), but were priced the lowest with a median price of 100 INR or $1.20 USD [41]. A study from Auckland, New Zealand, found that discretionary mixed meals—dishes that are meat-based or vegetable-based that are energy-dense and nutrient-poor—were significantly less expensive compared to mixed meals that predominantly comprised of the five food groups which align with dietary guidelines [35]. Contrarily, in Sydney, Australia, menu items that were assigned a 'discretionary' food category were found to be slightly more expensive than items of the 'five food groups' [34]. Despite this, discretionary foods were more likely to have a 'value bundle' as a price promotion strategy which would reduce the costs of these foods [34].

A study in Brazil showed that price discounts were mostly offered on unhealthier items such as beverages that were ultra-processed according to the NOVA classification system [59]. At the same time, healthier menu items such as water, vegetables, natural juice, and smoothies only comprised less than 5% of all price discounts offered [59]. One study also observed that compared to sugar-sweetened beverages, water was most likely to have an additional fee on OFD platforms in California, USA [51].

Differences in pricing of OFD across countries

Main meals In China, most participants reported spending less than 20 Chinese Yuan ($2.77 USD) per order [52]. In Malaysia, most participants reported spending between RM15 to RM19 on orders ($3–$4 USD) [43]. Similarly in India, the median average cost for an OFD order for two people was reported to be 300 INR ($3.60 USD) [41]. In contrast however, the median price for discretionary cereal-based mixed meals such as pizza in New Zealand was $12.60 NZD ($7.56 USD) and for a discretionary meat-based mixed meal such as fried chicken was $16.00 NZD ($9.60 USD) [35].

Delivery Delivery costs were reported in three studies. In Sydney, the median delivery cost was observed to be $5.99 AUD ($3.92 USD) [33], and in Auckland, New Zealand, the median delivery cost was $7.99 NZD ($4.79 USD) [33]. These prices differ greatly to the delivery costs reported from a study in China, which were between 2 and 3 Chinese Yuan ($0.30–$0.64 USD) [52].

Impact of price on consumer choices

A qualitative study revealed that price promotions on food items were found to be highly appealing to users of OFD [74]. Likewise, price and convenience were cited as the predominant factors impacting food choice on OFD apps by users in Malaysia [43]. In a study conducted in China, delivery charge was observed to have had the greatest impact on the likelihood of consumers using OFD [52]. The greatest probability of consumers 'certainly' using OFD is when the delivery charge is within the range of 0 ~ 1.4 Chinese Yuan ($0.19 USD). When delivery charge exceeded 3 Chinese Yuan ($0.64 USD), the probability of consumers choosing 'totally impossible' was the greatest [52].

One 'nudging' study examined the impact of proportional pricing on meal, sandwich, and drink size selection and subsequent money spent on a mock delivery app [65]. It was found that proportional pricing may prompt consumers to select smaller portion sizes—participants who were in the proportional pricing condition had a decreased likelihood of choosing a larger sized beverage from the virtual coffee shop (OR: 0.58) [65].

In another nudging study using a mock delivery app, an intervention where food options were repositioned to give more prominence in a higher screen position to lower-energy but higher-priced foods and restaurants, resulted in reduced energy content and increased basket price [71]. Authors from this study highlighted the potential of such an intervention widening inequalities as individuals of higher socioeconomic position may have more benefits from reducing the energy content of their baskets [71].

Food retail

Methods

There were 11 cross-sectional studies which have examined aspects of food retail [33, 37, 38, 40, 42, 50, 53–57], 3 longitudinal studies observed changes over time [60–62], 3 studies used spatial analyses and advanced geographical methods [58, 69, 70], and 1 study was a desktop review [73].

Most studies analysed the geographic location of retailers offering OFD, including elements of accessibility, in association with urbanisation, population density, and deprivation level.

Urbanisation, population density, and OFD accessibility

All the studies that examined urbanisation and population density, which included evidence from Iran [69], Netherlands [62], China (Shanghai [57] and Nanjing [58]), Canada [37], and New Zealand [73], showed that accessibility to food options available via OFDs was greatest in central, urban areas with high population density.

In two studies, restaurants offering home delivery were developed in wealthier sub-towns in Iran [69] or areas that were more economically developed in China [58].

Socioeconomic deprivation and OFD accessibility

Region-specific associations between area deprivation and OFD accessibility were observed in a study conducted in England [60]. In the North of England, areas of greatest deprivation had an increased number of delivering outlets compared to the least deprived quintile [60]. In London, higher postcode district deprivation was associated with lower numbers of delivering outlets [60]. This finding for London however contradicted results from another longitudinal study conducted in England which was conducted prior to COVID-19. Researchers found evidence of a positive dose–response relationship between deprivation and number of OFD outlets across *all* postcode districts in England [61].

A study which examined three international cities also showed differing results in access to OFD options and socioeconomic deprivation [50]. Whilst Amsterdam, Netherlands, and Melbourne, Australia, showed some indication of a relationship between increasing deprivation with OFD accessibility, Chicago, USA, showed no difference in delivery options between the most and least disadvantaged neighbourhoods [50].

Another longitudinal study which investigated changes in the food environment across the whole of the Netherlands found that there was an increase in outlets offering OFD in neighbourhoods of both lowest (IRR = 2.15, 95%CI = 1.90–2.44) and highest (IRR = 3.00, 95%CI = 2.32–3.97) socioeconomic status. This increase was more pronounced or greater, in areas of higher socioeconomic status [62].

A cross-sectional study conducted in Sydney, Australia, and Auckland, New Zealand, also showed some differences between cities. In Sydney, whilst 60% of food outlets were located in the most advantaged suburbs, food outlets were found to be more evenly distributed across deprivation quintiles in Auckland [33].

OFD accessibility and associations with use

One study from England used linked data to analyse associations between OFD accessibility and the use of OFD platforms. It was established that compared to those with the lowest number of accessible food outlets on an OFDS, those with a greater number of accessible outlets had 71% greater odds of OFDS use (OR: 1.71, 95%CI: 1.09, 2.68) [54].

A study in Melbourne, Australia, investigated associations between the use of OFD platforms with whether an individual had access to a '20-min neighbourhood' (20-MN), which is a part of a state-level strategy to accommodate urban growth and ensure liveable neighbourhoods [56]. It was hypothesised that those that do not live in a 20-min neighbourhood would order home delivery for takeaway foods more frequently. Despite this, the authors of this study did not find a significant difference in use of OFD platforms between those living in 20MN vs Non-20MN neighbourhoods [56].

Delivery distances

A few studies reported on the mean or median delivery distances between food retailers and delivery locations which was defined by postcode. Median delivery distance in Sydney was 3 km and 3.2 km in Auckland [33]. In Ontario, Canada, the mean delivery distance was 3.7 km and ranged between 0.3 and 9.4 k m [37]. A study conducted in Iran found restaurants developed widespread business by extending their service area by up to 15 km from their physical location [69].

Dark or 'ghost' kitchens

Two studies identified dark kitchens as a unique aspect of OFD platforms as these outlets only sell meals through delivery and do not offer any dine-in services [42, 70]. One of these studies which was conducted in England found 3 dark kitchens which rented its space to 116 food businesses [78]. Another study found that most of the businesses which used the dark kitchen space were virtual restaurants (21%), selling fast-food (47%), or dessert (21%) through online delivery platforms [42]. In China, it was found that dark kitchens may potentially reduce a restaurant's dependence on location and use more vertical space in high-rise office spaces [70].

Potential nutrition-related policy options

Only three nutrition-related policies that have specifically mentioned or designated responsibility to OFD platforms

Table 4 Existing policies or regulations in international jurisdictions that either apply specifically to OFD platforms or contain specific provisions related to OFD platforms

Food-EPI policy domain	Existing international policies or guidelines	Existing policy objective or scope with relevance to online food delivery
Food labelling	England: The Calorie Labelling (Out of Home Sector) Regulations 2021 [79]	Mandatory Effective date: 6 April 2022 Summary: Large businesses that have more than 250 employees must provide calorie information including businesses responsible for the website or mobile application ('remote' provider)
Food composition	Singapore: Healthier Dining Programme [81]	Voluntary Effective date: 2015 Summary: Food and beverage businesses including dark kitchens or businesses that only operate on OFD applications, are encouraged to provide healthier meals for customers—reducing calories, using wholegrains and healthier cooking oils
Food promotion	EU: The Digital Services Act (DSA) [80]	Mandatory Effective date: 17 February 2024 Summary: Digital services including online marketplaces and very large online platforms are prohibited from using dark patterns online to ensure more transparency around advertising. Services are not allowed to design, organise, or operate their online interfaces in a way that deceives, manipulates or impair the ability of users to make free and informed decisions

were identified from the policy scan (Table 4A). The Calorie Labelling (Out of Home Sector) Regulations 2021 introduced in England affects businesses responsible for the website or mobile application ('remote' providers) to ensure that calorie information is displayed [79]. In terms of food promotion, the European Union (EU) has initiated the 'Digital Services Act' to encourage more transparency around advertising through platforms and bans certain types of targeted advertising [80]. In Singapore, the voluntary 'Healthier Dining Programme' [81] allows food and beverage companies that operate solely on digital platforms to apply to get menu items endorsed by the Health Promotion Board in Singapore by offering three or more healthier food or beverage options which adhere to the guidelines.

We also identified several nutrition-related policies which target traditional local food environment settings and have the potential to adapt these to include or address the health impacts of OFD platforms (Table 5). Most of these policies have targeted food labelling, food promotion, and food composition. There was a lack of both existing and potential policies for food prices or food retail.

Discussion

Key findings

OFD platforms have been identified as a potential concern for population health and well-being that may require the creation and implementation of protective measures through policy and regulation. This systematic mapping review synthesised the current evidence to inform potential food environment policies for OFD platforms, under five main policy domains. Of the 70 relevant outcomes from the 43 included studies, 29% can largely inform nutrition-related policies for food promotion, 26% for food composition, and 21% for food retail aspects of OFD platforms. Globally, existing regulation of OFD platforms remains scarce, highlighting an important regulatory gap. Effective policy options may promote increased access to healthy and affordable meals on OFD platforms. This may be a promising opportunity to bridge inequities in food accessibility, particularly for vulnerable groups such as those with a physical disability or low income.

Do OFD platforms need specific nutrition policies?

OFD platforms have emerged as a disruptor to food environments and have yet to be widely included in existing nutrition-related policies. Results from the policy scan revealed only three existing nutrition-related policies that currently regulate or specifically apply to OFD platforms [79–81], with one of these only a voluntary guideline. We found several other international examples of existing policies that apply more broadly to takeaway foods and food outlets and have the potential to be amended to include OFD platforms. These were largely food labelling policies such as mandatory kilojoule labelling on menus from fast-food franchises that had yet to include OFD platforms as a type of food retailer subject to regulation. Studies included in the review showed that OFD platforms adhered poorly to existing menu labelling laws in Canada [47], USA [46], and recent research from Australia [99]. In addition, the policy scan indicated that current food promotion policies may need more refinement to specifically define OFD platforms as a 'digital platform' that advertise unhealthy foods and beverages to children. Policies which currently target food composition may improve the nutritional quality of foods offered on OFD platforms; however, most of the existing policies are voluntary initiatives.

In other Food-EPI policy areas, such as food retail, the applicability of existing policies to OFD platforms is complex and new types of policies may be required. For example, any existing zoning regulation would need to consider the impact of food delivery services and its link to dark kitchens, as these could deliver unhealthy foods within 400-m or 800-m restriction zone as defined in current policies [100]. Semi-structured interviews with policy experts in New Zealand suggested that density regulation would be impractical or less relevant, considering the wide coverage of on-demand delivery services [101]. Development plans may also need to consider how the existence of dark kitchens affect use of land and provision of services and amenities in a given area. Planning guidelines and zoning regulations must also be 'future-proof' to account for further innovations in food delivery. For instance, drone delivery is increasingly being tested in Australia [102] and is becoming more established in countries such as China [103] and the USA [104]. These are important factors for policymakers to consider in urban planning or designing policies around urbanisation of cities as evidence gathered in this review suggest that urbanised cities have the highest food delivery serviceability.

Similarly, new policies targeting food prices may need to be created as no existing or potential policies were identified. As the evidence from the mapping review component showed, effective fiscal measures could target the delivery costs of using OFD platforms. Findings from this review also showed that aspects of food promotion and food prices could be considered together when designing feasible policy options. Limiting the number of price promotions offered on OFD platforms could subsequently increase costs and thereby discourage frequent use of these services. At the same time, higher costs of

Table 5 Policies that apply to out-of-home foods and restaurants in traditional local food environments with no specific application to OFD platforms but have the potential for future amendments to consider the impact of OFD platforms

Food-EPI policy domain	Existing international policies or guidelines	Existing policy objective or scope with relevance to online food delivery
Food labelling	Saudi Arabia: Saudi Food Nutrition Labelling Policy [82]	Mandatory Effective date: 1 January 2019 Summary: All restaurants and coffee shops must disclose the calories of their selling items on menus, in all forms, whether physical or online
	Canada, Ontario: The Healthy Menu Choices Act [83]	Mandatory Effective date: 1 January 2017 Summary: Food service premises that are part of a chain of 20 or more in Ontario are required to display calories for standard food items on menus, labels and display tags. Menus include online menus or menu applications
	USA, New York: New York City Health Code Article 81.50 Posting of Calorie Information [84]	Mandatory Effective date: 1 December 2016 Summary: Establishments that are part of a chain with more than 15 locations in the US must display calorie labelling on menus and menu boards including electronic menus, menus on internet or electronic screens
	Australia (5 jurisdictions including New South Wales, Victoria, Queensland, Australian Capital Territory, South Australia): Menu labelling laws or '2011 Principles' [85]	Mandatory Effective date: Various dates between 2011 and 2018 Summary: Standard food outlets with more than 20 locations in a state or 7 locations in a territory, or > 50 nationally, must provide kilojoule labelling at point-of-sale
Food composition	United States, Philadelphia: Philadelphia Healthy Chinese Take-Out Initiative [86]	Voluntary Effective date: March 2010 Summary: Chefs from 206 Chinese take-out restaurants in Philadelphia were trained and taught strategies to reduce sodium in prepared dishes
	England: Local Authority Healthier Catering schemes or awards [87]	Voluntary Effective date: 2010 Summary: Food outlets in local councils are encouraged to switch to healthier ingredients, menus, and cooking practices. Examples include reduction in salt, fat, sugar, serving smaller portions, providing calorie information
	Portugal: Stamp of Excellence "Bread with less salt, same flavour" [88]	Voluntary Effective date: 2018 Summary: Portuguese bakeries encouraged to reach the 2021 target set for reformulation of salt content (1.1/100 g)
	Canada, British Columbia: The Public Health Impediments (BC Trans Fat) Regulation [89]	Mandatory Effective date: 2009 Summary: Food service outlets are not permitted to use margarines and oils with a trans-fat content > 2% and other food with a trans-fat content of > 5%
	Malta: Commission Regulation (EU) 2019/649 [90]	Mandatory Effective date: 24 April 2019 Summary: Foods intended for final consumer should not exceed 2 g/100 g of trans-fat

Table 5 (continued)

Food-EPI policy domain	Existing international policies or guidelines	Existing policy objective or scope with relevance to online food delivery
Food retail	England: National Planning Policy Framework and Planning Practice Guidance for Healthy and Safe Communities [91–93]	Voluntary Effective date: 2023 Summary: Government planning guidance to encourage healthier 'out of home' food provision. For example, local planning authorities have used guidance and supplementary planning documents to restrict takeaways and other food retail outlets in specific areas (e.g. within walking distance of schools)
	Scotland: National Planning Framework 4 [94]	Voluntary Effective date: 2023 Summary: Sets out spatial principles, regional priorities and new rules for local development plans in relation to hot food providers and should identify where proposals for healthy food and drink outlets can be supported
	USA, Detroit: Zoning Ordinance [95]	Mandatory Effective date: 1998 Summary: Requires a distance of at least 500 feet between elementary, junior and senior high schools, and restaurants including take-out, fast-food and drive-through restaurants

Table 5 (continued)

Food-EPI policy domain	Existing international policies or guidelines	Existing policy objective or scope with relevance to online food delivery
Food promotion	EU: The Digital Services Act (DSA) [80]	Mandatory Effective date: 17 February 2024 Summary: Digital services including online marketplaces and very large online platforms are prohibited from using dark patterns online to ensure more transparency around advertising. Services are not allowed to design, organise, or operate their online interfaces in a way that deceives, manipulates or impair ability of users to make free and informed decisions
	Chile: The Law on Nutritional Composition of Food and its Advertising (Ley 20.606) [96]	Mandatory Effective date: 27 June 2016 Summary: TV programmes and websites directed to children under the age of 14 must restrict their advertising of foods that contain high energy, salt, sugar and fat content
	Portugal: Law 30/2019 amending the Portuguese Advertising Code [97]	Mandatory Effective date: 1 October 2019 Summary: Advertising ban of food and beverages that contain high energy, fat, sugar, salt content directed to children under 16 years. Applies to websites, webpages, apps and social media profiles with content intended for this age group
	Brazil: Resolution 163 of the National Council for the Rights of Children and Adolescents [98]	Mandatory Effective date: 13 March 2014 Summary: Prohibits any abusive publicity of food via any form of market communication (TV, radio, internet, apps) intended to persuade children (up to 11 years) and adolescents (12 to 18 years), to consume a product or service using strategies that appeal to children
	Peru: The Law Promoting Healthy Eating for Children and Adolescents (Ley No 30021) [96]	Mandatory Effective date: May 2013 Summary: Restrictions for advertising of foods and drinks high in sugar, salt and saturated fat, aimed at children and adolescents under the age of 16 years through any medium

OFD platforms may further disadvantage individuals and groups at lower income levels who may potentially use price promotions to purchase healthier foods online. Future pricing policies relating to OFD platforms will therefore need to carefully consider the impact on various socioeconomic groups.

Platform vs food outlet—where should responsibility be delegated?

The World Health Organization, in their 'Slide to Order' report, envisaged the inevitability of the development of new OFD companies and recommended companies to prioritise health as a focus from their inception [105]. As such, it is important to consider delegating the responsibility of OFD platforms in nutrition-related policies. Evidence from studies for food promotion policies suggests that platforms themselves have a potential role to play in promoting more healthful choices online [68, 71]. Although the evidence is limited, the positioning of menu items appeared to have a significant effect on consumers' choices in virtual experiments using a simulated delivery app [68, 71]. Thus, reordering menu items and food outlets from lowest to highest kilojoule or calorie count may prove to be an effective policy option. These 'digital nudging' techniques have been shown to be effective in a range of other settings as well—for example, in virtual supermarkets [106] and in school canteens [107]. Moreover, The World Health Organization Representative Office in China has tested the effectiveness of health messages and changes to the choice architecture on a popular OFD app. Findings showed that when consumers were presented with a sub-menu that had 'reduced salt' options, they were able to choose healthier options with less salt compared to the control group [108].

Food labelling policies may also need to delegate accountability to third-party delivery platforms as studies show that energy labelling is often missing or incomplete [46, 47, 99]. Systematic reviews and meta-analyses have found that nutrition labelling [109, 110] and menu labelling [111] are effective policies and can reduce the total energy of foods that are purchased and consumed. From the policy scan, only England appeared to have regulations that explicitly and specifically designated accountability to the OFD platform to ensure menu labelling was present for all standard food outlets [79]. Food labelling may be the easiest regulation to target for OFD platforms, considering the nutrition labelling information for large food outlets already exists. This would therefore be a matter of transferring the information accurately online with thorough monitoring and enforcement and would provide consumers with a more consistent nutrition information environment across settings.

Improving the physical food environment to improve online environments

Results from the mapping review and policy scan revealed that food composition policies focus mainly on improving physical food environments in-person, by setting standards for nutritional quality of out-of-home foods. Improvements to the physical, offline food environment will result in parallel improvements in online food environments, and vice versa, as these environments are often overlapping. Several existing policy guidelines showed collaboration between food outlets and local government authorities to improve or endorse healthier menu items. A study from China conducted in 2020 observed substantial consumer demand for salt-reduced meals from the 'Eleme' food delivery app—with 40.6% of all order requests asking for reduced salt [112]. It was shown that over 90% of restaurants were willing to respond to these consumer requests and laboratory analyses revealed that these dishes were indeed lower in salt than regular meals [112]. This study shows a potential role for the delivery platform itself in enabling an option for requests to be made and for food retailers to observe and complete these requests. Thus, this highlights important potential for collaborative efforts between food retailers, the food delivery platform, and policymakers to improve the nutritional content of menu items. Clear definitions of what constitutes 'healthier' options in the restaurant sector with associated nutrient profiling methods would also support reformulation efforts.

Leveraging existing and impending regulation in other sectors

Leveraging existing or impending regulation in other sectors may also be a consideration for policymakers. In Australia, the 'Closing Loopholes' bill was introduced in early 2024 to protect and uphold the rights of gig economy workers. Despite this bill being primarily a workplace law, there may be subsequent effects on consumers of food delivery apps and their food choices. It is speculated that this bill will likely increase delivery costs and could deter use of a meal delivery app [113]. There is also potential however for some costs to be absorbed by large food retailers with small independent food businesses the most vulnerable to such changes [113]. It is therefore unknown whether long-term, these smaller retailers continue to partner with third-party delivery services and if they leave, whether that results in a further saturation of large franchise restaurants on OFD platforms mostly offering unhealthy fast-food options. Reduced accessibility to smaller independent food businesses may also increase the power that large franchises and multinational companies already hold in the current food system [12, 114].

Furthermore, in early 2024, the federal government in Australia called for a public consultation to design a feasibility study on options to limit unhealthy food marketing to children [115]. Impending regulation around unhealthy food marketing to children therefore may be applicable to OFD platforms and is an opportunity for policy change to be made. As shown in the policy scan component of this study, many countries especially in the Latin American region have existing policies in place to restrict junk food marketing to children on websites, apps, and platforms [96–98]. Further action could be initiated by redefining and updating 'unhealthy brands' or 'digital platforms' in current definitions to include OFD platforms as the evidence accrued in this review demonstrates the excessive promotion and abundance of unhealthy foods on these platforms.

Food safety, including the disclosure of allergen information through OFD platforms, is also a potential consideration for improved regulation. Deaths resulting from undisclosed information of menu items containing allergens that were ordered via a third-party delivery service [116] has prompted further scrutiny of food safety and allergen management. These cases highlight a great responsibility in which OFD platforms must ensure all relevant information is provided and procedures for rigorous assessment of partnered restaurants and their adherence to food safety standards are arranged and implemented.

Strengths and limitations

In terms of strengths, this study presents a comprehensive overview of the existing evidence from seven databases, covering key relevant policy areas. This review also identified gaps in the evidence base and synthesised relevant international policy examples that can be used as starting points for further policy action. Given the growing body of the literature on OFD platforms, this is a timely review that aims to provide direction for future research that is policy relevant. For example, complex issues such as the effect of OFD platforms on different socioeconomic groups must be explored further and need further policy attention.

There are limitations in this study that should be noted. Firstly, the search of relevant international policy examples may be incomplete due to the manual process and predominant use of one database (NOURSHING [30]). Nevertheless, the purpose of this component of the mapping review was to provide a preliminary overview of the policy environment for policymakers or academics to consider in pursuit of feasible policy options.

In addition, due to the broad nature of a mapping review, a critical appraisal of studies was not performed. As such, caution is warranted in the interpretation of the study results due to potential risk of bias present in the included studies. Despite this limitation, this mapping review has captured the emerging nutrition-related policy implications of OFD platforms in a timely manner.

Conclusions

OFD platforms are set to reach over 2.8 billion users globally by the next decade. Several policy avenues could be considered which may mitigate overexposure and increased accessibility to unhealthful foods offered on these platforms and could provide opportunities to increase access to healthy and healthier food options. Moreover, through their relationships with a large number of restaurants and food providers, there may be an opportunity for OFD platforms to positively influence the broader food environment. Creating a suite of suitable and effective policy options with monitoring and review mechanisms is needed to adapt to this rapidly changing food environment. This review demonstrated that whilst most of the current evidence can support new policies for food promotion, food retail, and food composition, the most feasible short-term strategy for regulation may be food labelling which has existing policies that can be adapted to include OFD platforms. Responsibility of OFD platforms to implement must be clearly outlined and designated in all relevant policies, and it is important to consider digital environments in regulation from other sectors that can be leveraged for population health benefits.

Abbreviations

INFORMAS	International Network for Food and Obesity and Non-communicable Disease Research, Monitoring and Action Support
Food-EPI	Healthy Food Environment Policy Index
NCD	Non-communicable disease
OFD	Online food delivery

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12916-024-03747-8.

Additional file 1: Tables S1 – S2. Table S1: Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist. Table S2: Full Medline Search Strategy.

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Authors' contributions

S.J. – Conceptualization, Literature search, Title, abstract and full-text screening, Data extraction, Writing – Original Draft, Writing – Review & Editing. A.R.T – Title, abstract and full-text screening, Writing – Review & Editing. S.R.P and A.A.G – Supervision, Writing – Review & Editing. P.F., M.A-F., L.V. and G.S. – Writing – Review & Editing. All authors have read and approved the final manuscript.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

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Competing interests
The authors declare no competing interests.

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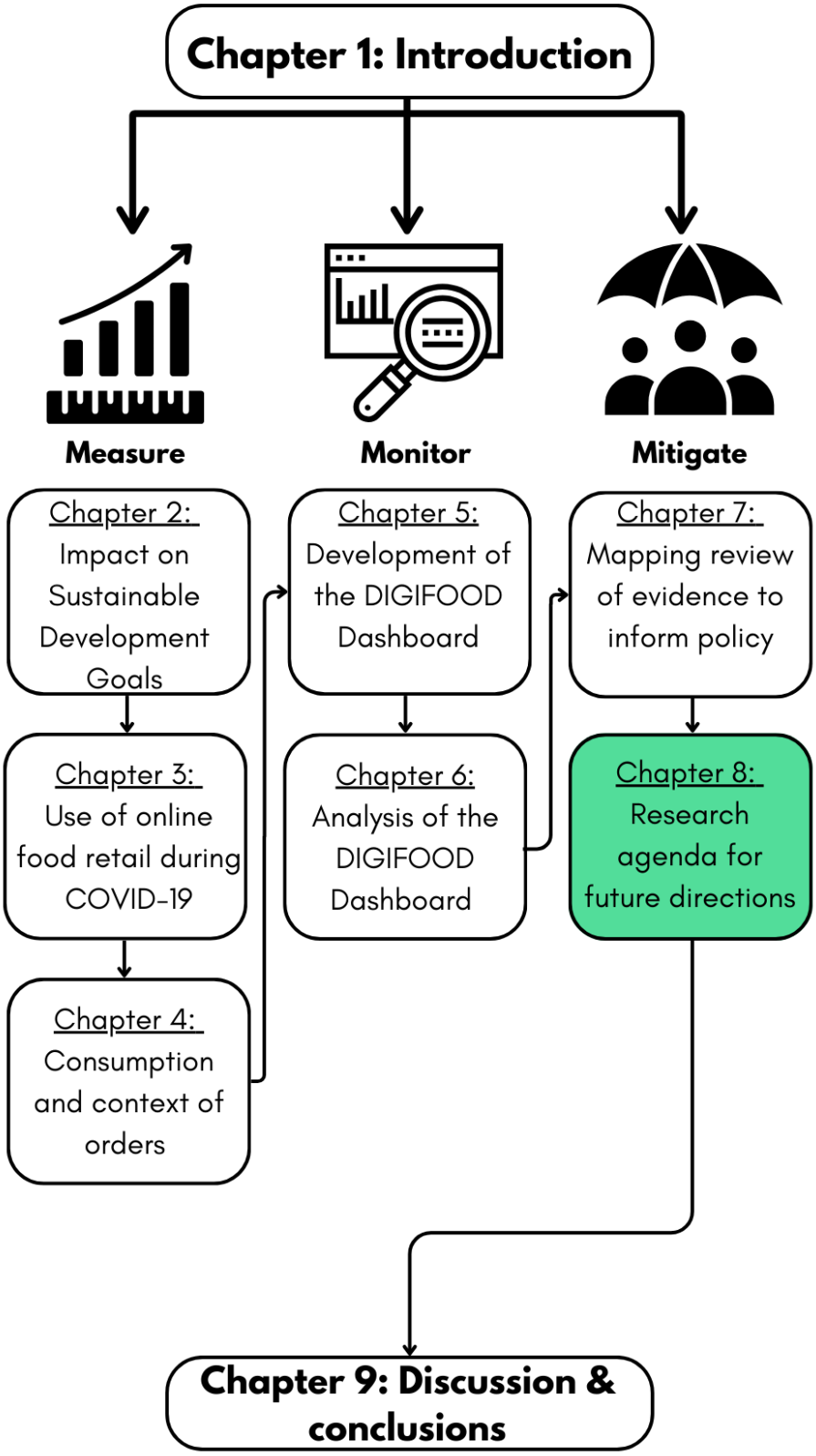
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Chapter 5: Development of the DIGIFOOD Dashboard
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Chapter 7: Mapping review of evidence to inform policy
Chapter 8: Research agenda for future directions
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CHAPTER 8 | RESEARCH AGENDA FOR FUTURE DIRECTIONS

Preface to the chapter

Chapter 8 has examined the evidence for meal delivery applications in context of the United Nations Decade of Action on Nutrition and proposed a research agenda on its population health impacts, to advance the Nutrition Decade into the future. This chapter thereby addresses Aim 7 of the thesis and contributes to the third sub-theme of 'mitigating risks which meal delivery applications pose to population diets and health'. As an emerging PhD researcher, I proactively reached out to two other emerging early-career researchers in this field who I met during my candidature, to collaborate on this research agenda. This article has been peer-reviewed (submitted 15th October 2024, revised 11th December 2024) and published (20th March 2025) in *European Journal of Clinical Nutrition*. Author contributions to this paper are outlined in the authorship attribution statement.

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I am the first author for this article which was published in *European Journal of Clinical Nutrition* in March 2025.

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Author attribution statement

This statement is to specify the contribution made by Si Si Jia in the preparation and submission of the following manuscript included in this chapter: “The emergence of meal delivery applications: A research agenda to advance the next decade of progress in nutrition”.

As first author, Si Si Jia was primarily responsible for formulating the research question, conducting the literature search of peer-reviewed publications and grey literature for policy examples, writing of the draft manuscript and subsequent revisions.

The individual roles of all co-authors are listed below:

Task	**Role of co-authors**
Conceptualisation	SJ
Writing – Original Draft	SJ, RB, AG
Writing – Revision	SJ, RB, AG

Si Si Jia 25 March 2025

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

Dr Stephanie Partridge 25 March 2025

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The emergence of meal delivery applications: a research agenda to advance the next decade of progress in nutrition

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The United Nations Decade of Nutrition was declared on 1 April 2016 to accelerate action to achieve global nutrition and diet-related non-communicable disease targets by 2025. Meal delivery applications offering takeaway meals and ready-to-eat foods from restaurant kitchen to doorstep via a third-party courier, have proliferated as a new digital dimension to traditional food environments. These digital platforms threaten to disrupt progress towards creating a health-enabling food environment. This article outlines the emergence of the digital food environment—its dimensions, actors and target users, and critically appraises the research on the public health impact of meal delivery applications to-date. We propose a research agenda to measure, monitor and mitigate the risks which meal delivery applications pose to population health and wellbeing, which may impact the United Nation's Decade of Action on Nutrition. The rapidly evolving digital era of new technologies and innovation presents a unique window of opportunity for public health research and policy.

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DIGITAL FOOD ENVIRONMENTS

Digitalisation and technological innovations have transformed all aspects of life—including the way people can access food. The term 'digital food environments' was first conceptualised by Granheim et al. in a systematic scoping review of 357 studies [1]. The review identified online grocery retail and online food delivery services of fast food and other ready meals, as part of the dominant typology of food vendors in the digital food environment [1]. A narrative review has further characterised the digital food environment into three main components including: (1) meal delivery applications 'apps' (or online food delivery of fast food and other ready meals), (2) online groceries and (3) meal-kit subscription services [2]. These online platforms have increased access to unhealthy foods [3].

MEAL DELIVERY APPLICATIONS

Meal delivery apps coordinate orders between customers and food retailers. High smartphone penetration, the growth of e-commerce, the rise of technology companies such as Uber, and the sharing economy have allowed meal delivery apps to flourish over the past decade [4]. The meal delivery market worldwide is projected to reach a revenue of US$435.30 billion in 2024, which reflects a tremendous increase from US$109.30 billion generated in 2017 [5]. By 2029, the number of meal delivery app users is expected to reach 2.7 billion worldwide [5]. The following are leading meal delivery apps in their respective markets across the globe [6]:

- China: Ele.me, Meituan, Dianping
- Australia and New Zealand: UberEats*, Menulog**, DoorDash
- North America: GrubHub, UberEats, Postmates*
- Europe: Gorillas, Deliveroo, Flink, Just Eat**, UberEats, Wolt
- Southeast Asia: Grab, Gojek, Delivery Hero
- South America: Rappi, iFood
- India: Zomato

*Postmates is a subsidiary of UberEats.
**Menulog is a subsidiary of the global Just Eat Takeaway.com network.

A growing body of evidence indicates that these applications predominantly offer unhealthy fast foods [7] which are heavily promoted through value bundles and have increased visibility on the platform [8, 9]. While the research to-date has largely been conducted in high-income countries [10], evidence indicates that the emergence of meal delivery applications ('apps') may exacerbate unhealthy diets contributing to non-communicable diseases [11, 12], and undermine global efforts to improve population diets and nutrition. In this article, we outline how meal delivery apps act as digital disruptors to the efforts undertaken to achieve the desired targets as outlined in the Nutrition Decade.

UNITED NATIONS DECADE OF ACTION ON NUTRITION

The United Nations General Assembly proclaimed the Decade of Action on Nutrition in 2016 to achieve global nutrition and diet-related non-communicable disease (NCD) targets by 2025 [13]. Creating safe and supportive environments for nutrition at all ages is one of six key action areas of the Nutrition Decade which aims to promote availability, affordability, promotion and quality of food supporting healthy diets.

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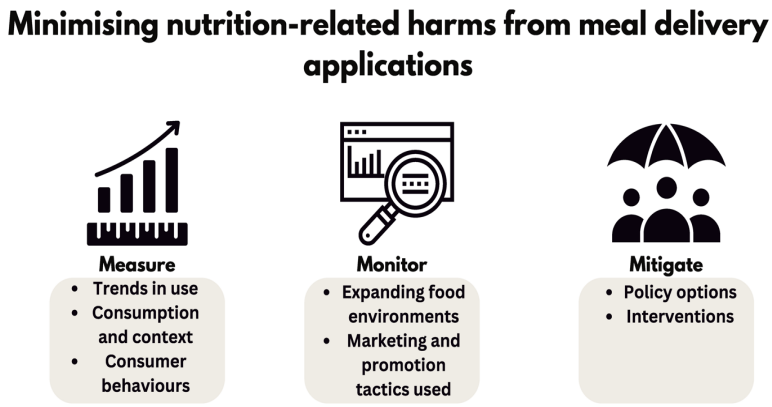

Fig. 1 Overview of the proposed research agenda to measure, monitor and mitigate the nutrition-related harms which meal delivery apps pose.

In a mid-term review of the Nutrition Decade, priority actions to achieve *safe and supportive environments for nutrition* were identified for 2021–2025. This included: first, to scale-up implementation of regulatory policies by leveraging recent momentum and learnings from country experiences such as sugar-sweetened beverage taxes, marketing restrictions and front-of-pack nutrition labelling [14]. Second, to develop and implement regulatory or voluntary approaches to increase availability of healthy choices and create a supportive environment for nutrition [14]. Third, to revitalise action in key policy areas which have stagnated or deteriorated recently [14].

The digitalisation of food environments and emergence of meal delivery applications have likely undermined efforts towards these priority actions which include creating safe and supportive environments for nutrition. We outline a research agenda to measure, monitor and mitigate the risks which meal delivery apps pose to population diets and health. This agenda aims to highlight meal delivery apps as a disruptor to the Nutrition Decade and advance actions on improving global nutrition into the next decade and beyond (Fig. 1).

RESEARCH AGENDA

Measuring the public health impact of meal delivery apps

It is essential for future research to measure the extent to which the meal delivery apps impact health and identify the risks which meal delivery apps pose to current food environments. This includes measuring what products are being sold and how, how and why consumers use meal delivery apps and the trends of its use across different time periods (when) and population groups (by whom).

In most countries globally, the popularity of meal delivery apps is rising rapidly, primarily due to the easy access and the convenience of ordering from a wide variety of food retailers with home delivery options [15, 16]. This has led to an increased use of, and dependence on, meal delivery apps for food purchases and consumption of food. A systematic review has also shown that meal delivery app use increased during COVID-19 restrictions when physical access to foods was limited [17]. Since the COVID-19 pandemic, these platforms are swiftly expanding their services to now include groceries, alcohol and other essentials (e.g., pharmacies), making them more lucrative for consumers. Moving forward, it is imperative to observe whether meal delivery apps continue to increase in usage or popularity, in addition to any changes in products (such as food, alcohol) or food outlets available over time.

Research has established that meal delivery apps offer an abundance of energy-dense and nutrient poor foods [18]. Moreover, a systematic scoping review suggests that meal delivery apps appear to have a negative impact on health by promoting the sale and consumption of unhealthy foods and beverages [19]. Despite these findings which suggest high availability and promotion of unhealthy foods, there is limited research on what users of meal delivery apps are purchasing and consuming, and how their intake of these foods, may be contributing to poorer health outcomes. Of concern, market research from Australia suggests that young people aged between 16 to 35 years are the highest users [20]. This is a critical life stage where many lifestyle behaviours are formed [21] which are known to be notoriously difficult to undo or change in later adulthood [22]. This is also the life stage when prevalence of overweight and obesity increases the fastest [23]. Adolescents especially, are a target market for food and beverage companies as they are viewed as 'lifelong' customers to build brand recognition, brand preference and brand loyalty [24]. It is therefore critical to continue measuring how young people are using meal delivery apps.

A study using mobile ecological momentary assessment, captured 124 meal delivery events from 58 unique participants between 16–35 years and showed majority of orders were unhealthy foods such as pizza and fried chicken [25]. Further research is needed to measure the use of meal delivery apps in real-time, and how meal delivery apps contribute to an individual's overall diet or used as a source of everyday food. Future studies could consider establishing large 'digital cohorts' to capture online food marketing data used by meal delivery apps targeting young people in near real time. These digital cohorts are currently being discussed as a data collection method in studies on diabetes [26] and e-cigarette use [27].

Monitoring the reach and public health impact of meal delivery apps

A vast amount of research on 'neighbourhood food environments' have typically focused on investigating associations between stores or restaurants within a geographic boundary such as postcodes or census tracts [28]. The evidence surrounding the influence of local food environments on health are mixed. A systematic review of 38 studies conducted by Caspi et al. in 2012, showed moderate evidence to support the hypothesis that neighbourhood food environments influence dietary health [29]. Many included studies reported an association between food accessibility and dietary outcomes such as a higher vegetable consumption among those that live furthest from a fast-food outlet. Despite this, several other studies reported a null association [29]. These inconsistent findings are reported widely across additional systematic reviews in the field [30–32].

Emerging research suggests that meal delivery apps allow users to order food from over 3 km away [18] and this could alter any existing associations between food environments and dietary outcomes. The expansive nature of meal delivery apps may change the concept of 'neighbourhood' or 'local food environments', which is typically comprised of food outlets within a 1 km radius of a person's home [33]. Meal delivery apps can now provide individuals access to a much wider range of outlets [7, 18]. Therefore, individuals and communities may now be experiencing 'hybrid' food environments with access to foods within their local environments, in addition to their online food environments [34]. Hybrid food environments may exacerbate local food environments by increasing access to all types of foods, including unhealthy foods. It is unclear how this may impact vulnerable groups of lower socioeconomic status, as research suggests there is a higher density of fast-food outlets in these deprived areas [35, 36]. Monitoring the reach and impact of meal delivery apps on local food environments is therefore a key research priority. The World Health Organization Regional Office for Europe and research groups in Australia have developed monitoring tools and dashboards [34, 37]. These have capacity for further surveillance of the meal delivery application market, sales volumes and customer profiles.

Marketing techniques used by meal delivery apps have also been highlighted as a concern that requires further monitoring. There is some evidence to suggest these have been employed to primarily promote energy-dense nutrient-poor foods on meal delivery apps [7]. However, there is no evidence on the extent to which the consumers are exposed to and engaged with the marketing techniques on meal delivery apps. The mechanism through which the marketing techniques influence purchase and consumption of foods on meal delivery apps also remains unclear. These are important areas for further monitoring which can be used to urge government action on the regulation of meal delivery apps.

Mitigating the public health risks associated with meal delivery apps

Currently, meal delivery apps operate with little government oversight [10]. This is despite calls from public health for greater regulation in this sector [38, 39] and demonstrates an important research gap needed to mitigate the public health risks associated with meal delivery apps. Research is needed to ascertain which existing policies do, or do not address meal delivery apps and to what extent. The novel, dynamic nature of these apps means that regulations targeting them will also need to be innovative, and adaptable as the platforms evolve and change over time. In response, research will need to inform the development and evaluation of new and existing regulations for their effectiveness in limiting the public health impact of meal delivery apps.

Importantly, while use of meal delivery apps is on the rise, access to the other traditional modes of food purchasing continue to remain relevant [16]. This indicates an opportunity to strengthen the existing regulations for traditional food environments affecting food served in restaurants or cafes. These policies may be adapted to include meal delivery apps and apply to online food environments. For example, ensuring existing kilojoule menu labelling laws are applied to the same standard online compared to physical stores could be a way to inform purchasing decisions [40]. Additionally, there have also been suggestions to enhance the positioning of healthy options in the app's menu, through algorithmic boosting of healthier options [38]. However, these initiatives need to be evaluated for their impact on food purchasing decisions.

Research analysing the corporate strategies and activities of meal delivery apps will be important to understand what activities they may use to attempt to resist government regulation and help to inform public health messaging to hold this sector accountable. Previous studies have analysed commercial activities of the food industry and found similarities in strategies and tactics used by food, alcohol and gambling industries [41]. This may provide insights into how meal delivery apps may also use their corporate power to influence the policy making process. Understanding these tactics can help inform the development of potential innovative solutions to minimise consumers' exposure and their impact on consumers' food purchasing behaviours [41].

Conclusion

This research agenda highlights the importance of addressing meal delivery apps as digital disruptors to safe and supportive environments for nutrition. Future research areas outlined in this article include measuring, monitoring and mitigating against risks which meal delivery apps pose to population diets and nutrition. As the end of the Nutrition Decade is approaching, it is critical to maintain the momentum of actions to improve safe and supportive environments for nutrition and advance the global nutrition agenda into the next decade.

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AUTHOR CONTRIBUTIONS

SJ: conceptualisation, writing—original draft preparation, writing—review & editing, RB: writing—original draft preparation, writing—review & editing, AG: writing—original draft preparation, writing—review & editing.

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COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

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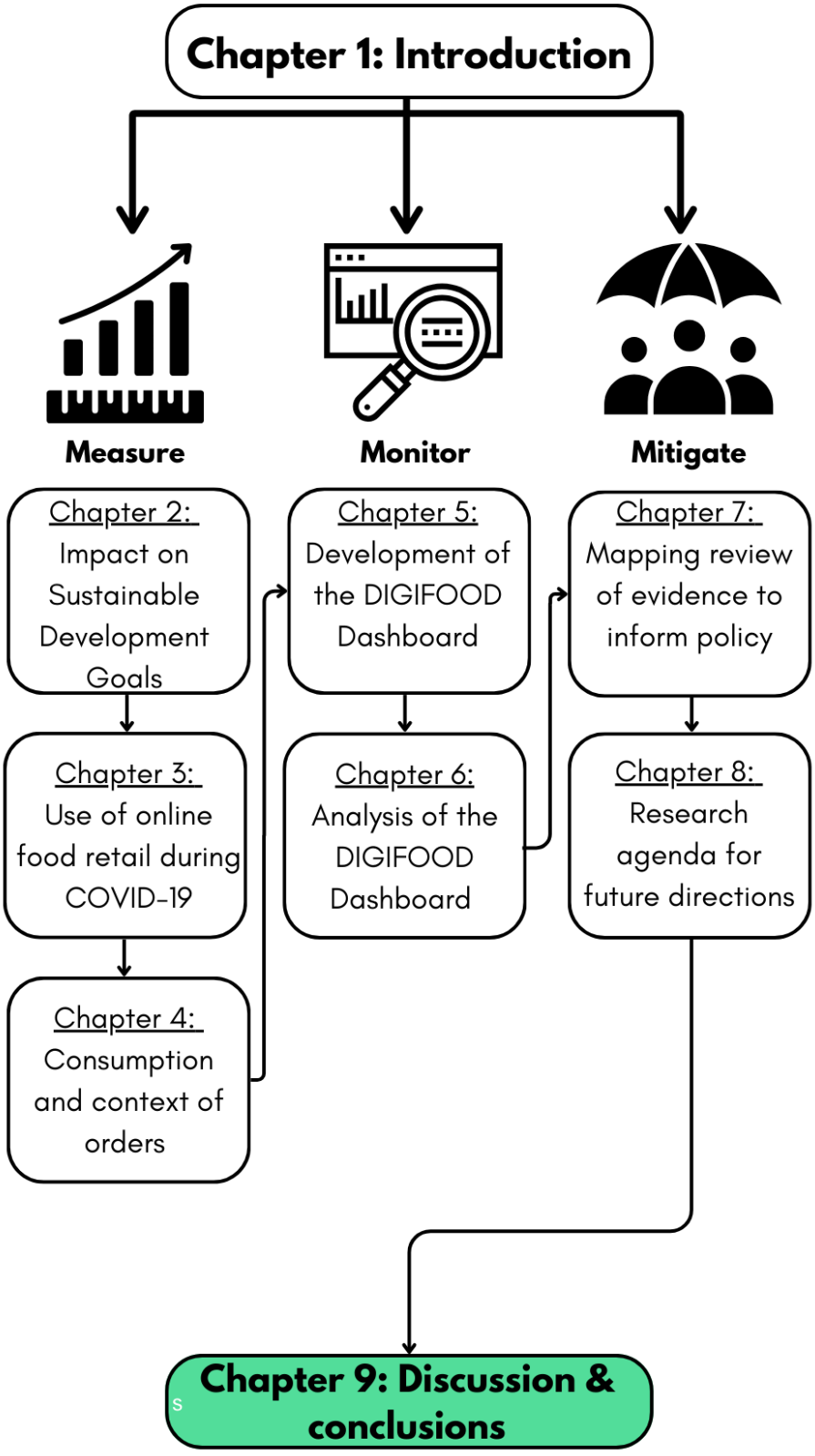
Chapter 1: Introduction
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CHAPTER 9 | DISCUSSION

Chapter Overview

This chapter summarises the key findings and discusses how the research in this thesis addressed the overarching aim that was to investigate *how meal delivery applications are disrupting food environments and affecting population diets and health.* Chapters 2-4 focused on measuring and outlining the risks which meal delivery apps pose to population diets. Chapters 5 and 6 outlined the development of a tool to monitor the impact of meal delivery apps on existing food environments, with a detailed analysis of how accessibility to foods has changed. Chapter 7 reviews the existing evidence to-date on the impacts of meal delivery apps and highlights ways which nutrition-related policies can be adapted or created, to mitigate the harms of meal delivery. Chapter 8 proposed a research agenda to address the risks which meal delivery apps pose to population diets and advance the next decade of action on nutrition. This chapter concludes by highlighting the strengths and limitations of this body of research, and important directions for future research.

Key findings from thesis and implications

This thesis began in the middle of 2021, a year into the COVID-19 pandemic. Over the past three and a half years, the research in this thesis has shown that modern food environments have undergone significant transformations driven by rapid digitalisation, a trend which was particularly intensified during the COVID-19 restrictions. Globally, individuals and communities are now exposed to ‘hybrid food environments’ which enable access to local and online food outlets. The rise of

hybrid food environments presents unique opportunities and challenges to population diets and health, with potentially more negative implications that outweigh the benefits. Moreover, as online food delivery may widen health inequalities, there needs to be further consideration of an intersectional approach when designing interventions or policies. These interventions or policies should consider unique challenges faced by vulnerable and lower socioeconomic groups, including people living with disabilities. Finally, it is evident that digital food environments are extensions of the local food environment. As such, it is critical that we continue efforts to improve local physical food environments, to thereby improve digital food environments.

Opportunities and challenges

Opportunities

Food accessibility

Chapter 3 systematically reviewed studies which captured use of online food retail platforms during the COVID-19 pandemic. This study found that there was widespread increase in use of online groceries and meal delivery apps throughout this period. Food accessibility and food insecurity were key issues of the pandemic and as such, delivery services enabled through online food retail platforms, appeared to play a significant role in improving access to foods during this time. Chapter 5 and 6 which present the development and analysis of the DIGIFOOD dashboard, also demonstrated that the expansive nature of meal delivery applications may also support and improve, better access to healthier foods, in areas where there are limited options. Collectively, these findings demonstrate a unique opportunity to leverage the ‘expansive’ nature of meal delivery apps to improve food

accessibility. This may help to alleviate food insecurity arising from a lack of access to healthy and affordable food due to geographical distance or transport barriers. Food insecurity and lack of access to nutritious, affordable foods, are strongly linked to multiple chronic diseases such as type 2 diabetes mellitus[1], cardiovascular diseases [2] and poor mental health including depression and anxiety[3].

It is noted however, that bridging physical access to foods through delivery services is only one aspect of addressing food insecurity. The wealth of literature on food insecurity suggests that the primary causes are rooted in material hardship or inadequate financial resources[4, 5].

Time-saving and convenience

The pilot EMA study in Chapter 4 showed 'convenience' was a key motivation for young people (aged 16-35 years) in nearly a third of all meal delivery app orders captured. This study also observed a positive association between number of dependents a person is caring for and number of online food orders in a week. That is, people with more dependents were more likely to have made online food delivery orders in a week. This indicates that meal delivery apps are potentially a 'modern' solution for time-poor and busy individuals seeking convenience. Demand for convenience food or meals via delivery apps, is likely driven by several factors. For example, increased labour-force participation with longer working hours, means individuals and households are spending less time and effort on preparing food. A study from Belgium has shown that the consumption of convenient options, including foods from restaurants, was more popular amongst younger, higher-educated and working households[6]. In Australia, ready-made meals are ultimate forms of

convenience foods that are packaged and sold in supermarkets[7]. Studies demonstrate that this food category has experienced a rapid increase in growth by over 10% per year from 2014 to 2020[7]. This demonstrates a growing appetite for convenience, and meal delivery apps may further fuel the demand for 'ready-made' meals. A qualitative study from England, supports this as 'less effort for more convenience' is a prevailing reason for use of meal delivery apps[8].

It is also important to consider how the convenience and time-saving aspect of meal delivery apps may also benefit some other vulnerable population groups. For instance, it may help those people living with chronic conditions or disabilities that may have difficulties preparing and cooking meals, or to dine-out in cafes or restaurants in person[9]. Services such as 'Meals on Wheels' – a community program in Australia, already utilise this 'delivery' aspect, to send prepared meals to the elderly or people living with a disability[10].

Challenges

Exacerbating poor nutrition, diets and related behaviours

Despite the proposed opportunities – such as improving food accessibility and helping individuals and households save time – these potential benefits to population health can only be actualised if users consistently choose and consume healthier options. The pilot research conducted in Chapter 4 however, indicated the opposite – a bulk of online food orders were unhealthy foods, largely comprised of burgers, pizza, fried chicken. Furthermore, these orders were placed largely on a Saturday, in the evening, at home and for one person. A study has shown that young people in Australia consume more 'discretionary' foods high in energy, fat and sugars, on

weekends, compared to weekdays[11]. In addition, research has established that self-regulation which assist healthy eating behaviours, is lower during lunch or dinner, compared to breakfast[12]. Therefore, there is indication to suggest that use of meal delivery apps are accompanied by a context which enables unhealthy behaviours. The systematic review in Chapter 3 also found evidence in six of nine studies which showed a positive association between meal delivery app use with emotional eating and weight gain, during COVID-19.

Thus, the potential benefits of meal delivery applications highlighted earlier, could ultimately be undermined, as the current evidence formed from the research in this thesis suggests. Meal delivery apps still pose a substantial risk to population health by exacerbating poor diets, if current food offerings and choices remain to be predominantly unhealthy. As underpinned by findings from Chapter 2 [Perspective], Chapter 4 [pilot EMA study] and Chapter 7 [Policy evidence review], excessive promotions and discount codes offered on meal delivery applications, are a key factor influencing unhealthy food choices. A review on digital marketing of unhealthy foods and beverages to young people, has identified meal delivery apps as a priority area of research due to the presence of multiple marketing strategies – including salient imagery and price promotions, and loyalty discount rewards[13]. Addressing this aggressive promotional or digital marketing aspect of meal delivery applications, is therefore critical to improving selection of healthier choices online.

Impact on 2030 Sustainable Development Goals

In addition, the growing demand for convenience and subsequent reliance or overuse of meal delivery apps may threaten decades of advancements towards the

2030 United Nations Sustainable Development Goals. Chapter 2 showed that meal delivery apps are potentially hindering progress towards a more sustainable future, considering the excessive amounts of plastic packaging and waste generated, as well as the unstable gig economy which impacts the livelihoods of meal delivery riders. Navigating the complex impacts of meal delivery apps on sustainability, therefore, requires an interdisciplinary approach that is systems-based or multisectoral. Indeed, several emerging studies have investigated the impact of meal delivery apps on the environment and on food waste[14] and whether carbon footprint information on meal delivery apps can reduce the reliance on price incentives[15].

Widening health inequalities

Chapter 5 and 6 which present the development and analysis of the DIGIFOOD dashboard, showed that meal delivery apps have increased access to food outlets which offer unhealthy and healthy foods. In NSW, areas experiencing less disadvantage had greater access to online food outlets, compared to areas experiencing more disadvantage. A recent analysis from researchers in Victoria, Australia, observed similar outcomes indicating that online food outlets were more available in areas of socioeconomic advantage, and in metropolitan areas[16]. At the same time, although Chapter 5 and 6 also suggest that meal delivery apps primarily affect urban areas, recent emerging evidence suggest a need for further monitoring of meal delivery apps and their infiltration in regional areas[16, 17]. As such, the improved access to healthier foods in more affluent and urban areas via meal delivery apps, may further widen existing health inequalities.

Research has also examined individual-level socioeconomic factors with use of meal delivery apps. A study in the UK established that individuals of lower occupational social grade, were more likely to use meal delivery apps, compared to individuals in the highest grade[18]. In addition, this study also observed an association between meal delivery app use and greater likelihood of living with obesity and yet, no association with income level. Together, these findings contrast to a multi-country study (UK, US, Mexico, Canada and Australia) which showed meal delivery app use was greatest amongst those with higher levels of education[19]. Although it was noted this association was observed for all countries except the UK[19]. These interesting patterns, at least in the UK, show a difference in use of meal delivery apps depending on social grade, income, or education. Thus, as the current evidence is mixed and inconclusive, further investigation is needed with a consistent measure for socioeconomic status across studies.

The extent to which meal delivery apps impact on different vulnerable groups may also greatly differ, depending on context and market settings. For example, the policy review in Chapter 7 revealed that the cost of foods and delivery services in Australian and New Zealand markets, was much higher than related costs in other countries, such as China and India. In China and India, the combination of cheaper costs and convenience, for example, could further disadvantage groups of lower socioeconomic status. In contrast, meal delivery apps may be more of a luxury service in Australia and impact higher socioeconomic groups to a greater extent. This is evidenced by findings from the analysis of the DIGIFOOD dashboard in Chapter 6, which showed that the least disadvantaged areas saw significantly higher

rates of alcohol retailers and healthy food franchises, compared to the most disadvantaged areas.

Research has also shown that during COVID-19, use of meal delivery apps was positively associated with loneliness[20]. Loneliness is defined as an "intense emotional response to perceived social isolation"[21]. Loneliness or social isolation may be linked to poorer dietary behaviours such as low fruit and vegetable intake, in addition to lower dietary quality[22]. The findings from Chapter 4 [pilot EMA Study] suggest that most people using meal delivery apps are ordering foods for themselves (one person), at home. Thus, it is possible that frequent use of meal delivery apps may exacerbate behaviours that contribute to loneliness through social isolation with more individuals eating alone at home. Use of meal delivery apps may also displace eating out at restaurants or cafes in-person, where there is likely more interaction between restaurant staff and other patrons.

Online food environments are extensions of local, physical food environments

Results from this thesis re-emphasise the importance of improving our local food environments, as many individuals access or interact with them in-person. Online food environments are mere extensions of our physical food environments. As such, communities or populations that reside or work in local food environments that are deprived of healthy food retail outlets, may not benefit from the expansion to foods resulting from meal delivery services. This was suggested by the conclusions drawn in Chapter 6 – which showed that online access to healthy foods was generally greater in areas with the least disadvantage. The findings also highlighted the

importance of the local food environment in enabling access to fresh produce. This type of food outlet had more presence locally, than online in areas experiencing greater socioeconomic disadvantage.

From a regulation perspective, existing policies which currently regulate meal delivery applications remain scarce, as shown by the findings from the systematic mapping review in Chapter 7. Therefore, existing regulation that applies to out-of-home foods in physical 'offline' contexts should also be examined for their transferability to online contexts. It was highlighted in Chapter 7 that the most feasible future direction for regulation of meal delivery applications, would be menu labelling policies. This is because many of the existing nutrition-related policies that are already implemented and in-place, involve some aspect of menu labelling. An example is the NSW Menu Labelling Scheme which mandates food outlets with more than 20 locations in NSW or more than 50 locations nationally, to display energy (kilojoule) information on menus at point-of-sale. A study included as Appendix E in this thesis, found that this law was poorly adhered to in online settings. Less than 5% of applicable food outlets on meal delivery apps had complete kilojoule labelling on all menu items[23] Thus, this again highlights the opportunity to extend policies which apply to physical 'offline' contexts, to 'online' settings as well.

Future research

Improving and expanding upon the methods used in this thesis

The research methodology and findings presented in this thesis can be extended upon, in multiple aspects. Firstly, it is evident that further investigation of consumer

data is needed – including characteristics of meal delivery app users and their orders. A pilot mobile EMA study was explored in Chapter 4, to capture meal delivery app orders and contextual factors. Although data was captured from 58 unique participants and 124 online food delivery events, this was a relatively small sample size as it was a pilot study, and the findings could be strengthened with a stronger representative sample of the population. Moreover, of the two sampling approaches used, it was found that the 'event-contingent' approach was more effective. Thus, moving forward, for optimal results studies should focus on recruiting widely and allow participants to record an online food delivery event, as it happens in real-time.

Related to this, there may be alternative methods that can measure use of meal delivery apps. For example, researchers could consider obtaining datasets from meal delivery app companies, should they be willing to share such data. Studies examining large-scale food purchasing behaviours in supermarkets, have successfully used loyalty card data supplied by large retailers[24, 25]. However, company non-participation, the commercially sensitive nature of the data and potential conflicts of interest are potential barriers to this approach.

In addition, acquiring screen captures of orders could be another viable way to understand what is being ordered and consumed from meal delivery apps. This has recently been used in research which observed how adolescents engage with their digital environments by capturing screenshots from smartphones[26]. Similarly, researchers investigating child and adolescent exposure to digital marketing of unhealthy foods across digital platforms, have used screen-capture methods[27, 28] that adhere to the WHO's CLICK framework[29]. As such, there is great opportunity to

apply and utilise these innovative methods to capture data on meal delivery apps which are mostly used by young people.

Using large cohort survey data may also be an effective method to estimate consumption and use of meal delivery apps. Recent studies[30] have used data from the International Food Policy Study which is an annual survey conducted in five countries – Australia, Canada, Mexico, the United Kingdom, and the United States to examine dietary patterns and policy-relevant behaviours[31]. This survey contains question items on the number of meals prepared outside of the home in the past 7 days, which were ordered using a food delivery service, whether meals/food/drinks were ordered online or using an app in the past 30 days, and the frequency of online ordering. To maximise reach, these question items could also be considered as an additional item in existing population health surveys for a more local Australian context such as the Australian National Health Survey or the NSW Population Health Survey. Moreover, future research could consider combining the approach of establishing large cohort surveys, with ways to capture contextual data in real time. These 'digital cohorts', are currently being discussed as a data collection method in studies on diabetes[32] and e-cigarette use[33].

Further monitoring of digital food environments

The DIGIFOOD dashboard which was developed in Chapter 5 to monitor the accessibility to online food outlets and impact of meal delivery apps on local food environments in NSW, has immense potential to be further upscaled. This dashboard can be expanded to look at patterns of online food outlet access across the whole of Australia, and this can be compared to established monitoring platforms for digital

food environments in other countries[34]. There may also be future opportunities to engage policymakers from local and state governments with the dashboard. Researchers from Western Australia have also developed an interactive tool ('WA Food Atlas') in partnership with state and local governments, to assess the physical food environment across local government areas over time[35]. Currently, this tool has yet to account for the impact of online food outlets delivering across different local government areas. As such, the DIGIFOOD dashboard and the WA Food Atlas may both help initiate action to improve local and digital food environments through urban planning and development proposals.

A significant challenge encountered during the development and analysis of the DIGIFOOD dashboard, was the categorisation of food outlet types and their potential impact on health. Although a 'healthfulness score' for each food outlet was initially proposed to be included in the dashboard, there were issues with generating a reliable and accurate score. Firstly, food outlets were scored based on their food outlet type – such as whether they were a fast-food franchise, or a sandwich/salad shop. Using a previously validated scoring tool, these food outlet types were each assigned a 'healthfulness score' ranging from -10 to +10. While fast-food franchises may be more easily assigned a 'unhealthful' score at the lower end of the scale, independent restaurants and cafes proved more difficult to classify. This was largely due to the ambiguity and diversity of recipes for menu items which range greatly from one restaurant to another.

Additionally, over 50% of all food outlets identified for the DIGIFOOD dashboard were comprised of these independent restaurants and cafes. Therefore, without

menu item data, it was difficult to assess the true potential impact of these food outlets on diets and health. Due to these difficulties, in Chapters 4 and 5, food outlets were only characterised by their 'food outlet types', although it is recognised that a comprehensive 'healthfulness' scoring tool may be more impactful and easily used in analyses and for overall interpretation. Researchers in the UK have developed a deep learning model which uses menu item data to calculate healthiness scores of out-of-home food outlets[36]. This has the potential to be applied to an Australian context, provided there are sufficient resources and capacity to web-scrape the entire menus of food outlets. As such, there remains to be substantial work to refine and develop a 'healthfulness score' for food outlets, which takes into consideration of menu items, the nutritional content of these menu items and their popularity amongst customers.

Working with independent food retailers

Although meal delivery apps may initially be responsible for entering menus online, food retailers themselves can edit or add new menu data once their profile is created[37]. Thus, independent food retailers have an important role to play in shaping healthier food environments *online*. Singapore's Health Promotion Board is pioneering the shift to healthier dining through their collaboration with food retailers, including independent restaurants, to reformulate, identify and endorse healthier food choices[38]. Since 2014, this programme has increased availability and accessibility of healthier food options in >300 businesses. Similarly, the UK has several award schemes with independent food retailers in varying local government areas[39]. Despite differing contexts and political environments, Australia is falling

behind in such initiatives with independent food retailers, and this is a major area for further research to improve the healthfulness of out-of-home foods.

Digital interfaces also present a unique opportunity to influence food choices. 'Digital choice architecture' which is rooted in nudging theory[40], indicates that the display of information and positioning of images can influence online food choices. Research has demonstrated efficacy of choice architecture in promoting healthier choices through virtual online grocery settings[41], and emerging research from the UK indicates promising results for rearranging menu items in virtual meal delivery app settings[42]. Thus, there is potential to utilise choice architecture in digital settings, to rearrange and promote more healthful menu items on meal delivery apps. This may be achieved by working collaboratively with independent food retailers.

In terms of nutrition-related policy options to regulate meal delivery apps, Chapter 7 has identified several starting points for future work. For example, existing menu-labelling policies may need to consider adapting definitions of 'electronic menu boards' or 'online menus' to specifically include meal delivery apps as well. Moreover, further technological advancements such as drone delivery must be considered in the revision or creation of relevant nutrition-related policies, to 'future-proof' policies and ensure that companies do not exploit any loopholes.

Strengths and Limitations

Limitations

Most of the primary research studies in this thesis has gathered data on only Uber Eats – which is the market-leading meal delivery app in Australia. This may have underestimated the impact of meal delivery applications on expanding access to unhealthy takeaway foods as outlined in Chapters 5 and 6, given that there are several other prominent meal delivery apps in Australia such as Menulog, Doordash and Deliveroo which went into administration in late 2022. Additionally, company or franchise-specific apps such as the MyMacca's, KFC or Domino's app, where consumers can order directly from these fast-food franchises, were not specifically investigated. There are also cuisine-specific apps such as EASI or HungryPanda which partner with food outlets offering Asian-based cuisines and these were not examined in this thesis. Importantly, these smaller meal delivery apps may play a pivotal role in providing culturally appropriate foods for specific population groups.

Additionally, this thesis has gathered limited pilot data, from a small sample size of 101 participants, on orders made on meal delivery apps which is critical to informing future public health interventions or policies. This limits the generalisability of the results and further research with a more representative sample size is needed to obtain a clearer understanding of young people's food orders and the context in which these decisions are made. For example, it would help researchers understand which foods or food outlets are generating the highest volumes of sales. It would clarify whether the meal delivery market is dominated by sales from big fast-food franchises, or if there is a more even mix of purchases from independent restaurants and cafes. This data on use of meal delivery apps, in combination with the DIGIFOOD dashboard data on accessibility to food outlets online (Chapter 5 and 6)

will paint a better picture of the impact of digital food environments on population health.

As mentioned in limitations sections of the previous chapters, another constraint of the research in this thesis was the use of postcodes to define 'local food environments'. This contrasts greatly to traditional measures used to define 'neighbourhood food environment' such as an 800 metre (1/2 mile) or 1600 metre (1 mile) radius. This was considered the best boundary to use for the analyses as linked socioeconomic disadvantage by postcode. Moreover, the web scraped data on online food outlets was based on postcode which was considered the best search input. In analyses conducted in Chapter 6, population size and remoteness was also accounted for as a co-variate in the models exploring associations between socioeconomic disadvantage and count of food outlets (online and physical).

Strengths

Prior to starting the research for this thesis in 2021, a search on PubMed indicated only four published studies had examined the risks which meal delivery apps posed to population health and diets. The body of research in this thesis has therefore contributed greatly to the emerging field of digital food environments by improving its conceptualisation, theorisation and measurement, as related to meal delivery apps specifically. As such, this thesis is a timely response to the urgent need for understanding the impact of these platforms, at a time when the COVID-19 pandemic altered access to foods. The variety of methods and breadth of studies presented in this thesis has identified and formed the foundation for several avenues

for further research. These studies have each focused on different aspects of meal delivery apps – from measuring its use, analysing changes in food accessibility and synthesising the emerging evidence to inform policies.

New theories such as the hybridisation of food environments were conceptualised which reflects the dual modality in which consumers now shop for food – in-person and online. To my knowledge, no other studies to date have examined the cumulative impact of online food outlets, in addition to food outlets accessible in-person within local areas. This has several implications for existing research on food environments as populations are not only exposed to food offerings in their physical surroundings but are also now exposed to an abundance of food options online. Thus, digital food environments may affect any existing associations observed between physical food deserts and poor health outcomes. It is also important to consider the overall increasing digitalisation of society, as high amounts of screentime may exacerbate the effects of digital marketing of unhealthy foods via meal delivery apps. This may take shape in the form of influencers who make long and short-form content online to promote retail brands and platforms and are widely popular amongst young people. As such, future and ongoing efforts to improve population diets and health must not overlook digital and physical aspects of food environments (‘hybrid food environments’) in which young people are actively engaging in.

The research presented in this thesis has also employed novel methods to measure the digital food environment and present opportunities for public health researchers to gain or utilise expertise in fields such as data science and computer science.

Chapter 5 and 6 used web-scraping services to obtain a large dataset from Google Maps and UberEats. Machine learning methods were also used to automate the categorisation process of food outlets in Chapter 5 with assistance from data scientists from the Sydney Informatics Hub. In addition, mobile Ecological Momentary Assessment was used as a novel method to collect data from smartphones and understand consumption and context of online food delivery orders. This method allows for real-time monitoring which is critical to ensuring ecological validity and accommodates the unpredictable nature of using a meal delivery app. Furthermore, unique contextual data surrounding each meal delivery event was obtained in real-time from participants via this method which would otherwise not be available, with only sales data. These methods contrast to those used in traditional physical food environment research, which may have drawn upon ground-truthing for food outlet information or obtaining data from food safety standards and similar authorities. Given the emerging and expansive nature of digital food environments, this data would have either been unavailable (no online food outlet data) or time-intensive to source. The methods explored in this thesis have therefore contributed new knowledge and innovative ways to measure the digital food environment.

Policy implications

Although Chapter 7, the systematic mapping review, has comprehensively outlined potential future directions for further regulation of meal delivery applications, the findings from other chapters also have important policy implications.

The perspective article in Chapter 2 highlights the need for a multisectoral approach to policy solutions – such as the consideration of both sustainability and nutrition. Findings from the systematic review in Chapter 3 discusses the potential for meal delivery apps to be considered in protocols for the management of future crises or pandemics, where physical accessibility to foods or meals, may be limited. Results from the mobile EMA study in Chapter 4 emphasises a need to better understand user characteristics and context around meal delivery orders, in order to develop effective interventions or policies. Using the data gathered from this chapter, it would seem appropriate to mitigate unhealthy orders and excessive promotional vouchers, particularly amongst younger adults and those living with dependents, who were the highest users.

Urban planners and policymakers may find the learnings from Chapter 5 and 6 useful to inform policies around development proposals or planning. Increasing online accessibility to fresh produce could be potentially considered as this will benefit those in the most disadvantaged areas. In more advantaged areas, future development plans and proposals should consider the impact of new food outlets as meal delivery apps may exacerbate the abundance of food available in these areas where there is already a saturation of food outlets.

Conclusion

Meal delivery apps have profoundly transformed our food environments by offering unprecedented convenience, enabling access to foods to a wide variety of foods with just a simple ‘swipe and tap’. To leverage potential positive opportunities for healthier

digital food environments, research should further examine ways to utilise the food accessibility and time-saving aspects of meal delivery apps. At the same time, further work needs to be conducted to ensure meal delivery apps do not further widen health inequities, exacerbate unhealthy diets or impede progress towards a sustainable future. Moreover, there is immense potential to adapt existing policies for the 'physical' food environment to address the digital food environment. This thesis has contributed new knowledge and understanding to an area that is relatively under-investigated through a public health nutrition lens. Studies included in this thesis have used innovative and improved methodology in e-health and m-health such as mobile Ecological Momentary Assessment and web-scraping of publicly available data. In addition, this thesis has produced policy-relevant research publications to navigate the potential negative impacts of the digital food environment on health outcomes and to ensure people have convenient access to healthy and nutritious food. As meal delivery apps are becoming increasingly embedded in our modern food environments, research and policy must keep pace with its opportunities and challenges to population health.

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APPENDIX A

A.1 Full Medline Search Strategy

1.	covid*.tw.
2.	SARS-COV2.tw.
3.	SARS-CoV-2.tw.
4.	2019-nCoV.tw.
5.	2019 coronavirus.tw.
6.	Covid-19/
7.	SARS-COV-2/
8.	(corona virus* or coronavirus* or novel coronavirus or novel corona virus).tw.
9.	Coronavirus Infections/
10.	1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9
11.	lockdown*.tw.
12.	stay-at-home*.tw.
13.	restriction*.tw.
14.	curfew*.tw.
15.	quarantine*.tw.
16.	shutdown*.tw.
17.	isolation.tw.
18.	social distanc*.tw.
19.	Physical Distancing/
20.	physical distanc*.tw.
21.	Pandemics/
22.	pandemic*.tw.
23.	11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22
24.	(online* or on-line*).tw.
25.	Online Systems/
26.	Mobile applications/
27.	((Phone or mobile) adj app*).tw.
28.	(website* or web page* or web-based).tw.
29.	(cyber or virtual or digital or technolog* or software).tw.
30.	((mobile or cellular or cell or smart) adj (phone* or telephone*)).tw.
31.	Computers/
32.	User computer interface/
33.	Digital Technology/
34.	internet/ or "internet of things"/ or "internet use"/
35.	internet*.tw.
36.	platform*.tw.
37.	(online system* or mobile app* or computer* or digital technolog*).tw.
38.	24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37
39.	((food* or meal*) adj1 deliver*).tw.
40.	(online food* adj2 (order* or purchas* or shop*)).tw.

41.	electronic grocer*.mp.
42.	online grocer*.tw.
43.	39 or 40 or 41 or 42
44.	10 and 23 and 38 and 43

A.2 Quality assessment using Joanna Briggs Institute checklists

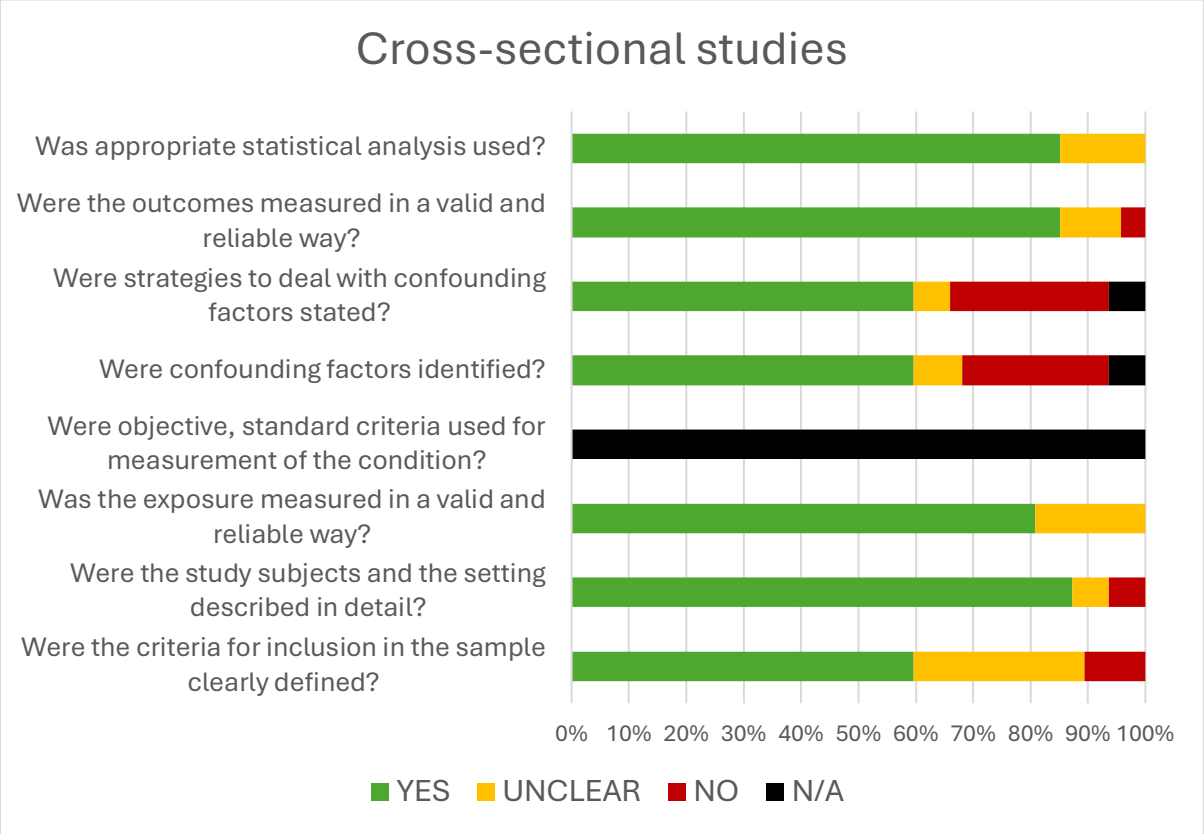


Figure S1. Quality assessment scoring using JBI checklist for cross-sectional studies (n = 46). As the condition of interest was the impact of the pandemic on the behaviours of study participants, it was determined that studies would have been unable to distinguish participants who were not impacted by COVID-19. Thus, all the cross-sectional studies received 'N/A' for the questionnaire item ['Were objective, standard criteria used for the measurement of the condition?'].

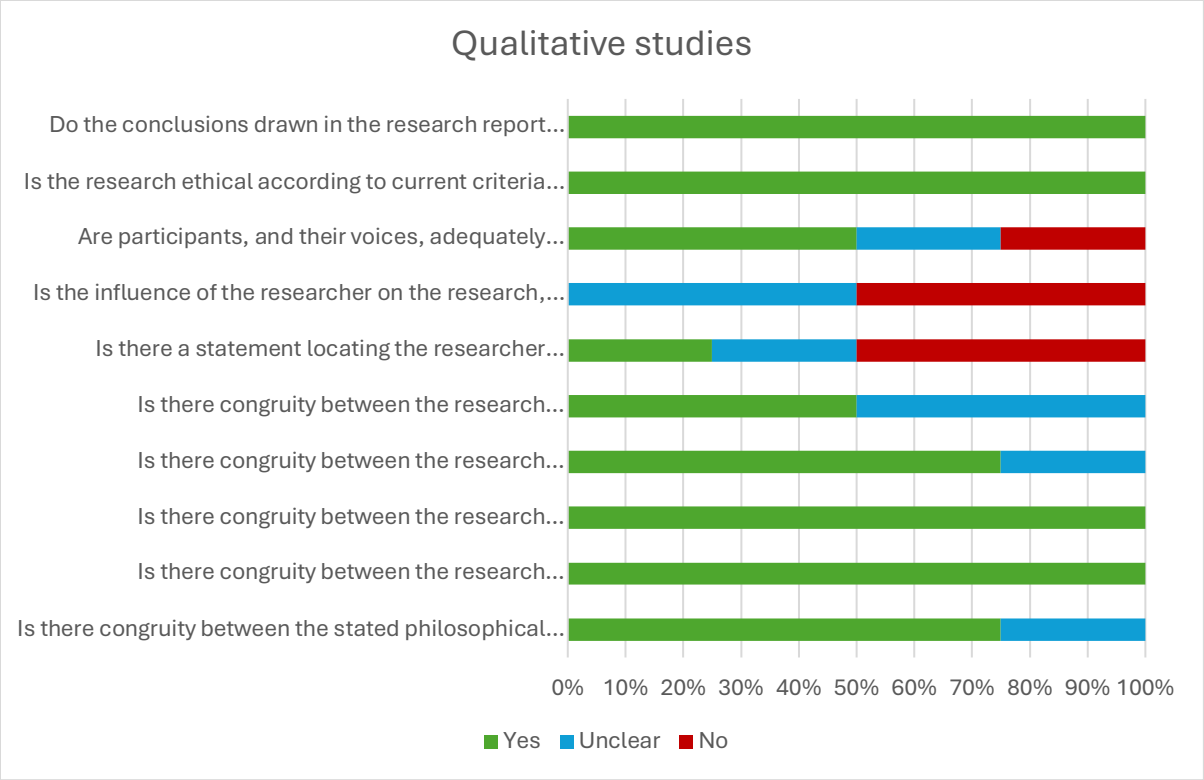


Figure S2. Quality assessment scoring using JBI checklist for qualitative studies (n = 4).

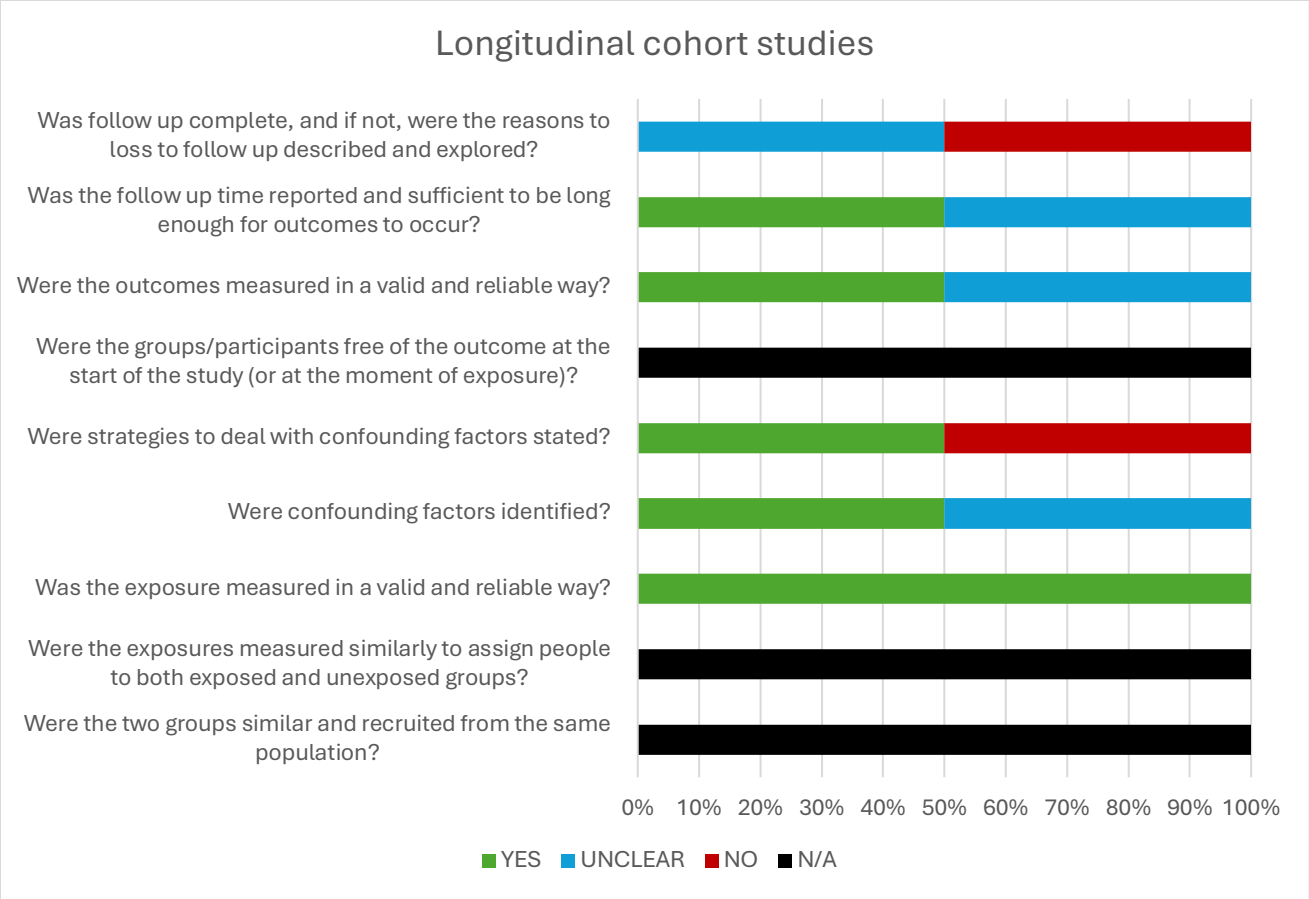


Figure S3. Quality assessment scoring using JBI checklist for longitudinal cohort studies (n = 2). Both studies examined a single cohort who were all exposed to the impacts of the COVID-19 pandemic, as such, the first two questions from the JBI checklist were not applicable ['Were the two groups similar and recruited from the same population?' and 'Were the exposures measured similarly to assign people to both exposed and unexposed groups?'].

A.3 PRISMA 2020 Statement

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title Page
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Abstract, Page 1
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Introduction, Pages 2-4
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Introduction, Page 4
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Methods, Page 5
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.	Methods, Page 6
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Supplementary Material, Table 1
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.	Methods, Page 6
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.	Methods, Page 7
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.	Methods, Page 7
	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.	Methods, Page 7
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.	Methods, Page 8
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.	N/A - No meta-analysis conducted
Synthesis	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention	Methods,

methods		characteristics and comparing against the planned groups for each synthesis (item #5)).	Pages 7-8
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Methods, Pages 7-8
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Methods, Pages 7-8
	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.	Methods, Pages 7-8
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	N/A - no meta-analysis conducted
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	N/A - no meta-analysis conducted
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Methods - Pages 8-9
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	N/A - No meta-analysis conducted
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.	Results, Figure 1
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Results, Figure 1
Study characteristics	17	Cite each included study and present its characteristics.	Results, Table 1
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Results, Page 21-22
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.	Supplementary Material, Data Extraction Table
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Supplementary Material, Figure 1, 2, 3, 4
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction	N/A

		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.	Discussion, Page 23-27
	23b	Discuss any limitations of the evidence included in the review.	Discussion, Page 28
	23c	Discuss any limitations of the review processes used.	Discussion, Page 28
	23d	Discuss implications of the results for practice, policy, and future research.	Discussion, Page 28
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.	Methods, Page 4
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Methods, Page 4
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Methods, Page 9
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Title Page
Competing interests	26	Declare any competing interests of review authors.	Title Page
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.	Supplementary Material

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71

For more information, visit: http://www.prisma-statement.org/

APPENDIX B

B.1 CREMAS Checklist

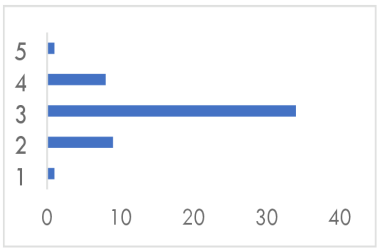
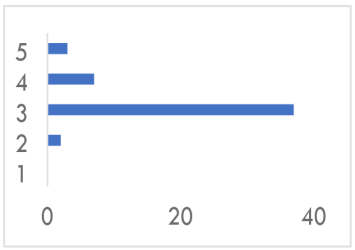
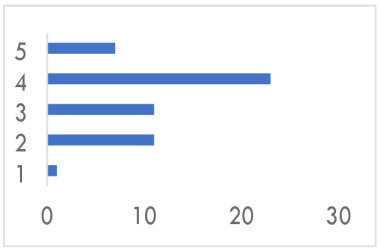
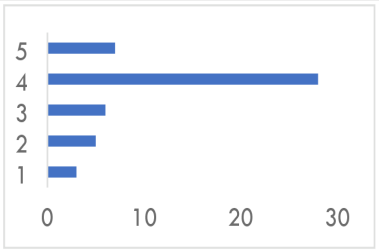
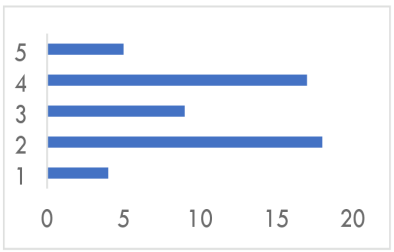
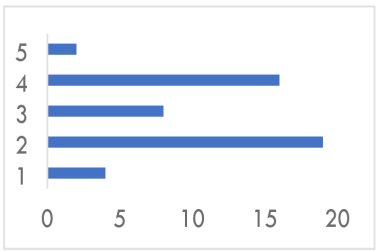
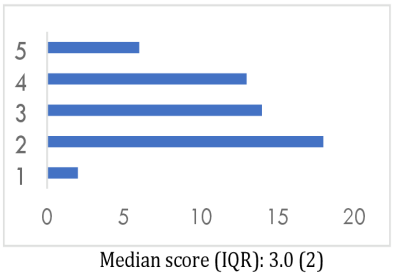
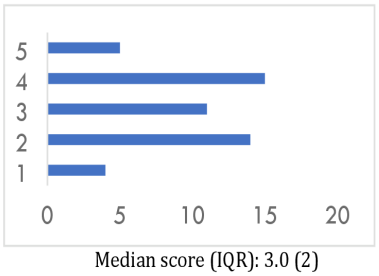
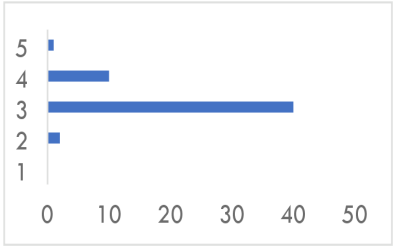
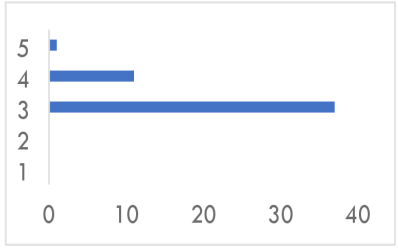
Table S1. Checklist for Reporting Ecological Momentary Assessment Studies[a]

	Item Number	Recommendation	Line
Title	1	Include ecological momentary assessment in title and key words	Title, Keywords
Introduction			
Rationale	2	Briefly introduce the concept of EMA and provide reasons for utilizing EMA for this study or topic of interests (eg, to examine time-varying predictors of unhealthy eating occasions in children's daily lives)	Introduction, Line 109-110, 117-122
Methods			
Training	3	Indicate if, and by what methods, training of participants for EMA protocol was used	Methods, Line 166-168
Technology	4	Describe what technology, if any, was used. Include the following information: device (eg, mobile phone, portable computer), model (eg, Nexus 4, iPod), operating system (eg, Android, Windows), and EMA program name	Methods, Line 156-157
Wave duration	5	State the number of waves for the study (eg, 2 monitoring periods over the course of 1 year)	Methods, Line 168
Monitoring period	6	State the number of days each wave of the study lasted, and how many weekdays versus weekend days	Methods, Line 171-209
Prompting design	7	Indicate the prompting strategy used for the study (eg, event-based, interval-based, or a combination of the two). If using interval-based strategy, indicate what type of schedule is used (eg, fixed, random, or hybrid interval)	Methods, Line 171-209
Prompt frequency	8	Intended frequency of prompts per day. Break down by weekdays and weekend days if applicable	Methods, Line 171-209
Design features	9	Describe any design feature to address potential sources of bias (eg, reactivity) or participant burden (eg, EMA questions appearing in different orders)	Methods, Line 189-192
Results			
Attrition	10	Indicate participant attrition throughout the study; report attrition rates both by monitoring days and waves, if applicable	Results, Figure 4, Line 327-334

Prompt delivery	11	Report number of EMA prompts that were planned to be delivered. If possible, also report the number of EMA prompts that were actually received by participants and indicate reasons for why prompts were not sent out (eg, technical issues or participant noncompliance reason such as phone was powered off)	Results, Line 387-394
Latency	12	Report the amount of time from prompt signal to answering of prompt	N/A
Compliance rate	13	Report total answered EMA prompts across all subjects and the average number of EMA prompts answered per person. Report compliance rate both by monitoring days and waves, if applicable. Indicate reasons for noncompliance, if known	Results, Line 387-401
Missing data	14	Report whether EMA compliance is related to demographic or time-varying variables	Results, Line 402 - 407, Table 3
Discussion			
Limitations	15	Discuss limitations of the study, taking into account sources of potential bias when using EMA methods (eg, reactivity, use of technology)	Discussion, Line 678-703
Conclusions	16	Provide a general interpretation of results and discuss the benefits of using EMA (eg, improving understanding of daily behaviors)	Conclusion, Line 706-708

[a]Table adapted from Kracht, C.L., Beyl, R.A., Maher, J.P. *et al.* Adolescents' sedentary time, affect, and contextual factors: An ecological momentary assessment study. *Int J Behav Nutr Phys Act* **18**, 53 (2021). https://doi.org/10.1186/s12966-021-01121-y **based on** Liao Y, Skelton K, Dunton G, Bruening M. A systematic review of methods and procedures used in ecological momentary assessments of diet and physical activity research in youth: An adapted STROBE checklist for reporting EMA studies (CREMAS). J Med Internet Res. 2016;18(6):e151. https://doi.org/10.2196/jmir.4954.

B.2 Acceptability outcomes

Acceptability measures	Prompts (signal-contingent) (N = 53)	No Prompts (event-contingent) (N = 49)
The number of prompts that were sent during the study period was... *(1 - too many, 5 - too few)*	 Median score (IQR): 3.0 (0)	 Median score (IQR): 3.0 (0)
The times of day that I received prompts was appropriate and not burdensome *(1 - strongly disagree, 5 - strongly agree)*	 Median score (IQR): 4.0 (1)	N/A
Without the end-of-day study reminders, I would have forgotten to log any instance where I ordered from an online food delivery service *(1 - strongly disagree, 5 - strongly agree)*	N/A	 Median score (IQR): 4.0 (1)
I found the mobile app easy to use *(1 - strongly disagree, 5 - strongly agree)*	 Median score (IQR): 3.0 (2)	 Median score (IQR): 3.0 (2)
The surveys made me more conscious of my diet and eating behaviours, which changed my behaviours throughout the study i.e. I ordered more or less online food delivery *(1 - strongly disagree, 5 - strongly agree)*	 Median score (IQR): 3.0 (2)	 Median score (IQR): 3.0 (2)
The length of the study was... *(1 - too long, 5 - too short)*	 Median score (IQR): 3.0 (0)	 Median score (IQR): 3.0 (0)

B.3 Online food delivery behaviours and contextual data

Table S2. Online food delivery (OFD) behaviors and contextual data captured from 58 unique participants.

Characteristics of OFD orders		Value
Online food ordering events captured, N		124
Number of OFD orders during study period per participant, mean (SD)		2.1 (1.9)
Time of day, n (%)		
	Morning (6 AM to 12 PM)	12 (9.7)
	Afternoon (12 PM to 6 PM)	35 (28.2)
	Evening (6 PM to 12 AM)	65 (52.4)
	Night (12 AM to 6 AM)	12 (9.7)
Weekday, n (%)		
	Monday	10 (8.1)
	Tuesday	22 (17.7)
	Wednesday	12 (9.7)
	Thursday	20 (16.1)
	Friday	21 (16.9)
	Saturday	25 (20.2)
	Sunday	14 (11.3)
Food order category, n (%)		
	Burger	17 (13.7)
	Pizza	23 (18.5)
	Fried chicken	18 (14.5)
	Chinese	18 (14.5)
	Sushi	7 (5.6)
	Indian	3 (2.4)
	Thai	3 (2.4)
	Other	35 (28.2)
	Mexican	11 (8.9)

	Bubble tea	3 (2.4)
	Fast-food franchise (Red Rooster, KFC, and McDonald's)	3 (2.4)
	Cakes, pastries, and bakery items	3 (2.4)
	Groceries	2 (1.6)
	Vietnamese	2 (1.6)
	Other (varied)[a]	11 (8.9)
OFD service, n (%)		
	Uber Eats	62 (50.0)
	DoorDash	23 (18.5)
	HungryPanda	9 (7.3)
	Deliveroo	7 (5.6)
	Menulog	5 (4)
	EASI	2 (1.6)
	Other	7
	WeChat takeaway	2 (1.6)
	PandaFresh	2 (1.6)
	HelloFresh	1 (0.8)
	Tuanyuan	1 (0.8)
	Fantuan	1 (0.8)
	Direct from café or restaurant	9 (7.3)
	Domino's	3 (2.4)
	KFC	1 (0.8)
	Crust Pizza	1 (0.8)
	Pizza Hut	1 (0.8)
	Starbucks	1 (0.8)
	Unspecified café/restaurant name	2 (1.6)
Number of people the order catered for, n (%)		
	Just yourself	69 (55.6)
	2	29 (23.4)
	3	9 (7.3)

	≥4	12 (9.7)
	—[b]	5 (4.0)
Whom the order catered for, n (%)		
	Just yourself	68 (54.8)
	Romantic partner	17 (13.7)
	Friends	14 (11.3)
	Work colleagues	1 (0.8)
	Family	19 (15.3)
	Other	0 (0)
	—[b]	5 (4.0)
Reason for ordering OFD, n (%)		
	Convenient	46 (37.1)
	Taste/cravings	26 (20.9)
	Busy	15 (12.1)
	Unmotivated to cook	12 (9.7)
	Price (cheap, transparent pricing, and discount)	10 (8.1)
	Social celebration/special treat	7 (5.6)
	Add variety to normal meals	3 (2.4)
	—[b]	5 (4.0)
Where the OFD order was delivered, n (%)		
	Home	98 (79.0)
	Workplace	7 (5.6)
	University or Technical and Further Education	10 (8.1)
	High school	0 (0)
	Other	4 (3.2)
	Recreational center	1 (0.8)
	Friend/partner's house	2 (1.6)
	Library	1 (0.8)
	—[b]	5 (4.0)
Distance from food outlet in walking minutes, n (%)		
	<15	17 (13.7)

	15-30	68 (54.8)
	30-60	27 (21.8)
	>60	6 (4.8)
	—[b]	6 (4.8)
Promotional offer used, n (%)		
	Yes	37 (29.8)
	No	82 (66.1)
	—[b]	5 (4.0)
Details on promotions used[c], n (%)		
	Free delivery	4 (10.8)
	Discount	30 (91.9)
	10% off	3 (8.1)
	50% off	3 (8.1)
	$10AUD ($6.56 USD) off	3 (8.1)
	$15AUD ($9.84 USD) off	3 (8.1)
	20% off	2 (5.4)
	$2AUD ($1.31 USD) off	2 (5.4)
	$5AUD ($3.28 USD) off	2 (5.4)
	Via email	2 (5.4)
	Pizza bundle	2 (5.4)
	Other (varied)[a]	8 (21.6)
	—[b]	3 (8.1)
Hunger level before ordering, n (%)		
	Full	7 (5.6)
	Quite full	11 (8.8)
	Not hungry or full	38 (30.6)
	Quite hungry	45 (36.2)
	Really hungry	18 (14.5)
	—[b]	5 (4.0)
Cravings satisfaction, n (%)		
	Yes	90 (72.5)

	No	29 (23.4)
	—[b]	5 (4.0)
Stress levels before ordering, n (%)		
	Very stressed	8 (6.5)
	Stressed	25 (20.2)
	Not stressed nor relaxed	57 (46.0)
	Quite relaxed	17 (13.7)
	Very relaxed	5 (4.0)
	—[b]	12 (9.7)

[a]Please refer to the manuscript for more details.
[b]—Not Available owing to missing values (empty field).
[c]Responses from those that answered 'Yes' to using a promotional offer.

B.4 R Script used for data analysis

```
# SUMMARY OF PROGRAM ------------------------------------------------
---------
# Author: Sisi Jia
# Date: 16/12/2022
# Purpose:    Data analysis for pilot mEMA Fasterfood study
#
# Background: This is a pilot study using mEMA methodology where 102
participants aged between 16-35 years were recruited.This research
question aims to test whether there was a difference between the
#             two sampling approaches (Prompts or No Prompts) in
capturing an online food delivery event. A mulivariable logistic
regression model was built, adjusting for covariates.
#
# Data used:  OFDEvents.xlsx
#
#
# This program has the following sections:
#     1. Set global options
#     2. Load packages
#     3. Import data
#     4. Check and edit data
#     5. Multivariable logistic regression model building
#     6. Model checking

# Section 1: SET GLOBAL OPTIONS -------------------------------------
---------
# Default in R is to add stars next to  statistically significant P-
values:
# To turn this off:
options(show.signif.stars = FALSE)

# CHECK & SAVE default graph options
par() # view current graph settings
default.par <- par(no.readonly = TRUE)  # SAVE default graph options

# Section 2: INSTALL & LOAD PACKAGES --------------------------------
--------------

library(readxl)
library(skimr)
library(summarytools)
library(packHV)
library(ggpubr)
library(ggplot2)
library(carData)
library(car)
library(jtools)
library(psych)
library(epiR)
library(rms)
library(DescTools)
library(survival)
library(date)
```

```
# Section 3: IMPORT DATA ----------------------------------------------
--
OFDEvents <- read_xlsx(file.choose())

# Summary statistics
skim(OFDEvents)
view(dfSummary(OFDEvents))
View(OFDEvents)

#Removing variables
OFDEvents[91,8] <- NA #genderfluid

# Section 4: EDITING DATA----------------------------------------------
-------

#Converting to categorical to factor variables
##Gender factor variable
OFDEvents$gender.f <- factor(OFDEvents$gender,
                             levels = c(1,2),
                             labels = c('Male',
                                        'Female'))
#Check labelling
freq(OFDEvents$gender.f, round.digits = 1)

##Group factor variable
OFDEvents$group.f <- factor(OFDEvents$group,
                            labels = c('No Prompts',
                                       'Prompts'))
#Check labelling
freq(OFDEvents$group.f, round.digits =1)

OFDEvents$group.f <- relevel(OFDEvents$group.f, ref = "Prompts")

##Baseline OFD frequency
OFDEvents$baselinefreq.f <- factor(OFDEvents$baseline_frequency,
                                   labels = c("1",
                                              "2",
                                              "3"))

#Check labelling
freq(OFDEvents$baselinefreq.f)

##Actual_OFDS_captured factor variable
OFDEvents$actualOFD.f <- factor(OFDEvents$Actual_OFDS_Captured,
                            labels = c('No',
                                       'Yes'))
#Check labelling
freq(OFDEvents$actualOFD.f, round.digits =1)


#Relevel outcome variable Actual_OFDS_Captured
OFDEvents$actualOFD.f <- relevel(OFDEvents$actualOFD.f, ref = "No")

#Section 5: UNIVARIABLE ANALYSIS--------------------------------------
--------
#Age
agelm <- glm(actualOFD.f ~ age, family = binomial(link="logit"), data =
OFDEvents)
```

```
summ(agelm, confint = TRUE, digits = 3) #p = 0.453, not significant

#Gender
genderlm <- glm(actualOFD.f ~ gender.f, family =
binomial(link="logit"), data = OFDEvents)
summ(genderlm, confint = TRUE, digits = 3) #p = 0.779, not significant

#Baseline ordering frequency
orderlm <- glm(actualOFD.f ~ baselinefreq.f, family =
binomial(link="logit"), data = OFDEvents)
summ(orderlm, confint = TRUE, digits = 3) #p = 0.989, not significant

#Sampling approach
grouplm <- glm(actualOFD.f ~ group.f, family = binomial(link="logit"),
data = OFDEvents)
summ(grouplm, confint = TRUE, digits = 3) #p = 0.005, very significant

#Section 6: MULTIPLE LOGISTIC REGRESSION ANALYSIS----------------------
-------------------------
logistic_OFDevents <- glm(actualOFD.f ~ group.f + age + gender.f +
baselinefreq.f, family = binomial(link="logit"), data = OFDEvents)
logistic_OFDevents_edit <- glm(actualOFD.f ~ group.f + age + gender.f,
family = binomial(link="logit"), data = OFDEvents)

#obtain estimates
summary(logistic_OFDevents)
summ(logistic_OFDevents, exp = TRUE, digits = 3)

summary(logistic_OFDevents_edit)
summ(logistic_OFDevents_edit, exp = TRUE, digits = 3)

#obtain likelihood ratio test
Anova(logistic_OFDevents)

Anova(logistic_OFDevents_edit)

#obtaining complete dataset
vars_cc <- c("group.f", "age", "gender.f", "baselinefreq.f",
"Actual_OFDS_Captured")

logistic_OFDevents_cc <- na.omit(OFDEvents[vars_cc]) #n = 101
View(logistic_OFDevents_cc)

vars_cc_edit <- c("group.f", "age", "gender.f", "Actual_OFDS_Captured")

logistic_OFDevents_cc_edit <- na.omit(OFDEvents[vars_cc_edit]) #n = 101
View(logistic_OFDevents_cc_edit)

#changing Actual OFD captured to numeric
OFDEvents$Actual_OFDS_Captured <-
as.numeric(OFDEvents$Actual_OFDS_Captured)
OFDEvents$Actual_OFDS_Captured_edit <-
as.numeric(OFDEvents$Actual_OFDS_Captured)

#Modified model
OFD_modified <- glm(logistic_OFDevents_cc$Actual_OFDS_Captured ~
logistic_OFDevents_cc$group.f + logistic_OFDevents_cc$age +
logistic_OFDevents_cc$gender.f + logistic_OFDevents_cc$baselinefreq.f,
```

```
family = binomial(link = "logit"), data = logistic_OFDevents_cc, x =
TRUE)
summ(OFD_modified, digits = 3, exp = TRUE)

OFD_modified_edit <-
glm(logistic_OFDevents_cc_edit$Actual_OFDS_Captured_edit ~
logistic_OFDevents_cc_edit$group.f + logistic_OFDevents_cc_edit$age +
logistic_OFDevents_cc_edit$gender.f, family = binomial(link = "logit"),
data = logistic_OFDevents_cc_edit, x = TRUE)
summ(OFD_modified_edit, digits = 3, exp = TRUE)

#Calculating predicted probabilities
logistic_OFDevents_cc$logistic_OFDpred <- predict(OFD_modified, type =
"response")
logistic_OFDevents_cc_edit$logistic_OFDpred <-
predict(OFD_modified_edit, type = "response")

#Hosmer-Lemeshow test
HosmerLemeshowTest(logistic_OFDevents_cc$logistic_OFDpred,
logistic_OFDevents_cc$Actual_OFDS_Captured, X = OFD_modified$x) #p-
value is NOT significant

#C-statistic for discrimination
Cstat(OFD_modified) #0.80

#Check calibration plot
val.prob(logistic_OFDevents_cc$logistic_OFDpred,
logistic_OFDevents_cc$Actual_OFDS_Captured, g = 10, statloc = FALSE)

#Diagnostic plots
dfbetaPlots(OFD_modified, id.n = 5)
influenceIndexPlot(OFD_modified, vars = c("hat"))

#DECISION: Model appears to be good fit
#v)FINAL MODEL ----------------------------------------------------------
-----------
#Refit model using all the available data
OFDEvents_final <- glm(Actual_OFDS_Captured ~ age + gender.f +
baselinefreq.f + group.f,
               family = binomial(link = "logit"), data = OFDEvents)
summ(OFDEvents_final, digits = 3,exp = TRUE)
Anova(OFDEvents_final)
```

B.5 Ethics approval letter

THE UNIVERSITY OF SYDNEY

Research Integrity & Ethics Administration
HUMAN RESEARCH ETHICS COMMITTEE

Monday, 4 April 2022

Dr Stephanie Partridge
Health Sciences; Faculty of Medicine and Health
Email: stephanie.partridge@sydney.edu.au

Dear Stephanie,

The University of Sydney Human Research Ethics Committee (HREC) has considered your application.

I am pleased to inform you that after consideration of your response, your project has been approved.

Details of the approval are as follows:

Project No.:	**2022/006**
Project Title:	**UNDERSTANDING FOOD SELECTION BEHAVIOURS AND DIETARY INTAKE OF ONLINE FOOD DELIVERY USERS: PROTOCOL FOR THE PILOT FASTERFOOD STUDY USING MOBILE ECOLOGICAL MOMENTARY ASSESSMENT**
Authorised Personnel:	**Partridge Stephanie; Allman-Farinelli Margaret; Gibson Alice; Jia Si; Phongsavan Philayrath; Roy Rajshri;**
Approval Period:	**04/04/2022** to **04/04/2026**
First Annual Report Due:	**04/04/2023**

Documents Approved:

Date Uploaded	Version Number	Document Name
29/03/2022	Version 3	Advertising material
29/03/2022	Version 3	Baseline demographics survey CLEAN
29/03/2022	Version 3	Participant Consent Form CLEAN
29/03/2022	Version 3	Participant Information Sheet CLEAN
21/02/2022	Version 2	Study Protocol_CLEAN
21/02/2022	Version 2	mEMA Survey_CLEAN
21/02/2022	Version 1	Australian Eating Survey Privacy
09/11/2021	Version 1	Perceived Stress Scale
09/11/2021	Version 1	Participant details survey
09/11/2021	Version 1	Australian Eating Survey
09/11/2021	Version 1	Sleep Quality Survey
09/11/2021	Version 1	Physical Activity Survey

Condition/s of Approval

- Research must be conducted according to the approved proposal.
- An annual progress report must be submitted to the Ethics Office on or before the anniversary of approval and on completion of the project.
- You must report as soon as practicable anything that might warrant review of ethical approval of the project including:
  - Serious or unexpected adverse events (which should be reported within 72 hours).
  - Unforeseen events that might affect continued ethical acceptability of the project.
- Any changes to the proposal must be approved prior to their implementation (except where an amendment is undertaken to eliminate *immediate* risk to participants).

Research Integrity & Ethics Administration
Research Portfolio
Level 3, F23 Administration Building
The University of Sydney
NSW 2006 Australia

T +61 2 9036 9161
E human.ethics@sydney.edu.au
W sydney.edu.au/ethics

ABN 15 211 513 464
CRICOS 00026A

- Personnel working on this project must be sufficiently qualified by education, training and experience for their role, or adequately supervised. Changes to personnel must be reported and approved.
- Personnel must disclose any actual or potential conflicts of interest, including any financial or other interest or affiliation, as relevant to this project.
- Data and primary materials must be retained and stored in accordance with the relevant legislation and University guidelines.
- Ethics approval is dependent upon ongoing compliance of the research with the *National Statement on Ethical Conduct in Human Research*, the *Australian Code for the Responsible Conduct of Research*, applicable legal requirements, and with University policies, procedures and governance requirements.
- The Ethics Office may conduct audits on approved projects.
- The Chief Investigator has ultimate responsibility for the conduct of the research and is responsible for ensuring all others involved will conduct the research in accordance with the above.

This letter constitutes ethical approval only.

Please contact the Ethics Office should you require further information or clarification.

Sincerely,

Associate Professor Haryana Dillon
Chair
Human Research Ethics Committee (HREC 3)

The University of Sydney of Sydney HRECs are constituted and operate in accordance with the National Health and Medical Research Council's (NHMRC) National Statement on Ethical Conduct in Human Research (2018) and the NHMRC's Australian Code for the Responsible Conduct of Research (2018)

B.6 Participant Information Sheet

Participant Information Statement

Research Study: The Pilot FASTERFOOD Study

Dr Stephanie Partridge (Responsible Researcher)
School of Health Sciences, Faculty of Medicine and Health, The University of Sydney
Phone: +61 2 8890 8187 | Email: stephanie.partridge@sydney.edu.au
Miss Sisi Jia (PhD student) | Email: sisi.jia@sydney.edu.au

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1. What is this study about?

We are conducting a research study about young people's use of online food delivery services in Australia. By online food delivery services, we mean companies such as UberEats, Menulog and Deliveroo. We want to know what young people are ordering, when they order, who they're with when eating and other related factors such as their mood and appetite. To investigate this further, we are conducting a survey study which will be collecting data in real-time from participants. This is a pilot study to test the feasibility and acceptability of this survey study in a sample of young people aged 16-35 years. Taking part in this study is voluntary.

Please read this sheet carefully and ask questions about anything that you don't understand or want to know more about.

2. Who is running the study?

The study is being carried out by the following researchers:

- Sisi Jia, Research Associate and PhD Candidate, School of Health Sciences, Faculty of Medicine and Health, Engagement and Co-Design Hub, The University of Sydney
- Stephanie Partridge, Senior Research Fellow, School of Health Sciences, Faculty of Medicine and Health, Engagement and Co-Design Hub, The University of Sydney
- Alice Gibson, Research Fellow, Menzies Centre for Health Policy and Economics, The University of Sydney
- Margaret Allman-Farinelli, Professor of Dietetics, School of Life and Environmental Sciences, Faculty of Medicine and Health, The University of Sydney
- Rajshri Roy, Senior Lecturer, Discipline of Nutrition and Dietetics, School of Medical Sciences, The University of Auckland
- Philayrath Phongsavan, Professor of Public Health, Charles Perkins Centre, The University of Sydney

Sisi Jia is conducting this study as the basis for the degree of Doctor of Philosophy at The University of Sydney.

3. Who can take part in the study?

As we are investigating the use of online food delivery services in young people, we are seeking participants who:

- Are aged between 16 and 35 years old
- Live in Australia
- Have access to a smartphone
- Are existing customers and have used online food delivery services within the last three months

4. What will the study involve for me?

If you decide to take part in this study, you will be asked to

- Complete one 5-minute online survey at baseline to obtain general information about your age, gender, education, income and current situation.
- Complete a 10-minute online survey about your physical activity levels, sleep quality and perceived stress levels.
- Complete one 15-minute online survey about your baseline dietary habits
- Download a free app from the Apple or Google Play store and complete a series of surveys over the course of 3 days. You will be randomly allocated to one of two groups: A) Prompts B) No Prompts
    - In Group A) Prompts:
        - Six prompts will be delivered throughout each of the three days from approximately 7:00 am to 11:00 pm to answer questions about an eating/drinking event related to online food delivery. Prompts may occur during an inconvenient time such as bathing, during a meeting, exercise, etc – you may ignore this and complete any missing information later during the study day. Each of the six surveys will take approximately 5 minutes to complete. If you are attending high-school, three prompts will be delivered during non-school hours only on weekdays (from 4:00 pm to 10:00 pm).
    - In Group B) No Prompts:
        - Over the 7 days after you are enrolled in the study, you will be required to enter the app and answer the survey/s appropriately whenever you have ordered a food or drink item from an online food delivery service.
        - If you are attending high-school you will only need to answer the surveys during non-school hours on weekdays (from 4:00 pm to 10:00 pm).

At the end of each survey study day, you will be offered a $15 gift voucher for completing all surveys. As there are 3 study days, you can redeem a maximum of $45 worth of gift vouchers. The gift voucher will be delivered to you at the end of the study period.

5. Can I withdraw once I've started?

Being in this study is completely voluntary and you do not have to take part.

Your decision will not affect your current or future relationship with the researchers or anyone else at The University of Sydney.

If you decide to take part in the study and then change your mind you can withdraw by stopping at any time. You will receive your gift vouchers according to how many full days of the study period are completed (i.e. if 1 full study day was completed, you will receive 1 voucher, if 2.5 study days were completed, you will receive 2 vouchers). One 'full' day of the study period would require a minimum completion of 4 of the 6 short surveys administered. Gift vouchers will be sent at the end of the study or if you withdraw.

If you choose to withdraw, we will not collect any more information from you. Please let us know at the time you withdraw what you would like us to do with information we have collected about you up to that point.

6. Are there any risks or costs?

Aside from giving up your time, we do not expect that there will be any risks or costs associated with taking part in this study. If any of the questions make you feel distressed or upset, we recommend that you stop the survey and first contact your General Practitioner. We have also provided a list of other contacts that may be of help:

Kids Helpline:	*T: 1800 551 800*	*W: kidshelpline.com.au*
Lifeline:	*T: 13 11 14*	*W: lifeline.org.au/crisis-chat/*
The Butterfly Foundation:	*T: 1800 334 673*	*W: thebutterflyfoundation.org.au*
ReachOut:		*W: au.reachout.com*

7. Are there any benefits?

By participating in the study, you will be helping us do our research which focuses on investigating the impact of online food delivery services on our health and food selection behaviours. There are no direct benefits from participating in the survey. However, by taking the survey you can redeem a maximum $45 worth of gift vouchers.

8. What will happen to information that is collected?

By providing your consent, you are agreeing to us collecting information about you for the purposes of this study. We will be using three platforms to collect data.

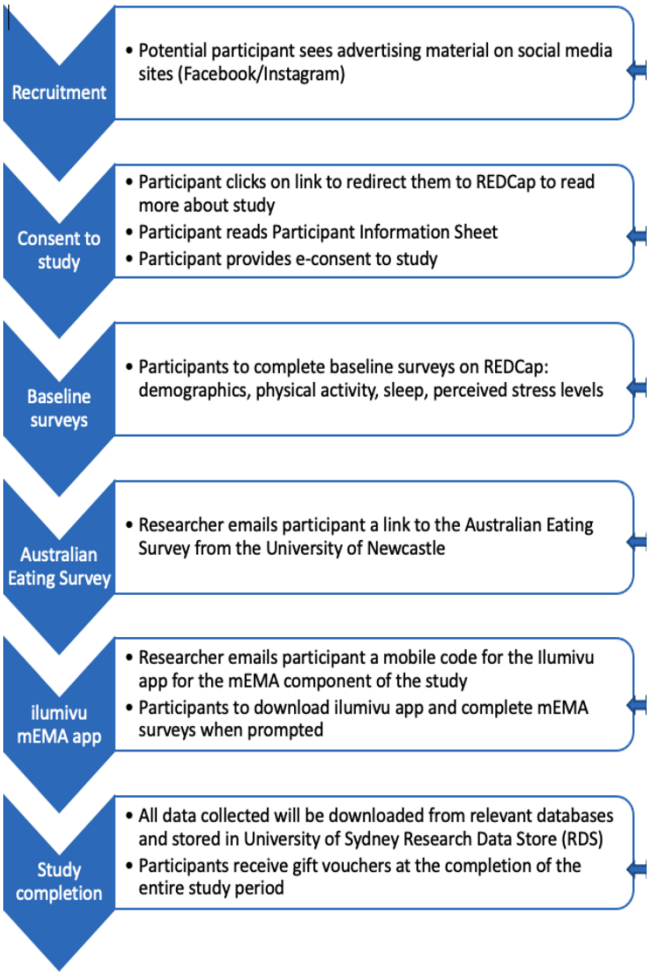
Firstly, general information about you and information about your physical activity levels, sleep quality and perceived stress levels will be collected using REDCap, a secure data software from The University of Sydney.

Secondly, data about your baseline dietary habits will be collected using the Australian Eating Survey, a validated tool from the University of Newcastle. The University of Newcastle has a

robust privacy policy about the storage and confidentiality of any personal data that is collected – only the research team for this study will have access to this data.

Finally, data about your eating/drinking event related to online food delivery will be collected using a secure mobile phone app (Ilumivu). **During the 3-days of the study, your data will be stored securely on the software's platform server located in the United States.** No personally identifying information about you will be stored on this server.

After the study is complete, your data will be downloaded from the three platforms to the University of Sydney's secure Research Data Storage servers. We will then notify the external software platforms including the Australian Eating Survey server, REDCap and ilumivu to delete the data in their cloud-based storage immediately. Please note that the researchers cannot guarantee that data will be immediately deleted upon request as these are third-party platforms. Please also see the following flowchart diagram for more clarity on where data is being collected from:



We will only disclose information with your permission or unless we are required by law to release information. We are planning for the study findings to be published.

You will not be individually identifiable in these publications.

We will only request your contact details if you want to:

- Redeem your gift vouchers (maximum 3 vouchers)
- Want to know about the study results once it is finished
- Be willing to be contacted for future research

9. Will I be told the results of the study?

You have a right to receive feedback about the overall results of this study. You can tell us that you wish to receive feedback by at the end of the survey, which asks you if you would like to receive a summary of the study results. If you answer 'Yes', when we finish the study, we will tell you what we learnt by emailing you a one-page summary. If you select 'Yes', you will receive this feedback after the study is finished.

10. What if I would like further information?

When you have read this information, the following researcher/s will be available to discuss it with you further and answer any questions you may have:

If you have any questions, please contact Sisi (PhD Student, Research Associate) from the research team at sisi.jia@sydney.edu.au or phone +61 2 8890 8187.

11. What if I have a complaint or any concerns?

The ethical aspects of this study have been approved by the Human Research Ethics Committee (HREC) of The University of Sydney [2022/006] according to the *National Statement on Ethical Conduct in Human Research (2007).*

If you are concerned about the way this study is being conducted or you wish to make a complaint to someone independent from the study, please contact the University:

Human Ethics Manager
human.ethics@sydney.edu.au
+61 2 8627 8176

This information sheet is for you to keep

B.7 Participant Consent Form

Participant Consent Form

Research Study: The Pilot FASTERFOOD Study

Dr Stephanie Partridge (Responsible Researcher)
School of Health Sciences, Faculty of Medicine and Health, The University of Sydney
Phone: +61 2 8890 8187| Email: stephanie.partridge@sydney.edu.au
Miss Sisi Jia (PhD student) | Email: sisi.jia@sydney.edu.au

Participant Name _____

I agree to take part in this research study. In giving my consent, I confirm that that:

- The details of my involvement have been explained to me, and I have been provided with a written Participant Information Statement to keep.
- I understand the purpose of the study is to investigate young people's use of online food delivery services
- I acknowledge that the risks and benefits of participating in this study have been explained to me to my satisfaction.
- I understand that in this study I will be required to:
    - Complete one 5-minute online survey at baseline to obtain general information about your age, gender, education, income and current situation.
    - Complete a 10-minute online survey about your physical activity levels, sleep quality and perceived stress levels.
    - Complete one 15-minute online survey about your baseline dietary habits
    - Download a free app from the Apple or Google Play store and complete a series of surveys over the course of 3 days. You will be randomly allocated to one of two groups: A) Prompts B) No Prompts
    - In Group A) Prompts:
        - Six prompts will be delivered throughout each of the three days from approximately 7:00 am to 11:00 pm to answer questions about an eating/drinking event related to online food delivery. Prompts may occur during an inconvenient time such as bathing, during a meeting, exercise, etc – you may ignore this and complete any missing information later during the study day. Each of the six surveys will take approximately 5 minutes to complete. If you are attending high-school, three prompts will be delivered during non-school hours only on weekdays (from 4:00 pm to 10:00 pm).
    - In Group B) No Prompts:
        - Over the 7 days after you are enrolled in the study, you will be required to enter the app and answer the survey/s appropriately whenever you have ordered a food or drink item from an online food delivery service.
        - If you are attending high-school you will only need to answer the surveys during non-school hours on weekdays (from 4:00 pm to 10:00 pm).
- I understand that my information may be used in future research
- I understand that being in this study is completely voluntary.

- I am assured that my decision to participate will not have any impact on my relationship with the research team or the University of Sydney

- I understand that I am free to withdraw from this study at any time and that I can choose to withdraw any information I have already provided (unless the data has already been de-identified or published).

- I have been informed that the confidentiality of the information I provide will be protected and will only be used for purposes that I have agreed to. I understand that information about me will only be told to others with my permission, except as required by law.

- **I have been informed that mobile app data gathered for a component of this study will be first securely stored on a server in the United States. I understand that this data will be removed upon request after researchers have retrieved all the data and have stored it securely on the university's Research Data Store.**

- I understand that the results of this study may be published, and that publications will not contain my name or any identifiable information about me.

- I confirm the following:

I consent to my data being used in future research	Yes ☐	No ☐
I would like feedback on the overall results of this study	Yes ☐	No ☐
I would like to receive the gift vouchers	Yes ☐	No ☐

  - If you answered **yes**, please provide your email address:

_____

_____

_____

_____

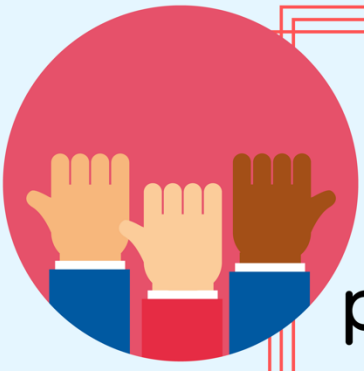
- I understand that after I sign and return this consent form it will be retained by the researcher, and that I may request a copy at any time.

Participant Name _____

Signature _____

Date _____

B.8 Recruitment Material – Social Media



We are seeking participants:

- Between 16-35 years
- Living in Sydney
- Have access to a smartphone
- Have used online food delivery before

Join to receive up to 3 vouchers!

FasterFood

B.9 mEMA Survey

mEMA Survey

1. Right before this prompt, were you eating or drinking?
   - ○ Yes
   - ○ No

2. Did you obtain the food/drink using an online food delivery service?
   - ○ Yes
   - ○ No

3. Was the food/drink obtained directly from a takeaway food outlet in person?
   - ○ Yes
   - ○ No

If participant answered 'Yes' to Question 2 and 'No' to Question 3, the following questions are asked:

4. What was your order?
   - ○ Burger
   - ○ Pizza
   - ○ Fried chicken
   - ○ Chinese
   - ○ Indian
   - ○ Thai
   - ○ Sushi
   - ○ Other, please specify: _____

5. How many people did you order for and consume this/these food and beverage item/s with?
   - ○ 1 (just yourself)
   - ○ 2
   - ○ 3
   - ○ 4 or more

6. Who were you eating or drinking with?
   - ○ Just yourself
   - ○ Romantic partner
   - ○ Friends
   - ○ Work colleagues
   - ○ Family
   - ○ Other

   If other, please specify: _____

7. What was your main reason for ordering takeaway?

Open text

8. Where were you when you consumed your food/beverage items?

- ○ Home
- ○ Workplace
- ○ University/TAFE
- ○ High school
- ○ Other

If other, please specify: _____

9. How far away was the physical food/beverage outlet you ordered from? (in walking mins)

- ○ 0 - 15 mins
- ○ 15 – 30 mins
- ○ 30 mins – 1 hour
- ○ More than 1 hour

10. Was a promotional code/offer used to purchase the items?

- ○ Yes
- ○ No

If yes, please provide details on the promo offer: _____

11. Please rate your level of hunger prior to ordering:

- ○ Full
- ○ Quite full
- ○ Not hungry or full
- ○ Quite hungry
- ○ Really hungry

12. Did the ordered food/drink satisfy cravings?

- ○ Yes
- ○ No

APPENDIX C

C.1 List of search locations used for web scraping on Uber Eats

Table S1. UberEats Australia locations across New South Wales in 2023. Locations data obtained from UberEats website, number of suburbs/localities obtained from Australia Post.

NSW Local Government Area	Number of suburbs or localities
Albury	15
Armidale	42
Ballina	35
Bathurst	75
Blue Mountains	29
Bonny Hills	1
Bowral - Mittagong	7
Byron Bay	40
Camden Haven	19
Central Coast	151
Cessnock	56
Coffs Harbour	31
Dubbo	47
Evans Head	1
Forster – Tuncurry	2
Galston	1
Gillieston Heights	1
Goulburn	26
Grafton	1
Griffith	15
Kiama	21
Kurri Kurri – Weston	7
Lake Cathie	1
Leeton	10
Leppington	1
Luddenham	1
Maitland	46
Minmi	1
Morisset – Cooranbong	10
Mulgoa	1
Murwillumbah	3
Nelson Bay - Corlette	3

Newcastle	50
Nowra – Bomaderry	5
Old Bar	1
Orange	8
Picton	1
Pitt Town	1
Port Macquarie	87
Queanbeyan	66
Raymond Terrace	2
Richmond North	1
Shoal Bay	1
Silverdale - Warragamba	2
Sydney	765
Tamworth	69
Taree	3
Thirlmere	1
Tweed Heads	11
Wagga Wagga	58
Wollongong	65
Young	1
Total	1898
Duplicates	70
Unique	**1828**

C.2 Dashboard terminology and definitions

Table S2. Terminology dictionary

Terminology	Definition	Example
Scraping terminology		
Name	Name of food outlet	Rosetti's Cafe
Suburb	A geographic subdivision in Australia, used mainly for address purposes for ***urban*** areas.	Burwood
Locality	A geographic subdivision in Australia, used mainly for address purposes for ***rural*** areas.	Borah Creek
State/Territory	Administrative divisions of Australia that are self-governing polities	New South Wales
Postcode	A four-digit number used by Australia Post to assist with mail delivery	2134
Opening hours	Opening hours of a food outlet	Monday – 10:00 AM – 10:00PM
Rating of food outlet	An average rating out of 5, provided by customers	4.4 (17 ratings)
Category	Category descriptors of food outlets to describe the cuisine and food offered. These descriptors differed between the UberEats and Google Maps datasets.	Vietnamese, Noodle
Delivery Fee	Cost to deliver from food outlet	$4.49
URL	The URL of a webpage that sends visitors to a specified site using a link	https://www.ubereats.com/au/store/rosettis-cafe/djF057OcSzSN52wsfJcsZQ
Scrape date	Date which data was scraped	3/9/2023 11:21

Restaurant ID	Unique ID for food outlets on UberEats	84ef9e1b-4cba-4181-9e88-2e7a93f00a7e
CID	Unique ID for food outlets on Google Maps	9097067965566814117
Conceptualisation of food environments terminology		
Local food outlets	Food outlets that have a physical presence. Data scraped from Google Maps.	Mario's Pasta, Carlton, 2218
Online food outlets	Food outlets that can deliver into a specified postcode. Data scraped from Uber Eats.	McDonald's (Hurstville) that can deliver to Carlton 2218
Hybrid food environment	The collective local and online food outlets in a specified postcode.	Mario's Pasta + McDonald's (Hurstville) in Carlton 2218
Dashboard terminology		
Postal Area (POA)	An approximation by the Australian Bureau of Statistics of postcodes	2000
Mesh Block	Smallest geographic area which form the building blocks for larger regions of the Australian Statistical Geography Standard. Typically includes 30-60 dwellings.	Mesh blocks are grouped into four increasingly large statistical areas.
Main category	Derived from the Food Environment Score, developed by public health experts to characterise the food environment.	The following categories below are examples of a main category.
Supermarket	Mainly sell groceries (fresh foods, canned, packaged foods, dry foods).	Woolworths
Sandwich shops/salad bars	Mainly sell salads, rolls, sandwiches or wraps.	Brooklyn Bridge Deli
Independent restaurants/cafes	A non-franchise restaurant or cafe mostly offering dine-	Gigi's Pizzeria

	in service, typically culture-based cuisine	
Takeaway Independent	A non-franchise store mostly offering foods for takeaway such as pizza, fish and chips, burgers, chicken, kebabs.	Shawarma Today
Fresh produce	Mainly sells fresh meat, seafood, fruit and vegetable grocers. Delicatessens have been included in this category.	LP's Quality Meats
Convenience store	Mainly sell convenience foods – mostly highly-processed foods such as packaged chips, soft drinks, lollies, packaged ice cream. Includes stores at petrol stations.	City Convenience Store
Alcohol retailer	Mainly sell alcoholic beverages. Includes pubs and bottle shops.	Dan Murphy's
Sweets/extra foods	Mainly sell sweets, desserts, pastries, cakes, bubble-tea, donuts and more.	Sweet Lu
Bakery	A non-franchise store that mainly offers bread and other baked products	Sonoma
Takeaway Franchise	An outlet brand with greater than 10 different locations in the dataset	
Bakery Franchise	Franchise that primarily sells bread and baked goods	Breadtop
Dessert Franchise	Franchise that sells sweets, sugar-sweetened beverages, desserts	Chatime

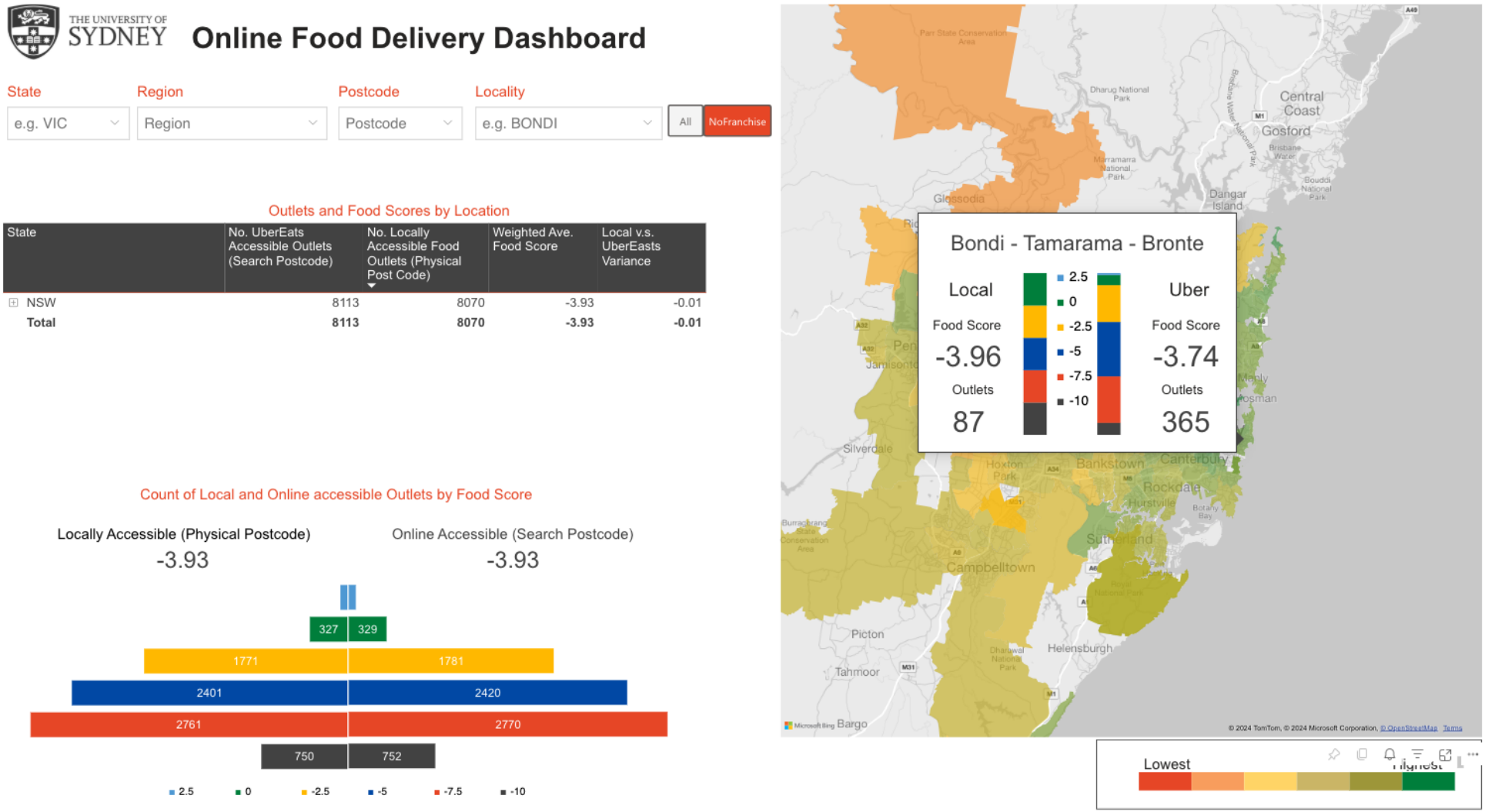
Healthy Food Franchise	Franchise that sells salads, sandwiches, wraps, rolls.	Sumo Salad
Juice Franchise	Franchise that sells juices or smoothies.	Top Juice
Unhealthy Food Franchise	Franchise that sells mostly fast-foods such as burgers, pizza, fried chicken, chips.	KFC
Cuisine	For easier interpretation on the dashboard, cuisine represents the 'category' data from scraping terminology.	Vietnamese

C.3 List of Google business categories used as search terms for web scraping on Google Maps

Afghani Restaurant	Salad Shop	Ice Cream Shop	Deli
African Restaurant	Sandwich Shop	Indian Restaurant	Vegetarian Cafe and Deli
Alsace Restaurant	Convenience Store	Indonesian Restaurant	Chocolate Cafe
American Restaurant	Candy Store	Italian Restaurant	Cocktail Bar
An Hui Restaurant	Delivery service	Japanese Restaurant	Wine Bar
Anago Restaurant	Fast Food Restaurant	Juice Shop	Fish & Chips Restaurant
Andalusian Restaurant	Fish and Chips Takeaway	Kebab Shop	Fresh Food Market
Angler Fish Restaurant	Fried Chicken Takeaway	Korean Barbecue Restaurant	Frozen Yogurt Shop
Argentinian Restaurant	Gas station	Korean Restaurant	Fruit and Vegetable Store
Armenian Restaurant	Hamburger Restaurant	Lebanese Restaurant	Grocery Delivery Service
Asian Fusion Restaurant	Meal Takeaway	Liquor Store	Butcher Shop Deli
Asian Grocery Store	Pie Shop	Malaysian Restaurant	Cajun Restaurant
Asian Restaurant	Pizza Restaurant	Market	Cake Shop
Asturian Restaurant	Pizza Takeaway	Meal delivery	Restaurant
Australian Restaurant	Pastry Shop	Mexican Restaurant	Cafe
Austrian Restaurant	Bakery	Milk Delivery Service	Grocery Store
Authentic Japanese Restaurant	Bistro	Noodle Shop	Supermarket
Bagel Shop	Pub	Pasta Shop	Vietnamese Restaurant
Bangladeshi Restaurant	Bar	Pho Restaurant	Wine Store
Bar Restaurant Furniture Store	Bar & Grill	Pizza delivery	Wholesale Bakery
Barbecue Restaurant	Chicken Restaurant	Ramen Restaurant	Donut Shop
Basque Restaurant	Chinese Noodle Restaurant	Seafood Market	Dumpling Restaurant
Belgian Restaurant	Chinese Restaurant	Seafood Restaurant	Fine Dining Restaurant
Berry Restaurant	Chinese Takeaway	Shanghainese Restaurant	Butcher Shop
Brazilian Restaurant	Coffee Shop	Sichuan Restaurant	
Breakfast Restaurant	Coffee Store	Singaporean Restaurant	
British Restaurant	Cookie Shop	Spanish Restaurant	
Brunch Restaurant	Cupcake Shop	Sri Lankan Restaurant	

Bubble Tea	Delivery Chinese Restaurant	Sushi Restaurant	
Buffet Restaurant	Dessert Restaurant	Taiwanese Restaurant	
Bulgarian Restaurant	Dessert Shop	Thai Restaurant	
Burmese Restaurant	Dim Sum Restaurant	Vegan Restaurant	
Burrito Restaurant	Discount Supermarket	Vegetarian Restaurant	

C.4 Prototype of DIGIFOOD dashboard in 2021



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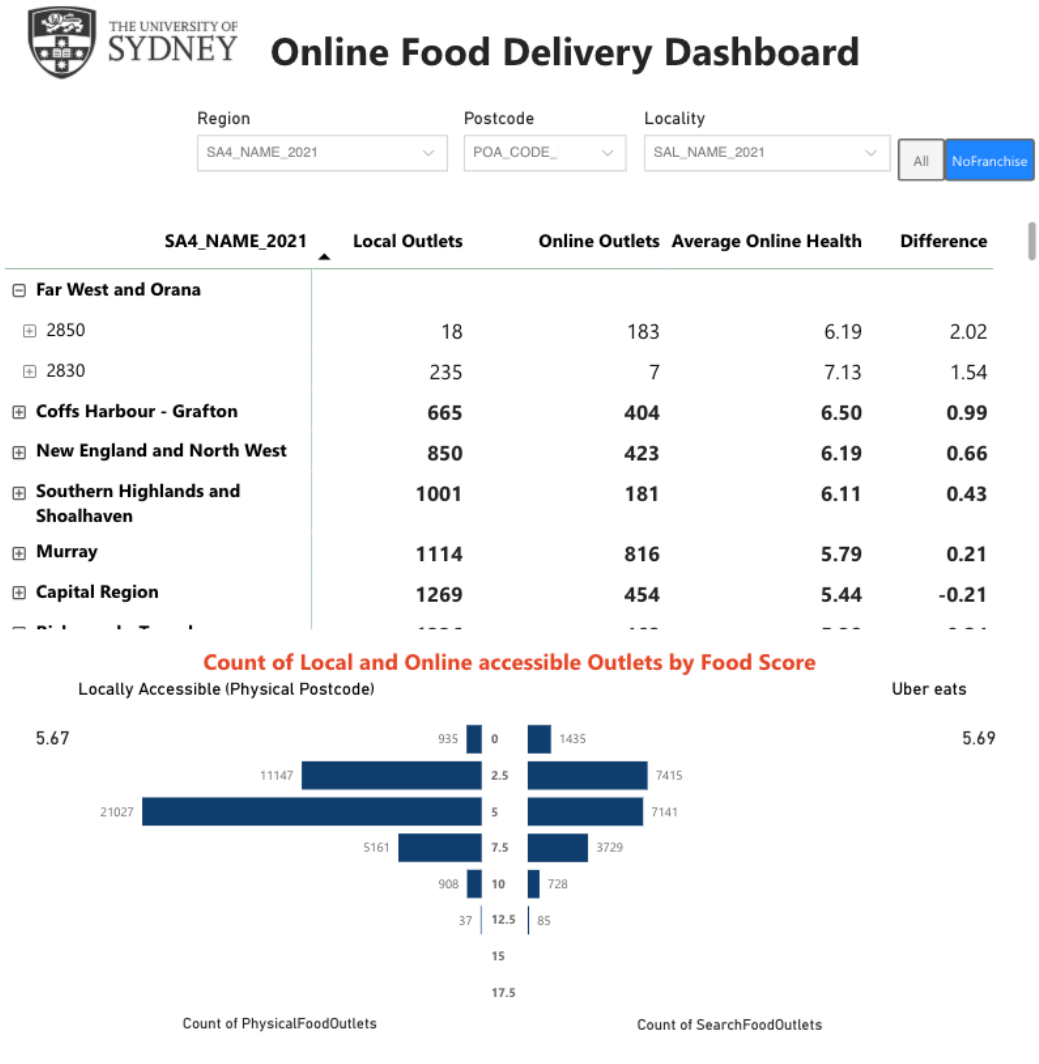
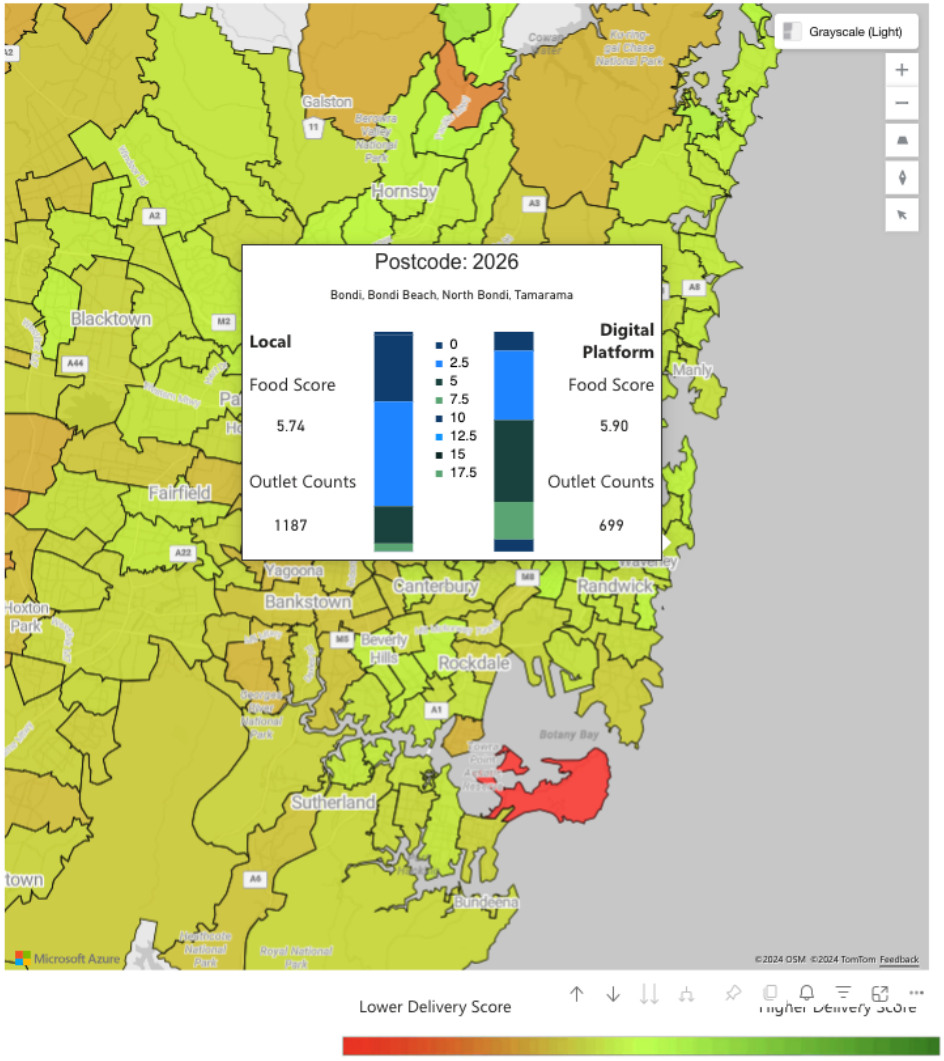
C.5 DIGIFOOD dashboard 2024 – updated Google Maps data version 1.0





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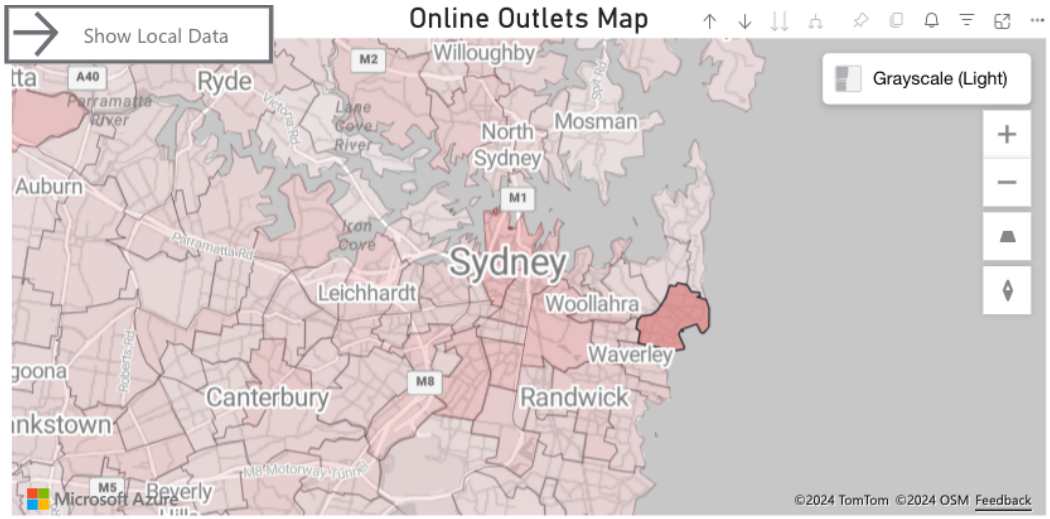
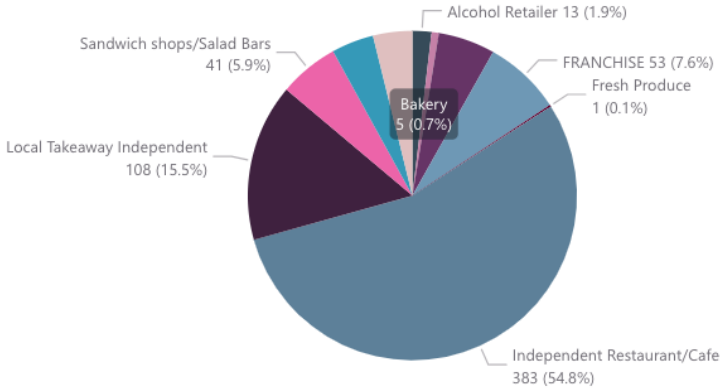
C.6 DIGIFOOD dashboard 2023 – updated Google Maps data version 2.0



Main Category: All | Franchise Category: All | Region: All | Postcode: All

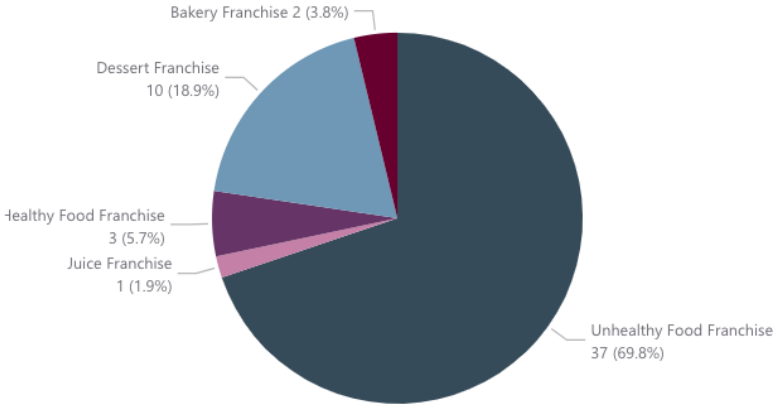
Main Categories



Postcode	Online Outlet Count
2026	708
Total Deliverable Outlets	708
Unique Outlets	699

Frequency of Cuisine Subcategories

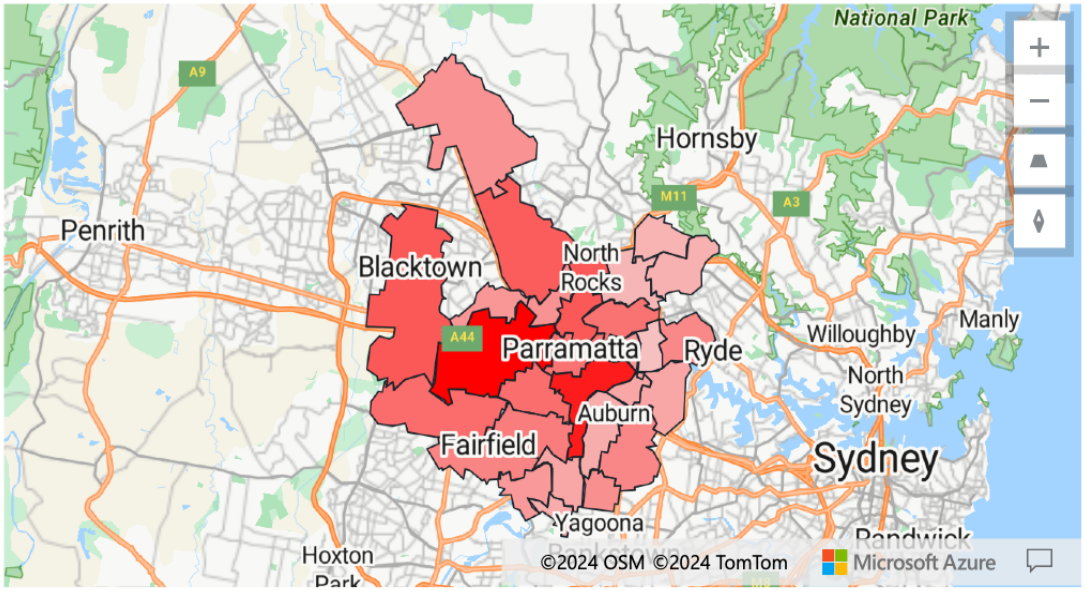
Franchise Categories



C.7 Final DIGIFOOD dashboard 2024 – Online food environment example in Sydney-Parramatta region

Online | Local | Hybrid

Online Food Environment



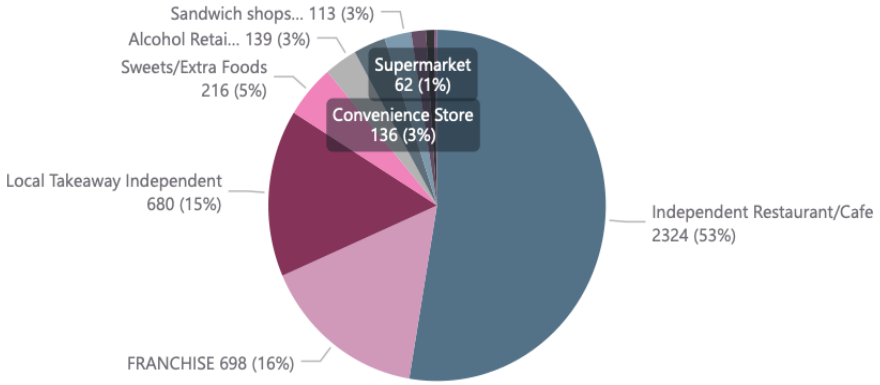
Main Category: All

Franchise Category: All

Region: Sydney - Parramatta

Postcode: All

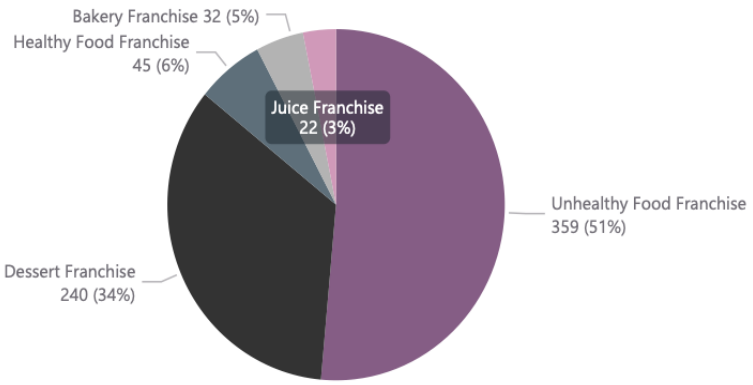
Online Outlets by Main Category



Postcode	Unique Outlets
2115	322
2118	375
2119	397
2121	407
2144	428
2197	432
2128	466
2127	468
2162	468
2116	537
2163	538
Accessible Online	**18128**
Unique Outlet Count	4,415

Frequency of Cuisine

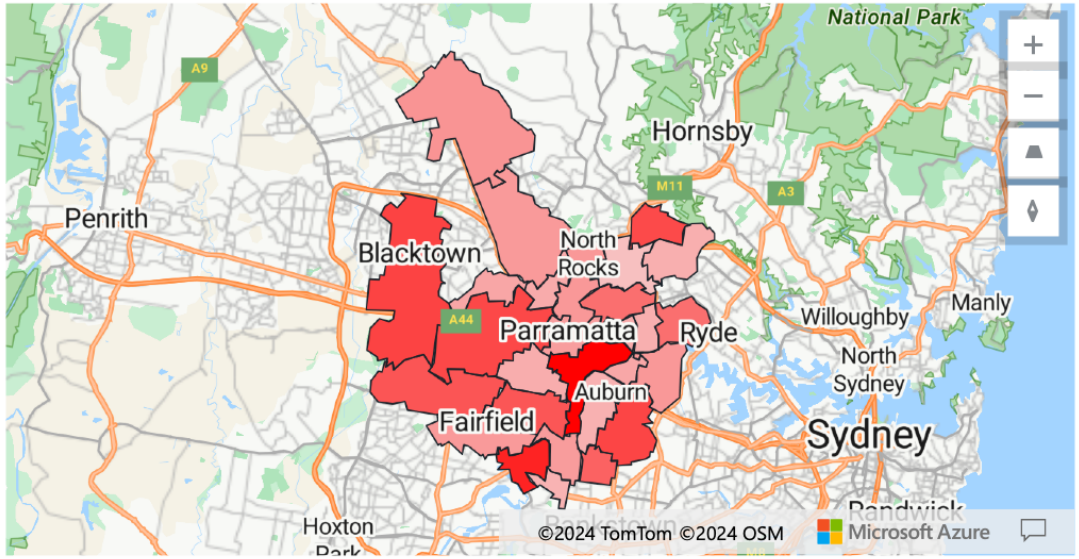
Online Outlets by Franchise Category



C.8 Final DIGIFOOD dashboard 2024 – Local food environment example in Sydney-Parramatta region

Online | Local | Hybrid

Local Food Environment



Main Category: All

Franchise Category: All

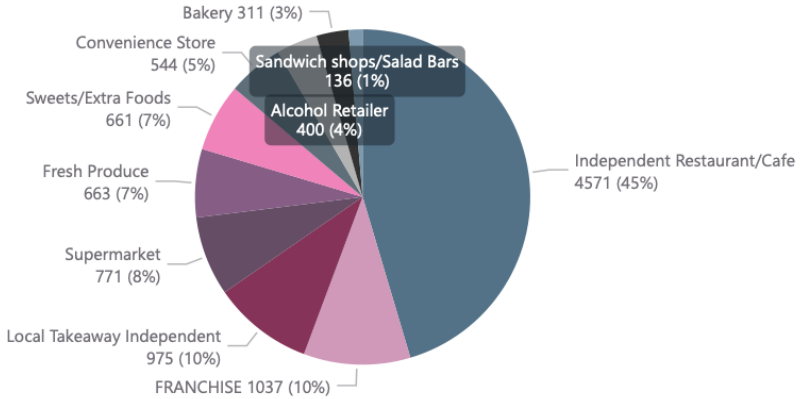
Region: Sydney - Parramatta

Postcode: All

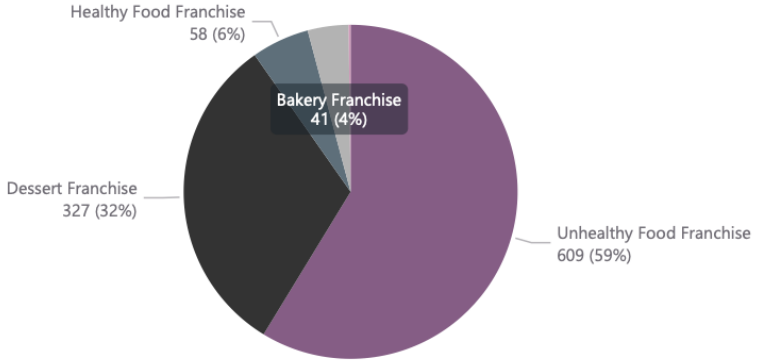
Postcode	Unique Outlets
2114	1555
2115	437
2116	512
2117	1557
2118	148
2119	2206
2121	451
2127	852
2128	587
2141	2297
2142	3498
Accessible Locally	**34655**
Unique Outlet Count	10,069

Frequency of Cuisine

Local Outlets by Main Category



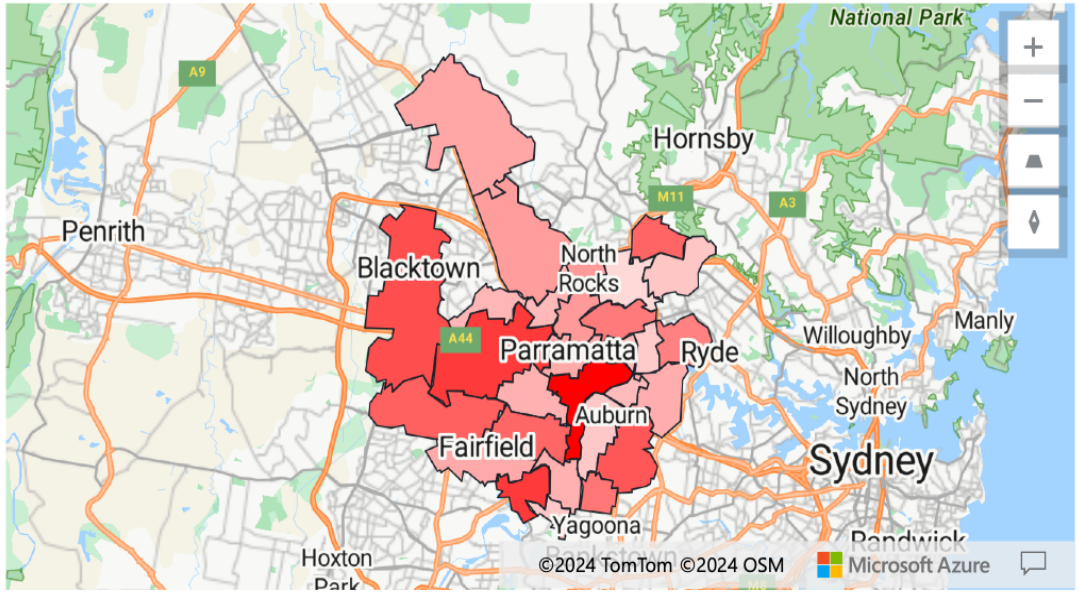
Local Outlets by by Franchise Category



C.9 Final DIGIFOOD dashboard 2024 – Hybrid food environment example in Sydney-Parramatta region

Online | Local | Hybrid

Hybrid Food Environment



Main Category: All

Franchise Category: All

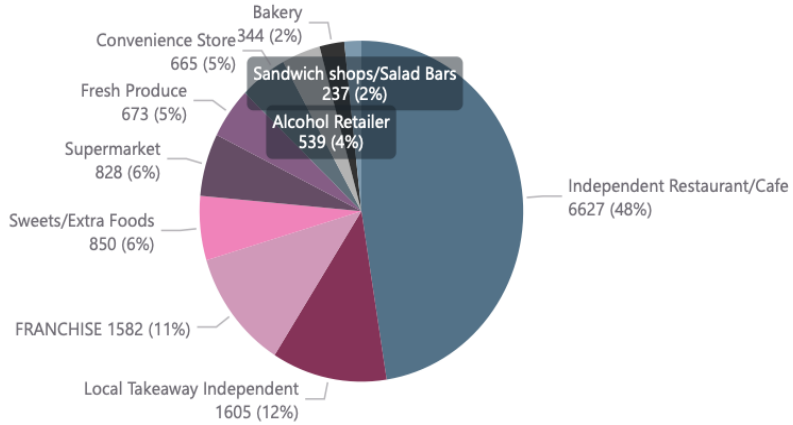
Region: Sydney - Parramatta

Postcode: All

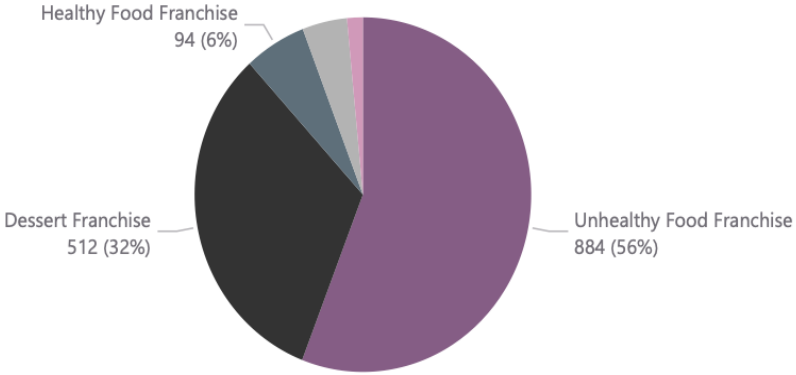
Postcode	Unique Outlets
2114	1975
2115	711
2116	987
2117	2084
2118	478
2119	2454
2121	782
2127	1225
2128	977
2141	2692
2142	4192
Accessible Hybrid	**47678**
Unique Outlet Count	13,950

Frequency of Cuisine

Hybrid Outlets by Main Category



Hybrid Outlets by Franchise Category



APPENDIX D

D.1. Extra information on methods

Study setting

The setting for this study was in NSW, Australia which is the most populous state in the country with more than 8.1 million residents[24]. There are 597 unique postcodes in total across the state of NSW. Of this, 506 were analysed as these were serviced by Uber Eats at the time of data acquisition. Uber Eats was selected as the meal delivery application representative of online food outlets as it is the market-leading app in Australia and comprised over 65% of all meal delivery bookings in 2024[25].

Postcodes are a four-digit number used by the Australia Post to assist with mail delivery and can be linked to a geographic area for spatial analysis. Data were extracted via web-scraping methods in January 2023 from Uber Eats to represent food outlets accessible online and Google Maps for food outlets that were locally accessible. The data extraction and food outlet categorisation process has been described in detail in our previous paper on the development of the DIGIFOOD dashboard[21]. Briefly, we obtained the following information for food outlets: postcode for the physical or deliverable location(s), food outlet name, unique business identifier, food outlet category and food outlet source (online from Uber Eats or local from Google Maps).

Measures

Exposure

The exposure variable for our analysis was the Index of Relative Socio-economic Disadvantage (IRSD) from the most updated version of the Socio-Economic Indexes for Areas in 2021 which uses edition 3 of the Australian Statistical Geography Standard from the Australian Bureau of Statistics[26]. This measure is a general socio-economic index that summarises information about the economic and social conditions of people and households within an area[26]. The index combines Census data such as income, education, employment, occupation, housing and family structure[26]. A low score indicates relatively greater disadvantage, and a high score indicates relative lack of disadvantage. IRSD was reported at the 2021 Postal Area (POA) code level in deciles. The POA dataset represents the Australian Bureau of Statistics' approximation of a general definition of postcodes[27]. The IRSD was therefore linked to the postcode in our DIGIFOOD dashboard dataset such that each postcode had an associated IRSD. We used quintiles as the measures of IRSD – lowest 20% of areas are given a quintile of 1 and the highest 20% of areas are given a quintile of 5. We combined decile 1 and 2 for Quintile 1 (most disadvantaged), decile 3 and 4 for Quintile 2, decile 5 and 6 for Quintile 3, decile 7 and 8 for Quintile 4 and decile 9 and 10 for Quintile 5 (least disadvantaged).

Outcome

In a previous paper, we have conceptualised 'hybrid' food environments as the collective number of food outlets accessible locally in-person within a specified postcode, in addition to food outlets accessible online via Uber Eats which can deliver into the specified postcode[21]. Online food outlets could have multiple duplicates across different postcodes as meal delivery apps enable food outlets to deliver into more than one neighbouring postcode. An example would be an Italian

restaurant that is physically located in postcode 2000, may have ‘online food outlets’ in postcodes 2006, 2010 and 2016.

As such, the outcome variables of interest for this study included the total number of hybrid food outlets which includes all online and local food outlets in a postcode that is serviced by Uber Eats across NSW. We analysed nine different categories of food outlets including: i) alcohol retailers, ii) fast-food franchises, iii) healthy food franchises, iv) fresh produce, v) supermarkets, vi) independent restaurants and cafes, vii) sandwich and salad bars, viii) sweets and extra foods and ix) independent takeaway shops. These were further grouped into either a healthy or unhealthy food retail category to allow an assessment of the potential impact of these food outlets on health. This was guided by previous studies in the food environment literature[10, 28, 29]. A definition of these food outlet categories is provided in a previous paper[21] .

Co-variates

Usual resident population at the 2021 Postal Area (POA) code were obtained from the IRSD file from the Australian Bureau of Statistics. Population size was considered a covariate as areas with higher population densities would plausibly service a greater amount of food outlets. In addition, the Accessibility/Remoteness Index of Australia Plus (ARIA+)[30] was used as a measure of relative geographic remoteness and was included in the statistical model as another covariate. The five classes of remoteness were: 0 indicating Major Cities of Australia, 1 – Inner Regional Australia, 2 – Outer Regional Australia, 3 – Remote Australia and 4 – Very Remote Australia. Due to very small sample sizes in Level 3 – Remote Australia and Level 4

– Very Remote Australia, these categories were combined with Level 2 – Outer Regional Australia for analysis. Therefore, the final variable for remoteness consists of three categories: Major Cities, Inner Regional and Outer Regional/Remote/Very Remote.

Statistical analyses

Quasi-Poisson regression models were used to analyse associations between relative socioeconomic disadvantage and number of food outlets within a hybrid food environment in NSW. Nine models were conducted, one for each of the nine food outlet categories. The Quasi-Poisson regression model accounts for overdispersion in count data, where the variance is greater than the mean[31]. Robust standard errors were used which account for certain violations of model assumptions (e.g., heteroscedasticity)[32]. Results of the models are presented as Incidence Rate Ratios (IRRs) and 95% Confidence Interval (CI).

Additional models included interaction terms between socioeconomic disadvantage quintiles and food environment type to investigate whether there were differences between online and local food outlets across the socioeconomic disadvantage gradient. Estimated marginal means were used to analyse pairwise comparisons of the online and local food environments in each quintile of socioeconomic disadvantage. Bonferroni tests were performed to account for multiple comparisons and reduce the risk of Type I errors. All analyses were performed in R Statistical Software (Version 4.4.1, R Core Team 2021).

D.2. Extra information on results

Summary statistics

A total of 140,514 food outlets were analysed across 506 unique postcodes in New South Wales. Of these, 35,523 food outlets were locally accessible, and 104,991 food outlets were accessible online via Uber Eats. Supplementary Table S1 displays the number of hybrid, online, and local food outlets across the nine food outlet categories and socioeconomic disadvantage quintiles.

Supplementary Table S1. Summary table of dataset including count of food outlets accessible online and locally across 506 unique postcodes in New South Wales, Australia.

	Hybrid (n)	Online (n)	Local (n)
Food Outlet Category			
Alcohol Retailer	5,191	2,183	3,008
Fast Food Franchise	7,854	5,966	1,888
Healthy Food Franchise	1,322	1,124	198
Fresh Produce	2,815	818	1,997
Supermarket	4,633	2,297	2,336
Independent Restaurant/Cafe	74,396	57,632	16,764
Sandwich Shops/Salad Bars	3,221	2,724	497
Sweets and Extra Foods	6,392	4,869	1,523
Independent Takeaway	19,984	16,096	3,888
Index of Relative Socioeconomic Disadvantage			
Quintile 1 (most disadvantaged)	21,141	15,084	6,057
Quintile 2	13,502	7829	5,673
Quintile 3	26,236	18,074	8,162
Quintile 4	33,353	25,772	7,581
Quintile 5 (least disadvantaged)	46,282	38,232	8,050

Research Question 1: Is there an association between socioeconomic disadvantage and access to food outlets in the 'hybrid food environment'?

Table 1 in Chapter 6 presents associations between the number of hybrid food outlets in nine different categories, and the quintiles of socioeconomic disadvantage. The following results describe the findings presented in Model 3 of Table 1.

Unhealthy Food Retail

We classified alcohol retailers, fast-food franchises, sweets and dessert shops, independent restaurants/cafes and independent takeaways, as unhealthy food retailers with the most potential for negative impacts on diets.

Compared to Quintile 1 (most disadvantaged), there was a higher count of hybrid alcohol retailers in Quintiles 3, 4 and 5 (IRR: 1.33, 95%CI: 1.06, 1.66; IRR: 1.43, 95%CI: 1.15, 1.79; IRR: 1.40, 95%CI: 1.15, 1.72, respectively). We did not observe any other significant associations between socioeconomic disadvantage and unhealthy food retailers (Table 1).

Healthy Food Retail

Fresh produce, supermarkets, healthy food franchises and sandwich and salad shops were classified as healthy food retailers with most potential for positive impacts on diets.

Results in Table 1 indicated that there was no significant association between socioeconomic disadvantage and number of hybrid fresh produce outlets. This was

also observed for hybrid supermarkets and hybrid sandwich/salad shops. A significantly higher count of hybrid healthy food franchises was noted in Quintile 4 (IRR: 1.44, 95%CI: 1.02, 2.02) and in Quintile 5, compared to Quintile 1 (IRR: 1.38, 95%CI: 1.02, 1.86).

Taken together, the results suggest that areas experiencing less socioeconomic disadvantage such as those in Quintiles 3, 4 and 5, have greater access to alcohol retailers and healthy food franchises, in the 'hybrid food environment' accounting for online and local outlets.

Research Question 2: Is there a difference between online and local food environments by food outlet category?

Unhealthy Food Retail

Results from the quasi-Poisson regression models showed that, compared to local alcohol retailers, there was a significantly higher count of online alcohol retailers (IRR: 1.65, 95%CI:1.39, 1.96), (P <0.001) (Table 1). Fast-food franchises also observed a higher count of online outlets, compared to local outlets (IRR: 3.65, 95%CI: 3.22, 4.14) (P<0.001). Likewise, the rate of sweets and dessert shops accessible online were 3.58 times (95%CI: 2.99, 4.29) greater than sweets and dessert shops accessible locally (P<0.001). In terms of independent restaurants and cafes, the rate of online outlets was 3.91 times (95%CI: (3.31, 4.63) greater than local outlets (P<0.001). The rate of independent takeaways accessible online was 4.76 times (95%CI: 4.26, 5.31) greater than independent takeaways accessible locally (P<0.001) (Table 1).

Healthy Food Retail

The rate of supermarkets accessible online was 1.14 times (95%CI: 0.99, 1.31) greater than supermarkets accessible locally (P<0.001). Similarly, the rate of healthy food franchises accessible online was 6.03 times (95%CI: 4.37, 8.34) greater than those accessible locally (P<0.001) (Table 1). For sandwich and salad shops, the rate of online outlets was 5.98 times (95%CI: 4.76, 7.51) higher than local outlets (P<0.001).

In contrast to other food outlet categories, the rate of fresh produce outlets accessible online was 49% lower (IRR: 0.51, 95%CI: 0.42, 0.61) than the rate of fresh produce outlets accessible locally (P<0.001) (Table 1).

In general, the analyses showed that there were significantly more food outlets accessible online compared to those accessible locally across most food outlet categories, after adjusting for socioeconomic disadvantage, remoteness and population size (Table 1).

Research Question 3: Is there a difference between online vs local food environments across quintiles of socioeconomic disadvantage?

The interactions between socioeconomic disadvantage and food environment on the number of food outlets, and adjusted for population size and remoteness, are displayed in Figure 1 of Chapter 6. Significant interactions were observed for unhealthy food retailers including alcohol (p<0.05), fast-food franchises (p<0.05),

and independent takeaways ($p<0.01$). In addition, significant interactions were also observed for healthy food retailers such as healthy-food franchises ($p<0.05$), fresh produce ($p<0.001$), supermarkets ($p<0.001$).

For supermarkets, in Quintile 1 (most disadvantaged) there was a higher number of local outlets, compared to online outlets. Whereas, in Quintile 5 (least disadvantaged), there was a higher number of online supermarkets compared to local supermarkets. For alcohol, in Quintiles 4 and 5, there was a higher number of online alcohol outlets compared to local alcohol outlets, but no difference between online and local alcohol outlets in Quintiles 1-3. Conversely, the difference between local and online access to fresh produce outlets appeared to be greatest in Quintile 1, with more fresh produce accessible locally than online. This difference was weaker in higher quintiles with increasing advantage, as fresh produce outlets were more accessible online (Figure 1).

For fast food outlets, healthy food franchises and takeaways, there were a higher number of online outlets across all quintiles (except healthy food franchises in Quintile 2), and the gap between online and local outlets was largest in Quintile 5 (Figure 1).

Altogether, the results show that compared to areas experiencing the most disadvantage, areas with the least disadvantage have greater access to online, than local food outlets. This includes both unhealthy food retail and healthy food retail such as alcohol retailers, fast-food franchises, independent takeaways, healthy food franchises, fresh produce and supermarkets (Figure 1).

D.3. R Script for data analysis

```
# SUMMARY OF PROGRAM ------------------------------------------------
---------
# Author: Sisi Jia
# Date: 25/6/2024
# Purpose:    Data analysis for DIGIFOOD Dashboard study
#
# Background: This study aims to investigate whether there is an
association between deprivation (socioeconomic status) and
accessibility of food outlets online (via UberEats) vs local (in-
person) (e.g. fast-food franchises, dessert stores, alcohol retailers).
#
# Data used:  combined.csv
#
#
# This program has the following sections:
#     1. Set global options
#     2. Load packages
#     3. Import data
#     4. Check and edit data
#     5. Model building
#     6. Model checking

# Section 1: SET GLOBAL OPTIONS -------------------------------------
---------
# Default in R is to add stars next to  statistically significant P-
values:
options(digits = 5)
options(scipen = 999)

# CHECK & SAVE default graph options
par() # view current graph settings
default.par <- par(no.readonly = TRUE)  # SAVE default graph options

# Section 2: INSTALL & LOAD PACKAGES --------------------------------
--------------
install.packages("emmeans")
install.packages("sjPlot")
install.packages("sjmisc")
install.packages("ggeffects")

library(readxl)
library(skimr)
library(summarytools)
library(packHV)
library(ggpubr)
library(ggplot2)
library(carData)
library(car)
library(jtools)
library(psych)
library(epiR)
library(rms)
library(DescTools)
library(survival)
library(date)
library(dplyr)
```

```
library(MASS)
library(pscl)
library(sandwich)
library(lmtest)
library(gridExtra)
library(msm)
library(patchwork)
library(ggsignif)
library(effects)
library(broom)
library(emmeans)
library(sjPlot)
library(sjmisc)
library(ggeffects)
library(cowplot)

# Section 3: IMPORT DATA ----------------------------------------------
--
HybridFoodEnv <- read.csv("C:/Users/kowe2286/OneDrive - The University
of Sydney (Staff)/DIGIFOOD Dashboard Analysis/combined.csv")
#combined.csv
HybridFoodEnv <- read.csv(file.choose()) #combined.csv

IRSD <- read_excel("C:/Users/kowe2286/OneDrive - The University of
Sydney (Staff)/DIGIFOOD Dashboard Analysis/IRSD.xlsx") #IRSD
IRSD <- read_excel(file.choose()) #IRSD

ARIA <- read.csv("C:/Users/kowe2286/OneDrive - The University of Sydney
(Staff)/DIGIFOOD Dashboard Analysis/ARIA.csv") #ARIA
ARIA <- read.csv(file.choose()) #ARIA

# Summary statistics
skim(HybridFoodEnv)
view(dfSummary(HybridFoodEnv))
View(HybridFoodEnv)
freq(HybridFoodEnv$main_category_based_on_labels)
freq(HybridFoodEnv$Franchise_Category)
freq(HybridFoodEnv$dataset)

View(IRSD)
colnames(IRSD)[colnames(IRSD) == "2021 Postal Area (POA) Code"] =
"SearchPostCode"
View(ARIA)
colnames(ARIA)[colnames(ARIA) == "Postcode"] = "SearchPostCode"

# Section 4: EDITING DATA----------------------------------------------
-------
#Linking postcodes with IRSD Decile

HybridFoodEnv <- merge(HybridFoodEnv, IRSD, by=c("SearchPostCode"),
all=TRUE)
View(HybridFoodEnv)
freq(HybridFoodEnv$Decile)

#Checking rows with any NA values
rows_with_na <- HybridFoodEnv[is.na(HybridFoodEnv$Outlet) |
is.na(HybridFoodEnv$Decile),]
View(rows_with_na)
```

```
#Remove rows with NA from dataset
HybridFoodEnv_cleaned <- HybridFoodEnv[complete.cases(HybridFoodEnv[,
c("Outlet", "Decile")]), ]
View(HybridFoodEnv_cleaned)

#Remove rows with NA for deciles due to missing postcode index
HybridFoodEnv_cleaned <- subset(HybridFoodEnv_cleaned, !SearchPostCode
%in% c('2308', '2624', '2678', '2620'))
View(HybridFoodEnv_cleaned)

#Linking cleaned file with ARIA
HybridFoodEnv_rural <- merge(HybridFoodEnv_cleaned, ARIA, by =
c("SearchPostCode"), all = TRUE)
View(HybridFoodEnv_rural)

#Remove rows with NA from dataset
HybridFoodEnv_rural_clean <-
HybridFoodEnv_rural[complete.cases(HybridFoodEnv_rural[, c("Outlet")]),
]
View(HybridFoodEnv_rural_clean)
view(dfSummary(HybridFoodEnv_rural_clean))

#remaining rows with NA
rows_with_na_rural <-
HybridFoodEnv_rural_clean[is.na(HybridFoodEnv_rural_clean$asgc2001.remo
teness.category),]
View(rows_with_na_rural) #1228 missing values - can't link remoteness
to postcode

#manually entering ARIA values for missing postcodes
missing_rurality <-
HybridFoodEnv_rural_clean[is.na(HybridFoodEnv_rural_clean$asgc2001.remo
teness.category), ]

unique_missing_postcodes <- unique(missing_rurality$SearchPostCode)
print(unique_missing_postcodes)

manual_rurality <- data.frame(
  SearchPostCode = c("2172","2175", "2178", "2179", "2555", "2556",
"2557", "2769", "2818"),
  asgc2001.remoteness.category = c("0", "0", "0", "0", "0", "0", "0",
"0", "1")
)

#merge data frame into main dataset
HybridFoodEnv_rural_cleaned <- merge(HybridFoodEnv_rural_clean,
manual_rurality, by = "SearchPostCode", all.x = TRUE, suffixes = c("",
"_manual"))
HybridFoodEnv_rural_cleaned$asgc2001.remoteness.category <-
ifelse(is.na(HybridFoodEnv_rural_cleaned$asgc2001.remoteness.category),
HybridFoodEnv_rural_cleaned$asgc2001.remoteness.category_manual,
HybridFoodEnv_rural_cleaned$asgc2001.remoteness.category)
HybridFoodEnv_rural_cleaned$asgc2001.remoteness.category_manual <- NULL
View(HybridFoodEnv_rural_cleaned)
rows_with_na_rural_remaining <-
HybridFoodEnv_rural_cleaned[is.na(HybridFoodEnv_rural_cleaned$asgc2001.
remoteness.category),]
```

```
View(rows_with_na_rural_remaining) #All missing values dealt with!

#Converting categorical to factor variables
##Main category factor variable
HybridFoodEnv_rural_cleaned$main_category.f <-
factor(HybridFoodEnv_rural_cleaned$main_category_based_on_labels,
                                                  labels = c('Alcohol
Retailer',
                                                             'Bakery',
                                                             'Convenience
Store',
                                                             'Franchise',
                                                             'Fresh
Produce',
                                                             'Independent
Restaurant/Cafe',
                                                             'Local
Takeaway Independent',
                                                             'Sandwich
shops/Salad Bars',

'Supermarket',

'Sweets/Extra Foods'))

#Check labelling
freq(HybridFoodEnv_rural_cleaned$main_category.f, round.digits = 1)

##Franchise category factor variable
HybridFoodEnv_rural_cleaned$franchise_category.f <-
factor(HybridFoodEnv_rural_cleaned$Franchise_Category,
                                                    labels = c('Non-
franchise',
                                                               'Bakery
Franchise',

'Dessert Franchise',

'Healthy Food Franchise',
                                                               'Juice
Franchise',

'Unhealthy Food Franchise'))
#Check labelling
freq(HybridFoodEnv_rural_cleaned$franchise_category.f, round.digits =1)

##Food environment factor variable
HybridFoodEnv_rural_cleaned$food_environment.f <-
factor(HybridFoodEnv_rural_cleaned$dataset,
                                                 labels = c("Local",

"Online"))

#Check labelling
freq(HybridFoodEnv_rural_cleaned$food_environment.f, round.digits = 1)

##Decile factor variable
```

```
HybridFoodEnv_rural_cleaned$decile.f <-
factor(HybridFoodEnv_rural_cleaned$Decile,
                                          labels = c('1',
                                                     '2',
                                                     '3',
                                                     '4',
                                                     '5',
                                                     '6',
                                                     '7',
                                                     '8',
                                                     '9',
                                                     '10'))

#Decile into quintile groups
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 1] <- 1
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 2] <- 1
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 3] <- 2
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 4] <- 2
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 5] <- 3
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 6] <- 3
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 7] <- 4
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 8] <- 4
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 9] <- 5
HybridFoodEnv_rural_cleaned$quintile[HybridFoodEnv_rural_cleaned$Decile
== 10] <- 5

#Quintile factor variable ------------------------------------------
-----------------
HybridFoodEnv_rural_cleaned$quintile.f <-
factor(HybridFoodEnv_rural_cleaned$quintile,
                                            labels = c("Quintile 1",
                                                       "Quintile 2",
                                                       "Quintile 3",
                                                       "Quintile 4",
                                                       "Quintile 5"))


#Check labelling
freq(HybridFoodEnv_rural_cleaned$quintile.f, round.digits = 1)

#changing name of usual resident population to population_size
HybridFoodEnv_rural_cleaned <- HybridFoodEnv_rural_cleaned %>%
rename(population_size = "Usual Resident Population")
View(HybridFoodEnv_rural_cleaned)
view(dfSummary(HybridFoodEnv_rural_cleaned))

#ARIA measure factor variable
HybridFoodEnv_rural_cleaned$remoteness.f <-
factor(HybridFoodEnv_rural_cleaned$asgc2001.remoteness.category,
                                                 labels = c("0",
```

```
                                                                    "1",
                                                                    "2",
                                                                    "3",
                                                                    "4"))

#Combining categories 2, 3 and 4 into one category (2 and above)
HybridFoodEnv_rural_cleaned$remoteness.merged[HybridFoodEnv_rural_clean
ed$asgc2001.remoteness.category == 0] <- 0
HybridFoodEnv_rural_cleaned$remoteness.merged[HybridFoodEnv_rural_clean
ed$asgc2001.remoteness.category == 1] <- 1
HybridFoodEnv_rural_cleaned$remoteness.merged[HybridFoodEnv_rural_clean
ed$asgc2001.remoteness.category == 2] <- 2
HybridFoodEnv_rural_cleaned$remoteness.merged[HybridFoodEnv_rural_clean
ed$asgc2001.remoteness.category == 3] <- 2
HybridFoodEnv_rural_cleaned$remoteness.merged[HybridFoodEnv_rural_clean
ed$asgc2001.remoteness.category == 4] <- 2

#Creating new factor variable for merged remoteness variable
HybridFoodEnv_rural_cleaned$remoteness.merged.f <-
factor(HybridFoodEnv_rural_cleaned$remoteness.merged,
                                                                  labels =
c('Major City',

'Inner Regional',

'Outer regional and remote'))
#Check labelling
freq(HybridFoodEnv_rural_cleaned$remoteness.merged.f, round.digits = 1)


#EXPLORATORY ANALYSIS-----------------------
##ALCOHOL
#Grouping online vs local by postcode
summary_data_alcohol_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
    Count_alcohol_retailers = sum(main_category.f == "Alcohol
Retailer"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
    Population = unique(population_size)
  )

print(summary_data_alcohol_onlinevlocal_postcode)
View(summary_data_alcohol_onlinevlocal_postcode)


#scatterplot of online vs local alcohol by postcode
ggplot(summary_data_alcohol_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_alcohol_retailers, fill =
food_environment.f)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Alcohol Retailers",
       fill = "Food Environment",
       title = "Comparison of Alcohol Retailers by Food Environment
Type and Socioeconomic Disadvantage")
```

```
## FAST FOOD-------------------------------------------------------------
--------
#Grouping online vs local fastfood by postcode
summary_data_fastfood_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
    Count_fastfood = sum(franchise_category.f == "Unhealthy Food
Franchise"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
    Population = unique(population_size)
  )

print(summary_data_fastfood_onlinevlocal_postcode)
View(summary_data_fastfood_onlinevlocal_postcode)

#scatterplot of online vs local fastfood by postcode
ggplot(summary_data_fastfood_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_fastfood, fill = food_environment.f))
+
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Fast Food Franchises",
       fill = "Food Environment",
       title = "Comparison of Fast Food Franchises by Food Environment
Type and Socioeconomic Disadvantage")

##HEALTHY FOOD FRANCHISES-----------------------------------------------
---------------
#Grouping online vs local healthy food franchise by postcode
summary_data_healthyfood_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
    Count_healthyfood = sum(franchise_category.f == "Healthy Food
Franchise"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
    Population = unique(population_size)
  )

print(summary_data_healthyfood_onlinevlocal_postcode)

#scatterplot of online vs local healthyfood by postcode
ggplot(summary_data_healthyfood_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_healthyfood, fill =
food_environment.f)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Healthy Food Franchises",
       fill = "Food Environment",
       title = "Comparison of Healthy Food Franchises by Food
Environment Type and Socioeconomic Disadvantage")
```

```
##FRESH PRODUCE-------------------------------------------------------------
-----
#Grouping online vs local fresh produce by postcode
summary_data_freshproduce_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
    Count_freshproduce = sum(main_category.f == "Fresh Produce"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
    Population = unique(population_size)
  )

print(summary_data_freshproduce_onlinevlocal_postcode)

#scatterplot of online vs local fresh produce by postcode
ggplot(summary_data_freshproduce_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_freshproduce, fill =
food_environment.f)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Fresh Produce",
       fill = "Food Environment",
       title = "Comparison of Fresh Produce by Food Environment Type
and Socioeconomic Disadvantage")

##SUPERMARKET---------------------------------------------------------------
--------------
#Grouping online vs local supermarkets by postcode
summary_data_supermarkets_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
    Count_supermarkets = sum(main_category.f == "Supermarket"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
    Population = unique(population_size)
  )

print(summary_data_supermarkets_onlinevlocal_postcode)

#scatterplot of online vs local supermarkets by postcode
ggplot(summary_data_supermarkets_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_supermarkets, fill =
food_environment.f)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Supermarkets",
       fill = "Food Environment",
       title = "Comparison of Supermarkets by Food Environment Type and
Socioeconomic Disadvantage")

##INDEPENDENT RESTAURANTS AND CAFES-----------------------------------
#Grouping online vs local independent restaurants and cafes by postcode
summary_data_independents_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
```

```
    Count_independents = sum(main_category.f == "Independent
Restaurant/Cafe"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
    Population = unique(population_size)
  )

print(summary_data_independents_onlinevlocal_postcode)

#scatterplot of online vs local independents by postcode
ggplot(summary_data_independents_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_independents, fill =
food_environment.f)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Independent Restaurants/Cafes",
       fill = "Food Environment",
       title = "Comparison of Independent Restaurants/Cafes by Food
Environment Type and Socioeconomic Disadvantage")

##SANDWICH SHOPS AND SALAD BARS----------------------------------------
--
#Grouping online vs local sandwich shops/salad bars by postcode
summary_data_sandwichsalad_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
    Count_sandwichsalad = sum(main_category.f == "Sandwich shops/Salad
Bars"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
    Population = unique(population_size)
  )

print(summary_data_sandwichsalad_onlinevlocal_postcode)

#scatterplot of online vs local sandwich shops/salad bars by postcode
ggplot(summary_data_sandwichsalad_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_sandwichsalad, fill =
food_environment.f)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Sandwich shops/Salad bars",
       fill = "Food Environment",
       title = "Comparison of Sandwich shops/Salad bars by Food
Environment Type and Socioeconomic Disadvantage")

##SWEETS AND DESSERTS--------------------------------------------------
--------
#Grouping online vs local sweets and desserts by postcode
summary_data_sweetsdesserts_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
    Count_sweetsdesserts = sum(main_category.f == "Sweets/Extra
Foods"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
```

```
    Population = unique(population_size)
  )

print(summary_data_sweetsdesserts_onlinevlocal_postcode)

#scatterplot of online vs local sweets and desserts by postcode
ggplot(summary_data_sweetsdesserts_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_sweetsdesserts, fill =
food_environment.f)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Sweets and Dessert Foods",
       fill = "Food Environment",
       title = "Comparison of Sweets and Dessert Foods by Food
Environment Type and Socioeconomic Disadvantage")

##TAKEAWAY INDEPENDENT-----------------------------------------------
-----------
#Grouping online vs local takeaways by postcode
summary_data_takeaways_onlinevlocal_postcode <-
HybridFoodEnv_rural_cleaned %>%
  group_by(SearchPostCode, food_environment.f) %>%
  summarise(
    Count_takeaways = sum(main_category.f == "Local Takeaway
Independent"),
    Disadvantage_quintile = unique(quintile.f),
    Remoteness = unique(remoteness.merged.f),
    Population = unique(population_size)
  )

print(summary_data_takeaways_onlinevlocal_postcode)

#scatterplot of online vs local takeaways by postcode
ggplot(summary_data_takeaways_onlinevlocal_postcode, aes(x =
Disadvantage_quintile, y = Count_takeaways, fill = food_environment.f))
+
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Socioeconomic Disadvantage",
       y = "Count of Local Takeaways",
       fill = "Food Environment",
       title = "Comparison of Local Takeaways by Food Environment Type
and Socioeconomic Disadvantage")

#Section 5:ANALYSIS AND MODEL BUILDING-----------------------------------
--------------
#Alcohol----------------------
#Poisson Model
alcohol_poisson_univariate <- glm(Count_alcohol_retailers ~
Disadvantage_quintile, family = poisson, data =
summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_poisson_univariate, confint = TRUE, digits = 3)
alcohol_poisson <- glm(Count_alcohol_retailers ~ Disadvantage_quintile
+ Population + food_environment.f, family = poisson, data =
summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_poisson, confint = TRUE, digits = 3) #p < .001 significant
but AIC and BIC values very high >6700
```

```
overdispersion_test <- sum(residuals(alcohol_poisson, type =
"pearson")^2)/ df.residual(alcohol_poisson)
print(overdispersion_test) #Ratio is 8.8 which is significantly >1 -
overdispersion present

#Quasipoisson Model
alcohol_quasipoisson <- glm(Count_alcohol_retailers ~
Disadvantage_quintile + Population + food_environment.f, family =
quasipoisson, data = summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_quasipoisson, confint = TRUE, digits = 3)

#remoteness model
alcohol_rural <-  glm(Count_alcohol_retailers ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_rural, confint = TRUE, vifs = TRUE,  digits = 3)

#Bivariate quasipoisson
alcohol_bivariate <- glm(Count_alcohol_retailers ~
Disadvantage_quintile + food_environment.f, family = quasipoisson, data
= summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_bivariate, confint = TRUE, digits = 3)

cov.alcohol.bivariate <- vcovHC(alcohol_bivariate, type = "HC0")
std.err.alcohol.bivariate <- sqrt(diag(cov.alcohol.bivariate))
r.est.alcohol.bivariate <- cbind(Estimate = coef(alcohol_bivariate),
"Robust SE" = std.err.alcohol.bivariate,
                        "Pr(>|z|)" = 2 *
pnorm(abs(coef(alcohol_bivariate)/std.err.alcohol.bivariate),
lower.tail = FALSE),
                        LL = coef(alcohol_bivariate) - 1.96
*std.err.alcohol.bivariate,
                        UL = coef(alcohol_bivariate) +
1.96*std.err.alcohol.bivariate)
r.est.alcohol.bivariate <- exp(r.est.alcohol.bivariate[, -3])
r.est.alcohol.bivariate


#check standard errors
#UCLA method
cov.alcohol <- vcovHC(alcohol_quasipoisson, type = "HC0")
std.err.alcohol <- sqrt(diag(cov.alcohol))
r.est.alcohol <- cbind(Estimate = coef(alcohol_quasipoisson), "Robust
SE" = std.err.alcohol,
                        "Pr(>|z|)" = 2 *
pnorm(abs(coef(alcohol_quasipoisson)/std.err.alcohol), lower.tail =
FALSE),
                        LL = coef(alcohol_quasipoisson) - 1.96
*std.err.alcohol,
                        UL = coef(alcohol_quasipoisson) +
1.96*std.err.alcohol)
r.est.alcohol

#Goodness of fit?
with(alcohol_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                 p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?
```

```
#Incident rate ratios
rexp.est.alcohol <- exp(r.est.alcohol[, -3])
rexp.est.alcohol

#RURAL
cov.alcohol.rural <- vcovHC(alcohol_rural, type = "HC0")
std.err.alcohol.rural <- sqrt(diag(cov.alcohol.rural))
r.est.alcohol.rural <- cbind(Estimate = coef(alcohol_rural), "Robust
SE" = std.err.alcohol.rural,
                        "Pr(>|z|)" = 2 *
pnorm(abs(coef(alcohol_rural)/std.err.alcohol.rural), lower.tail =
FALSE),
                        LL = coef(alcohol_rural) - 1.96
*std.err.alcohol.rural,
                        UL = coef(alcohol_rural) +
1.96*std.err.alcohol.rural)
r.est.alcohol.rural
rexp.est.alcohol.rural <- exp(r.est.alcohol.rural[, -3])
rexp.est.alcohol.rural

#Fast food----------------------------------------------------
#Poisson model
fastfood_poisson <- glm(Count_fastfood ~ Disadvantage_quintile +
Population + food_environment.f, family = poisson, data =
summary_data_fastfood_onlinevlocal_postcode)
summ(fastfood_poisson, confint = TRUE, digits = 3) #p < .001
significant but AIC and BIC very high (>7000)

#Quasipoisson
fastfood_quasipoisson <- glm(Count_fastfood ~ Disadvantage_quintile +
Population + food_environment.f, family = quasipoisson, data =
summary_data_fastfood_onlinevlocal_postcode)
summ(fastfood_quasipoisson, confint = TRUE, digits = 3) #Dispersion
parameter is 6.5

#CHATGPT method
#check standard errors
robust_se_fastfood <- coeftest(fastfood_quasipoisson, vcov =
vcovHC(fastfood_quasipoisson, type = "HC0"))
summary(robust_se_fastfood)
print(robust_se_fastfood)

#Exponentiate coefficients
exp_coef_fastfood <- exp(robust_se_fastfood[, "Estimate"])
exp_confint_fastfood <- exp(confint(fastfood_quasipoisson))
print(exp_coef_fastfood)

#check standard errors
#UCLA method
cov.fastfood <- vcovHC(fastfood_quasipoisson, type = "HC0")
std.err.fastfood <- sqrt(diag(cov.fastfood))
r.est.fastfood <- cbind(Estimate = coef(fastfood_quasipoisson), "Robust
SE" = std.err.fastfood,
                        "Pr(>|z|)" = 2 *
pnorm(abs(coef(fastfood_quasipoisson)/std.err.fastfood), lower.tail =
FALSE),
```

```
                        LL = coef(fastfood_quasipoisson) - 1.96
*std.err.fastfood,
                        UL = coef(fastfood_quasipoisson) +
1.96*std.err.fastfood)
r.est.fastfood

#Goodness of fit?
with(fastfood_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                  p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?

#Incident rate ratios
rexp.est.fastfood <- exp(r.est.fastfood[, -3])
rexp.est.fastfood

#Bivariate quasipoisson
fastfood_bivariate <- glm(Count_fastfood ~ Disadvantage_quintile +
food_environment.f, family = quasipoisson, data =
summary_data_fastfood_onlinevlocal_postcode)
summ(fastfood_bivariate, confint = TRUE, digits = 3)

cov.fastfood.bivariate <- vcovHC(fastfood_bivariate, type = "HC0")
std.err.fastfood.bivariate <- sqrt(diag(cov.fastfood.bivariate))
r.est.fastfood.bivariate <- cbind(Estimate = coef(fastfood_bivariate),
"Robust SE" = std.err.fastfood.bivariate,
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(fastfood_bivariate)/std.err.fastfood.bivariate),
lower.tail = FALSE),
                                  LL = coef(fastfood_bivariate) - 1.96
*std.err.fastfood.bivariate,
                                  UL = coef(fastfood_bivariate) +
1.96*std.err.fastfood.bivariate)
r.est.fastfood.bivariate <- exp(r.est.fastfood.bivariate[, -3])
r.est.fastfood.bivariate


#RURAL
fastfood_rural <- glm(Count_fastfood ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_fastfood_onlinevlocal_postcode)
summ(fastfood_rural, confint = TRUE, digits = 3)

cov.fastfood.rural <- vcovHC(fastfood_rural, type = "HC0")
std.err.fastfood.rural <- sqrt(diag(cov.fastfood.rural))
r.est.fastfood.rural <- cbind(Estimate = coef(fastfood_rural), "Robust
SE" = std.err.fastfood.rural,
                              "Pr(>|z|)" = 2 *
pnorm(abs(coef(fastfood_rural)/std.err.fastfood.rural), lower.tail =
FALSE),
                              LL = coef(fastfood_rural) - 1.96
*std.err.fastfood.rural,
                              UL = coef(fastfood_rural) +
1.96*std.err.fastfood.rural)
r.est.fastfood.rural
rexp.est.fastfood.rural <- exp(r.est.fastfood.rural)
rexp.est.fastfood.rural
```

```
formatted_fastfood.rural <- format(rexp.est.fastfood.rural, scientific
= FALSE)
print(formatted_fastfood.rural)

#Healthy food-----------------------------------------------------
#Poisson
healthyfood_poisson <- glm(Count_healthyfood ~ Disadvantage_quintile +
Population + food_environment.f, family = poisson, data =
summary_data_healthyfood_onlinevlocal_postcode)
summ(healthyfood_poisson, confint = TRUE, digits = 3) #p < .001
significant but AIC and BIC are >2800

#Quasipoisson
healthyfood_quasipoisson <- glm(Count_healthyfood ~
Disadvantage_quintile + Population + food_environment.f, family =
quasipoisson, data = summary_data_healthyfood_onlinevlocal_postcode)
summ(healthyfood_quasipoisson, confint = TRUE, digits = 3) #Dispersion
parameter is 4.2

#check standard errors
#UCLA method
cov.healthyfood <- vcovHC(healthyfood_quasipoisson, type = "HC0")
std.err.healthyfood <- sqrt(diag(cov.healthyfood))
r.est.healthyfood <- cbind(Estimate = coef(healthyfood_quasipoisson),
"Robust SE" = std.err.healthyfood,
                           "Pr(>|z|)" = 2 *
pnorm(abs(coef(healthyfood_quasipoisson)/std.err.healthyfood),
lower.tail = FALSE),
                           LL = coef(healthyfood_quasipoisson) - 1.96
*std.err.healthyfood,
                           UL = coef(healthyfood_quasipoisson) +
1.96*std.err.healthyfood)
r.est.healthyfood

#Goodness of fit?
with(healthyfood_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                     p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?

#Incident rate ratios
rexp.est.healthyfood <- exp(r.est.healthyfood[, -3])
rexp.est.healthyfood

#Bivariate quasipoisson
healthyfood_bivariate <- glm(Count_healthyfood ~ Disadvantage_quintile
+ food_environment.f, family = quasipoisson, data =
summary_data_healthyfood_onlinevlocal_postcode)
summ(healthyfood_bivariate, confint = TRUE, digits = 3)

cov.healthyfood.bivariate <- vcovHC(healthyfood_bivariate, type =
"HC0")
std.err.healthyfood.bivariate <- sqrt(diag(cov.healthyfood.bivariate))
r.est.healthyfood.bivariate <- cbind(Estimate =
coef(healthyfood_bivariate), "Robust SE" =
std.err.healthyfood.bivariate,
```

```
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(healthyfood_bivariate)/std.err.healthyfood.bivariate),
lower.tail = FALSE),
                                  LL = coef(healthyfood_bivariate) -
1.96 *std.err.healthyfood.bivariate,
                                  UL = coef(healthyfood_bivariate) +
1.96*std.err.healthyfood.bivariate)
r.est.healthyfood.bivariate <- exp(r.est.healthyfood.bivariate[, -3])
r.est.healthyfood.bivariate

#RURAL
healthyfood_rural <- glm(Count_healthyfood ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_healthyfood_onlinevlocal_postcode)
summ(healthyfood_rural, confint = TRUE, digits = 3)

cov.healthyfood.rural <- vcovHC(healthyfood_rural, type = "HC0")
std.err.healthyfood.rural <- sqrt(diag(cov.healthyfood.rural))
r.est.healthyfood.rural <- cbind(Estimate = coef(healthyfood_rural),
"Robust SE" = std.err.healthyfood.rural,
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(healthyfood_rural)/std.err.healthyfood.rural),
lower.tail = FALSE),
                                  LL = coef(healthyfood_rural) - 1.96
*std.err.healthyfood.rural,
                                  UL = coef(healthyfood_rural) +
1.96*std.err.healthyfood.rural)
r.est.healthyfood.rural
rexp.est.healthyfood.rural <- exp(r.est.healthyfood.rural)
rexp.est.healthyfood.rural
formatted_healthyfood.rural <- format(rexp.est.healthyfood.rural,
scientific = FALSE)
print(formatted_healthyfood.rural)

#Fresh produce----------------------------
#Poisson
freshproduce_poisson <- glm(Count_freshproduce ~ Disadvantage_quintile
+ Population + food_environment.f, family = poisson, data =
summary_data_freshproduce_onlinevlocal_postcode)
summ(freshproduce_poisson, confint = TRUE, digits = 3) #p < .001
significant but AIC and BIC >4700

#Quasipoisson
freshproduce_quasipoisson <- glm(Count_freshproduce ~
Disadvantage_quintile + Population + food_environment.f, family =
quasipoisson, data = summary_data_freshproduce_onlinevlocal_postcode)
summ(freshproduce_quasipoisson, confint = TRUE, digits = 3) #Dispersion
parameter = 4.09

#check standard errors
#UCLA method
cov.freshproduce <- vcovHC(freshproduce_quasipoisson, type = "HC0")
std.err.freshproduce <- sqrt(diag(cov.freshproduce))
r.est.freshproduce <- cbind(Estimate = coef(freshproduce_quasipoisson),
"Robust SE" = std.err.freshproduce,
                            "Pr(>|z|)" = 2 *
pnorm(abs(coef(freshproduce_quasipoisson)/std.err.freshproduce),
lower.tail = FALSE),
```

```
                              LL = coef(freshproduce_quasipoisson) - 1.96
*std.err.freshproduce,
                              UL = coef(freshproduce_quasipoisson) +
1.96*std.err.freshproduce)
r.est.freshproduce

#Goodness of fit?
with(freshproduce_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                      p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?

#Incident rate ratios
rexp.est.freshproduce <- exp(r.est.freshproduce[, -3])
rexp.est.freshproduce

#Bivariate quasipoisson
freshproduce_bivariate <- glm(Count_freshproduce ~
Disadvantage_quintile + food_environment.f, family = quasipoisson, data
= summary_data_freshproduce_onlinevlocal_postcode)
summ(freshproduce_bivariate, confint = TRUE, digits = 3)

cov.freshproduce.bivariate <- vcovHC(freshproduce_bivariate, type =
"HC0")
std.err.freshproduce.bivariate <-
sqrt(diag(cov.freshproduce.bivariate))
r.est.freshproduce.bivariate <- cbind(Estimate =
coef(freshproduce_bivariate), "Robust SE" =
std.err.freshproduce.bivariate,
                                      "Pr(>|z|)" = 2 *
pnorm(abs(coef(freshproduce_bivariate)/std.err.freshproduce.bivariate),
lower.tail = FALSE),
                                      LL = coef(freshproduce_bivariate)
- 1.96 *std.err.freshproduce.bivariate,
                                      UL = coef(freshproduce_bivariate)
+ 1.96*std.err.freshproduce.bivariate)
r.est.freshproduce.bivariate <- exp(r.est.freshproduce.bivariate[, -3])
r.est.freshproduce.bivariate

#RURAL
freshproduce_rural <- glm(Count_freshproduce ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_freshproduce_onlinevlocal_postcode)
summ(freshproduce_rural, confint = TRUE, digits = 3)

cov.freshproduce.rural <- vcovHC(freshproduce_rural, type = "HC0")
std.err.freshproduce.rural <- sqrt(diag(cov.freshproduce.rural))
r.est.freshproduce.rural <- cbind(Estimate = coef(freshproduce_rural),
"Robust SE" = std.err.freshproduce.rural,
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(freshproduce_rural)/std.err.freshproduce.rural),
lower.tail = FALSE),
                                  LL = coef(freshproduce_rural) - 1.96
*std.err.freshproduce.rural,
                                  UL = coef(freshproduce_rural) +
1.96*std.err.freshproduce.rural)
r.est.freshproduce.rural
rexp.est.freshproduce.rural <- exp(r.est.freshproduce.rural)
```

```
rexp.est.freshproduce.rural
formatted_freshproduce.rural <- format(rexp.est.freshproduce.rural,
scientific = FALSE)
print(formatted_freshproduce.rural)


#Supermarkets-----------------------------------------------------
#Poisson
supermarket_poisson <- glm(Count_supermarkets ~ Disadvantage_quintile +
Population + food_environment.f, family = poisson, data =
summary_data_supermarkets_onlinevlocal_postcode)
summ(supermarket_poisson, confint = TRUE, digits = 3) #p < .001
significant but AIC and BIC > 6300

#Quasipoisson
supermarket_quasipoisson <- glm(Count_supermarkets ~
Disadvantage_quintile + Population + food_environment.f, family =
quasipoisson, data = summary_data_supermarkets_onlinevlocal_postcode)
summ(supermarket_quasipoisson, confint = TRUE, digits = 3) #Dispersion
parameter = 5.77

#check standard errors
#UCLA method
cov.supermarket <- vcovHC(supermarket_quasipoisson, type = "HC0")
std.err.supermarket <- sqrt(diag(cov.supermarket))
r.est.supermarket <- cbind(Estimate = coef(supermarket_quasipoisson),
"Robust SE" = std.err.supermarket,
                           "Pr(>|z|)" = 2 *
pnorm(abs(coef(supermarket_quasipoisson)/std.err.supermarket),
lower.tail = FALSE),
                           LL = coef(supermarket_quasipoisson) - 1.96
*std.err.supermarket,
                           UL = coef(supermarket_quasipoisson) +
1.96*std.err.supermarket)
r.est.supermarket

#Goodness of fit?
with(supermarket_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                     p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?

#Incident rate ratios
rexp.est.supermarket <- exp(r.est.supermarket[, -3])
rexp.est.supermarket

#Bivariate quasipoisson
supermarkets_bivariate <- glm(Count_supermarkets ~
Disadvantage_quintile + food_environment.f, family = quasipoisson, data
= summary_data_supermarkets_onlinevlocal_postcode)
summ(supermarkets_bivariate, confint = TRUE, digits = 3)

cov.supermarkets.bivariate <- vcovHC(supermarkets_bivariate, type =
"HC0")
std.err.supermarkets.bivariate <-
sqrt(diag(cov.supermarkets.bivariate))
```

```
r.est.supermarkets.bivariate <- cbind(Estimate =
coef(supermarkets_bivariate), "Robust SE" =
std.err.supermarkets.bivariate,
                                      "Pr(>|z|)" = 2 *
pnorm(abs(coef(supermarkets_bivariate)/std.err.supermarkets.bivariate),
lower.tail = FALSE),
                                      LL = coef(supermarkets_bivariate)
- 1.96 *std.err.supermarkets.bivariate,
                                      UL = coef(supermarkets_bivariate)
+ 1.96*std.err.supermarkets.bivariate)
r.est.supermarkets.bivariate <- exp(r.est.supermarkets.bivariate[, -3])
r.est.supermarkets.bivariate

#RURAL
supermarkets_rural <- glm(Count_supermarkets ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_supermarkets_onlinevlocal_postcode)
summ(supermarkets_rural, confint = TRUE, digits = 3)

cov.supermarkets.rural <- vcovHC(supermarkets_rural, type = "HC0")
std.err.supermarkets.rural <- sqrt(diag(cov.supermarkets.rural))
r.est.supermarkets.rural <- cbind(Estimate = coef(supermarkets_rural),
"Robust SE" = std.err.supermarkets.rural,
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(supermarkets_rural)/std.err.supermarkets.rural),
lower.tail = FALSE),
                                  LL = coef(supermarkets_rural) - 1.96
*std.err.supermarkets.rural,
                                  UL = coef(supermarkets_rural) +
1.96*std.err.supermarkets.rural)
r.est.supermarkets.rural
rexp.est.supermarkets.rural <- exp(r.est.supermarkets.rural)
rexp.est.supermarkets.rural
formatted_supermarkets.rural <- format(rexp.est.supermarkets.rural,
scientific = FALSE)
print(formatted_supermarkets.rural)


#Independents-----------------------------------------------------
#Poisson
independent_poisson <- glm(Count_independents ~ Disadvantage_quintile +
Population + food_environment.f, family = poisson, data =
summary_data_independents_onlinevlocal_postcode)
summ(independent_poisson, confint = TRUE, digits = 3) #p < .001
significant - very very high AIC and BIC values - >66K

#Quasipoisson
independent_quasipoisson <- glm(Count_independents ~
Disadvantage_quintile + Population + food_environment.f, family =
quasipoisson, data = summary_data_independents_onlinevlocal_postcode)
summ(independent_quasipoisson, confint = TRUE, digits = 3) #Dispersion
parameter of 107 - very high

#check standard errors
#UCLA method
cov.independent <- vcovHC(independent_quasipoisson, type = "HC0")
std.err.independent <- sqrt(diag(cov.independent))
```

```
r.est.independent <- cbind(Estimate = coef(independent_quasipoisson),
"Robust SE" = std.err.independent,
                           "Pr(>|z|)" = 2 *
pnorm(abs(coef(independent_quasipoisson)/std.err.independent),
lower.tail = FALSE),
                           LL = coef(independent_quasipoisson) - 1.96
*std.err.independent,
                           UL = coef(independent_quasipoisson) +
1.96*std.err.independent)
r.est.independent

#Goodness of fit?
with(independent_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                     p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?

#Incident rate ratios
rexp.est.independent <- exp(r.est.independent[, -3])
rexp.est.independent

#Bivariate quasipoisson
independents_bivariate <- glm(Count_independents ~
Disadvantage_quintile + food_environment.f, family = quasipoisson, data
= summary_data_independents_onlinevlocal_postcode)
summ(independents_bivariate, confint = TRUE, digits = 3)

cov.independents.bivariate <- vcovHC(independents_bivariate, type =
"HC0")
std.err.independents.bivariate <-
sqrt(diag(cov.independents.bivariate))
r.est.independents.bivariate <- cbind(Estimate =
coef(independents_bivariate), "Robust SE" =
std.err.independents.bivariate,
                                      "Pr(>|z|)" = 2 *
pnorm(abs(coef(independents_bivariate)/std.err.independents.bivariate),
lower.tail = FALSE),
                                      LL = coef(independents_bivariate)
- 1.96 *std.err.independents.bivariate,
                                      UL = coef(independents_bivariate)
+ 1.96*std.err.independents.bivariate)
r.est.independents.bivariate <- exp(r.est.independents.bivariate[, -3])
r.est.independents.bivariate

#RURAL
independents_rural <- glm(Count_independents ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_independents_onlinevlocal_postcode)
summ(independents_rural, confint = TRUE, digits = 3)

cov.independents.rural <- vcovHC(independents_rural, type = "HC0")
std.err.independents.rural <- sqrt(diag(cov.independents.rural))
r.est.independents.rural <- cbind(Estimate = coef(independents_rural),
"Robust SE" = std.err.independents.rural,
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(independents_rural)/std.err.independents.rural),
lower.tail = FALSE),
```

```
                                    LL = coef(independents_rural) - 1.96
*std.err.independents.rural,
                                    UL = coef(independents_rural) +
1.96*std.err.independents.rural)
r.est.independents.rural
rexp.est.independents.rural <- exp(r.est.independents.rural)
rexp.est.independents.rural
formatted_independents.rural <- format(rexp.est.independents.rural,
scientific = FALSE)
print(formatted_independents.rural)

#Sandwich shops and salad bars-----------------------------------------
---------------------------------
#Poisson
sandwich_poisson <- glm(Count_sandwichsalad ~ Disadvantage_quintile +
Population + food_environment.f, family = poisson, data =
summary_data_sandwichsalad_onlinevlocal_postcode)
summ(sandwich_poisson, confint = TRUE, digits = 3) #p < .001
significant but AIC and BIC >4800

#Quasipoisson
sandwich_quasipoisson <- glm(Count_sandwichsalad ~
Disadvantage_quintile + Population + food_environment.f, family =
quasipoisson, data = summary_data_sandwichsalad_onlinevlocal_postcode)
summ(sandwich_quasipoisson, confint = TRUE, digits = 3) #Dispersion
parameter is 6.2

#check standard errors
#UCLA method
cov.sandwich <- vcovHC(sandwich_quasipoisson, type = "HC0")
std.err.sandwich <- sqrt(diag(cov.sandwich))
r.est.sandwich <- cbind(Estimate = coef(sandwich_quasipoisson), "Robust
SE" = std.err.sandwich,
                            "Pr(>|z|)" = 2 *
pnorm(abs(coef(sandwich_quasipoisson)/std.err.sandwich), lower.tail =
FALSE),
                            LL = coef(sandwich_quasipoisson) - 1.96
*std.err.sandwich,
                            UL = coef(sandwich_quasipoisson) +
1.96*std.err.sandwich)
r.est.sandwich

#Goodness of fit?
with(sandwich_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                      p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?

#Incident rate ratios
rexp.est.sandwich <- exp(r.est.sandwich[, -3])
rexp.est.sandwich

#Bivariate quasipoisson
sandwich_bivariate <- glm(Count_sandwichsalad ~ Disadvantage_quintile +
food_environment.f, family = quasipoisson, data =
summary_data_sandwichsalad_onlinevlocal_postcode)
summ(sandwich_bivariate, confint = TRUE, digits = 3)
```

```
cov.sandwich.bivariate <- vcovHC(sandwich_bivariate, type = "HC0")
std.err.sandwich.bivariate <- sqrt(diag(cov.sandwich.bivariate))
r.est.sandwich.bivariate <- cbind(Estimate = coef(sandwich_bivariate),
"Robust SE" = std.err.sandwich.bivariate,
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(sandwich_bivariate)/std.err.sandwich.bivariate),
lower.tail = FALSE),
                                  LL = coef(sandwich_bivariate) -
1.96 *std.err.sandwich.bivariate,
                                  UL = coef(sandwich_bivariate) +
1.96*std.err.sandwich.bivariate)
r.est.sandwich.bivariate <- exp(r.est.sandwich.bivariate[, -3])
r.est.sandwich.bivariate

#RURAL
sandwich_rural <- glm(Count_sandwichsalad ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_sandwichsalad_onlinevlocal_postcode)
summ(sandwich_rural, confint = TRUE, digits = 3)

cov.sandwich.rural <- vcovHC(sandwich_rural, type = "HC0")
std.err.sandwich.rural <- sqrt(diag(cov.sandwich.rural))
r.est.sandwich.rural <- cbind(Estimate = coef(sandwich_rural), "Robust
SE" = std.err.sandwich.rural,
                                "Pr(>|z|)" = 2 *
pnorm(abs(coef(sandwich_rural)/std.err.sandwich.rural), lower.tail =
FALSE),
                                LL = coef(sandwich_rural) - 1.96
*std.err.sandwich.rural,
                                UL = coef(sandwich_rural) +
1.96*std.err.sandwich.rural)
r.est.sandwich.rural
rexp.est.sandwich.rural <- exp(r.est.sandwich.rural)
rexp.est.sandwich.rural
formatted_sandwich.rural <- format(rexp.est.sandwich.rural, scientific
= FALSE)
print(formatted_sandwich.rural)


#Sweets and dessert shops-----------------------------------------------
------------
#Poisson
sweets_poisson <- glm(Count_sweetsdesserts ~ Disadvantage_quintile +
Population + food_environment.f, family = poisson, data =
summary_data_sweetsdesserts_onlinevlocal_postcode)
summ(sweets_poisson, confint = TRUE, digits = 3) #p < .001 significant
but AIC and BIC values >8400

#Quasipoisson
sweets_quasipoisson <- glm(Count_sweetsdesserts ~ Disadvantage_quintile
+ Population + food_environment.f, family = quasipoisson, data =
summary_data_sweetsdesserts_onlinevlocal_postcode)
summ(sweets_quasipoisson, confint = TRUE, digits = 3) #Dispersion
paramater is 10.6

#check standard errors
#UCLA method
cov.sweets <- vcovHC(sweets_quasipoisson, type = "HC0")
```

```
std.err.sweets <- sqrt(diag(cov.sweets))
r.est.sweets <- cbind(Estimate = coef(sweets_quasipoisson), "Robust SE"
= std.err.sweets,
                          "Pr(>|z|)" = 2 *
pnorm(abs(coef(sweets_quasipoisson)/std.err.sweets), lower.tail =
FALSE),
                          LL = coef(sweets_quasipoisson) - 1.96
*std.err.sweets,
                          UL = coef(sweets_quasipoisson) +
1.96*std.err.sweets)
r.est.sweets

#Goodness of fit?
with(sweets_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                  p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?

#Incident rate ratios
rexp.est.sweets <- exp(r.est.sweets[, -3])
rexp.est.sweets

#Bivariate quasipoisson
sweets_bivariate <- glm(Count_sweetsdesserts ~ Disadvantage_quintile +
food_environment.f, family = quasipoisson, data =
summary_data_sweetsdesserts_onlinevlocal_postcode)
summ(sweets_bivariate, confint = TRUE, digits = 3)

cov.sweets.bivariate <- vcovHC(sweets_bivariate, type = "HC0")
std.err.sweets.bivariate <- sqrt(diag(cov.sweets.bivariate))
r.est.sweets.bivariate <- cbind(Estimate = coef(sweets_bivariate),
"Robust SE" = std.err.sweets.bivariate,
                                "Pr(>|z|)" = 2 *
pnorm(abs(coef(sweets_bivariate)/std.err.sweets.bivariate), lower.tail
= FALSE),
                                LL = coef(sweets_bivariate) - 1.96
*std.err.sweets.bivariate,
                                UL = coef(sweets_bivariate) +
1.96*std.err.sweets.bivariate)
r.est.sweets.bivariate <- exp(r.est.sweets.bivariate[, -3])
r.est.sweets.bivariate

#RURAL
sweets_rural <- glm(Count_sweetsdesserts ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_sweetsdesserts_onlinevlocal_postcode)
summ(sweets_rural, confint = TRUE, digits = 3)

cov.sweets.rural <- vcovHC(sweets_rural, type = "HC0")
std.err.sweets.rural <- sqrt(diag(cov.sweets.rural))
r.est.sweets.rural <- cbind(Estimate = coef(sweets_rural), "Robust SE"
= std.err.sweets.rural,
                            "Pr(>|z|)" = 2 *
pnorm(abs(coef(sweets_rural)/std.err.sweets.rural), lower.tail =
FALSE),
                            LL = coef(sweets_rural) - 1.96
*std.err.sweets.rural,
```

```
                              UL = coef(sweets_rural) +
1.96*std.err.sweets.rural)
r.est.sweets.rural
rexp.est.sweets.rural <- exp(r.est.sweets.rural)
rexp.est.sweets.rural
formatted_sweets.rural <- format(rexp.est.sweets.rural, scientific =
FALSE)
print(formatted_sweets.rural)


#Local independent takeaway shops-------------------------------------
#Poisson
local_takeaway_poisson <- glm(Count_takeaways ~ Disadvantage_quintile +
Population + food_environment.f, family = poisson, data =
summary_data_takeaways_onlinevlocal_postcode)
summ(local_takeaway_poisson, confint = TRUE, digits = 3) #p < .001
significant but AIC and BIC >16000

#Quasipoisson
takeaway_quasipoisson <- glm(Count_takeaways ~ Disadvantage_quintile +
Population + food_environment.f, family = quasipoisson, data =
summary_data_takeaways_onlinevlocal_postcode)
summ(takeaway_quasipoisson, confint = TRUE, digits = 3) #Dispersion
paramater is 14.9

#check standard errors
#UCLA method
cov.takeaway <- vcovHC(takeaway_quasipoisson, type = "HC0")
std.err.takeaway <- sqrt(diag(cov.takeaway))
r.est.takeaway <- cbind(Estimate = coef(takeaway_quasipoisson), "Robust
SE" = std.err.takeaway,
                              "Pr(>|z|)" = 2 *
pnorm(abs(coef(takeaway_quasipoisson)/std.err.takeaway), lower.tail =
FALSE),
                              LL = coef(takeaway_quasipoisson) - 1.96
*std.err.takeaway,
                              UL = coef(takeaway_quasipoisson) +
1.96*std.err.takeaway)
r.est.takeaway

#Goodness of fit?
with(takeaway_quasipoisson, cbind(res.deviance = deviance, df =
df.residual,
                                        p = pchisq(deviance, df.residual,
lower.tail=FALSE))) #doesn't appear to be a good fit?

#Incident rate ratios
rexp.est.takeaway <- exp(r.est.takeaway[, -3])
rexp.est.takeaway

#Bivariate quasipoisson
takeaway_bivariate <- glm(Count_takeaways ~ Disadvantage_quintile +
food_environment.f, family = quasipoisson, data =
summary_data_takeaways_onlinevlocal_postcode)
summ(takeaway_bivariate, confint = TRUE, digits = 3)

cov.takeaway.bivariate <- vcovHC(takeaway_bivariate, type = "HC0")
std.err.takeaway.bivariate <- sqrt(diag(cov.takeaway.bivariate))
```

```
r.est.takeaway.bivariate <- cbind(Estimate = coef(takeaway_bivariate),
"Robust SE" = std.err.takeaway.bivariate,
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(takeaway_bivariate)/std.err.takeaway.bivariate),
lower.tail = FALSE),
                                  LL = coef(takeaway_bivariate) - 1.96
*std.err.takeaway.bivariate,
                                  UL = coef(takeaway_bivariate) +
1.96*std.err.takeaway.bivariate)
r.est.takeaway.bivariate <- exp(r.est.takeaway.bivariate[, -3])
r.est.takeaway.bivariate

#RURAL
takeaway_rural <- glm(Count_takeaways ~ Disadvantage_quintile +
Population + food_environment.f + Remoteness, family = quasipoisson,
data = summary_data_takeaways_onlinevlocal_postcode)
summ(takeaway_rural, confint = TRUE, digits = 3)

cov.takeaway.rural <- vcovHC(takeaway_rural, type = "HC0")
std.err.takeaway.rural <- sqrt(diag(cov.takeaway.rural))
r.est.takeaway.rural <- cbind(Estimate = coef(takeaway_rural), "Robust
SE" = std.err.takeaway.rural,
                              "Pr(>|z|)" = 2 *
pnorm(abs(coef(takeaway_rural)/std.err.takeaway.rural), lower.tail =
FALSE),
                              LL = coef(takeaway_rural) - 1.96
*std.err.takeaway.rural,
                              UL = coef(takeaway_rural) +
1.96*std.err.takeaway.rural)
r.est.takeaway.rural
rexp.est.takeaway.rural <- exp(r.est.takeaway.rural)
rexp.est.takeaway.rural
formatted_takeaway.rural <- format(rexp.est.takeaway.rural, scientific
= FALSE)
print(formatted_takeaway.rural)

#Printing output altogether - model without interaction terms
rexp.est.alcohol.rural
rexp.est.fastfood.rural
rexp.est.healthyfood.rural
rexp.est.freshproduce.rural
rexp.est.supermarkets.rural
rexp.est.independents.rural
rexp.est.sandwich.rural
rexp.est.sweets.rural
rexp.est.takeaway.rural

#SECTION 6-- INTERACTION TESTS: SEIFA X FOOD ENVIRONMENT TYPE
#ALCOHOL
alcohol_interaction <- glm(Count_alcohol_retailers ~
Disadvantage_quintile + Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_interaction, confint = TRUE, digits = 3) #individual
interaction terms not significant?

#Quasipoisson Model - no interaction
```

```
alcohol_quasipoisson <- glm(Count_alcohol_retailers ~
Disadvantage_quintile + Population + food_environment.f, family =
quasipoisson, data = summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(alcohol_quasipoisson, alcohol_interaction, test = "Chisq")
#significant result indicating relationship between socioeconomic
disadvantage and count of alcohol retailers varies depending on local
vs online food environment

#Using robust standard errors
alcohol_interaction <- glm(Count_alcohol_retailers ~
Disadvantage_quintile + Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_interaction, confint = TRUE, digits = 3)

cov.alcohol.interaction <- vcovHC(alcohol_interaction, type = "HC0")
std.err.alcohol.interaction <- sqrt(diag(cov.alcohol.interaction))
r.est.alcohol.interaction <- cbind(Estimate =
coef(alcohol_interaction), "Robust SE" = std.err.alcohol.interaction,
                                   "Pr(>|z|)" = 2 *
pnorm(abs(coef(alcohol_interaction)/std.err.alcohol.interaction),
lower.tail = FALSE),
                                   LL = coef(alcohol_interaction) - 1.96
*std.err.alcohol.interaction,
                                   UL = coef(alcohol_interaction) +
1.96*std.err.alcohol.interaction)
r.est.alcohol.interaction <- exp(r.est.alcohol.interaction[, -3])
r.est.alcohol.interaction

#RURAL
alcohol_rural_interaction <- glm(Count_alcohol_retailers ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_alcohol_onlinevlocal_postcode)
summ(alcohol_rural_interaction, confint = TRUE, digits = 3)

cov.alcohol.rural.interaction <- vcovHC(alcohol_rural_interaction, type
= "HC0")
std.err.alcohol.rural.interaction <-
sqrt(diag(cov.alcohol.rural.interaction))
r.est.alcohol.rural.interaction <- cbind(Estimate =
coef(alcohol_rural_interaction), "Robust SE" =
std.err.alcohol.rural.interaction,
                                    "Pr(>|z|)" = 2 *
pnorm(abs(coef(alcohol_rural_interaction)/std.err.alcohol.rural.interac
tion), lower.tail = FALSE),
                                    LL = coef(alcohol_rural_interaction)
- 1.96 *std.err.alcohol.rural.interaction,
                                    UL = coef(alcohol_rural_interaction)
+ 1.96*std.err.alcohol.rural.interaction)
r.est.exp.alcohol.rural <- cbind(
  exp(r.est.alcohol.rural.interaction[, c("Estimate", "Robust SE",
"LL", "UL")]),
  'Pr(>|z|)' = r.est.alcohol.rural.interaction[, "Pr(>|z|)"]
)
```

```
get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.alcohol.rural[, "Pr(>|z|)"],
get_significance)
print(significance_levels)

emm_alcohol <- emmeans(alcohol_rural_interaction, ~food_environment.f |
Disadvantage_quintile)
emm_alcohol_results <- pairs(emm_alcohol, adjust = "bonferroni")
summary_alcohol <- summary(emm_alcohol_results, infer = FALSE)
summary_alcohol$estimate <- exp(summary_alcohol$estimate)
print(summary_alcohol)
pairwise_alcohol <- summary(emm_alcohol)
ci_alcohol <- confint(emm_alcohol)
exp_coef <- exp(coef(emm_alcohol))
exp_ci <- exp(ci_alcohol)

#FAST FOOD FRANCHISE
fastfood_interaction <- glm(Count_fastfood ~ Disadvantage_quintile +
Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_fastfood_onlinevlocal_postcode)
summ(fastfood_interaction, confint = TRUE, digits = 3) #SIGNIFICANT
result for disadvantage quintile 5?

#Quasipoisson Model - no interaction
summ(fastfood_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(fastfood_quasipoisson, fastfood_interaction, test = "Chisq")
#SIGNIFICANT

#using robust standard errors
cov.fastfood.interaction <- vcovHC(fastfood_interaction, type = "HC0")
std.err.fastfood.interaction <- sqrt(diag(cov.fastfood.interaction))
r.est.fastfood.interaction <- cbind(Estimate =
coef(fastfood_interaction), "Robust SE" = std.err.fastfood.interaction,
                                    "Pr(>|z|)" = 2 *
pnorm(abs(coef(fastfood_interaction)/std.err.fastfood.interaction),
lower.tail = FALSE),
                                    LL = coef(fastfood_interaction) -
1.96 *std.err.fastfood.interaction,
                                    UL = coef(fastfood_interaction) +
1.96*std.err.fastfood.interaction)
r.est.fastfood.interaction <- exp(r.est.fastfood.interaction[, -3])
r.est.fastfood.interaction #In quintile 5 - there were 1.72 times more
online fastfood than local fastfood.
```

```
#RURAL
fastfood_rural_interaction <- glm(Count_fastfood ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_fastfood_onlinevlocal_postcode)
summ(fastfood_rural_interaction, confint = TRUE, digits = 3)

cov.fastfood.rural.interaction <- vcovHC(fastfood_rural_interaction,
type = "HC0")
std.err.fastfood.rural.interaction <-
sqrt(diag(cov.fastfood.rural.interaction))
r.est.fastfood.rural.interaction <- cbind(Estimate =
coef(fastfood_rural_interaction), "Robust SE" =
std.err.fastfood.rural.interaction,
                                          "Pr(>|z|)" = 2 *
pnorm(abs(coef(fastfood_rural_interaction)/std.err.fastfood.rural.inter
action), lower.tail = FALSE),
                                          LL =
coef(fastfood_rural_interaction) - 1.96
*std.err.fastfood.rural.interaction,
                                          UL =
coef(fastfood_rural_interaction) +
1.96*std.err.fastfood.rural.interaction)
r.est.exp.fastfood.rural <- cbind(
  exp(r.est.fastfood.rural.interaction[, c("Estimate", "Robust SE",
"LL", "UL")]),
  'Pr(>|z|)' = r.est.fastfood.rural.interaction[, "Pr(>|z|)"]
)

get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.fastfood.rural[, "Pr(>|z|)"],
get_significance)
print(significance_levels)

emm_fastfood <- emmeans(fastfood_rural_interaction, ~food_environment.f
| Disadvantage_quintile)
emm_fastfood_results <- pairs(emm_fastfood, adjust = "bonferroni")
summary_fastfood <- summary(emm_fastfood_results, infer = FALSE)
summary_fastfood$estimate <- exp(summary_fastfood$estimate)
print(summary_fastfood)

#HEALTHY FOOD FRANCHISE
healthyfood_interaction <- glm(Count_healthyfood ~
Disadvantage_quintile + Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_healthyfood_onlinevlocal_postcode)
```

```
summ(healthyfood_interaction, confint = TRUE, digits = 3)  #no
significant interaction terms

#Quasipoisson Model - no interaction
summ(healthyfood_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(healthyfood_quasipoisson, healthyfood_interaction, test =
"Chisq") #NO SIGNIFICANCE

#using robust standard errors
cov.healthyfood.interaction <- vcovHC(healthyfood_interaction, type =
"HC0")
std.err.healthyfood.interaction <-
sqrt(diag(cov.healthyfood.interaction))
r.est.healthyfood.interaction <- cbind(Estimate =
coef(healthyfood_interaction), "Robust SE" =
std.err.healthyfood.interaction,
                                       "Pr(>|z|)" = 2 *
pnorm(abs(coef(healthyfood_interaction)/std.err.healthyfood.interaction
), lower.tail = FALSE),
                                       LL = coef(healthyfood_interaction)
- 1.96 *std.err.healthyfood.interaction,
                                       UL = coef(healthyfood_interaction)
+ 1.96*std.err.healthyfood.interaction)
r.est.healthyfood.interaction <- exp(r.est.healthyfood.interaction[, -
3])
r.est.healthyfood.interaction

#RURAL
healthyfood_rural_interaction <- glm(Count_healthyfood ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_healthyfood_onlinevlocal_postcode)
summ(healthyfood_rural_interaction, confint = TRUE, digits = 3)

cov.healthyfood.rural.interaction <-
vcovHC(healthyfood_rural_interaction, type = "HC0")
std.err.healthyfood.rural.interaction <-
sqrt(diag(cov.healthyfood.rural.interaction))
r.est.healthyfood.rural.interaction <- cbind(Estimate =
coef(healthyfood_rural_interaction), "Robust SE" =
std.err.healthyfood.rural.interaction,
                                             "Pr(>|z|)" = 2 *
pnorm(abs(coef(healthyfood_rural_interaction)/std.err.healthyfood.rural
.interaction), lower.tail = FALSE),
                                             LL =
coef(healthyfood_rural_interaction) - 1.96
*std.err.healthyfood.rural.interaction,
                                             UL =
coef(healthyfood_rural_interaction) +
1.96*std.err.healthyfood.rural.interaction)
r.est.exp.healthyfood.rural <- cbind(
  exp(r.est.healthyfood.rural.interaction[, c("Estimate", "Robust SE",
"LL", "UL")]),
  'Pr(>|z|)' = r.est.healthyfood.rural.interaction[, "Pr(>|z|)"]
)
```

```
get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.healthyfood.rural[,
"Pr(>|z|)"], get_significance)
print(significance_levels)

emm_healthyfood <- emmeans(healthyfood_rural_interaction,
~food_environment.f | Disadvantage_quintile)
emm_healthyfood_results <- pairs(emm_healthyfood, adjust =
"bonferroni")
summary_healthyfood <- summary(emm_healthyfood_results, infer = FALSE)
summary_healthyfood$estimate <- exp(summary_healthyfood$estimate)
print(summary_healthyfood)

#FRESH PRODUCE
freshproduce_interaction <- glm(Count_freshproduce ~
Disadvantage_quintile + Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_freshproduce_onlinevlocal_postcode)
summ(freshproduce_interaction, confint = TRUE, digits = 3)
#SIGNIFICANT INTERACTIONS in Quintile 4 and 5.

#Quasipoisson Model - no interaction
summ(freshproduce_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(freshproduce_quasipoisson, freshproduce_interaction, test =
"Chisq") #very significant, P<0.001

#using robust standard errors
cov.freshproduce.interaction <- vcovHC(freshproduce_interaction, type =
"HC0")
std.err.freshproduce.interaction <-
sqrt(diag(cov.freshproduce.interaction))
r.est.freshproduce.interaction <- cbind(Estimate =
coef(freshproduce_interaction), "Robust SE" =
std.err.freshproduce.interaction,
                                        "Pr(>|z|)" = 2 *
pnorm(abs(coef(freshproduce_interaction)/std.err.freshproduce.interacti
on), lower.tail = FALSE),
                                        LL =
coef(freshproduce_interaction) - 1.96
*std.err.freshproduce.interaction,
                                        UL =
coef(freshproduce_interaction) + 1.96*std.err.freshproduce.interaction)
r.est.freshproduce.interaction <- exp(r.est.freshproduce.interaction[,
-3])
r.est.freshproduce.interaction
```

```
#RURAL
freshproduce_rural_interaction <- glm(Count_freshproduce ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_freshproduce_onlinevlocal_postcode)
summ(freshproduce_rural_interaction, confint = TRUE, digits = 3)

cov.freshproduce.rural.interaction <-
vcovHC(freshproduce_rural_interaction, type = "HC0")
std.err.freshproduce.rural.interaction <-
sqrt(diag(cov.freshproduce.rural.interaction))
r.est.freshproduce.rural.interaction <- cbind(Estimate =
coef(freshproduce_rural_interaction), "Robust SE" =
std.err.freshproduce.rural.interaction,
                                              "Pr(>|z|)" = 2 *
pnorm(abs(coef(freshproduce_rural_interaction)/std.err.freshproduce.rur
al.interaction), lower.tail = FALSE),
                                              LL =
coef(freshproduce_rural_interaction) - 1.96
*std.err.freshproduce.rural.interaction,
                                              UL =
coef(freshproduce_rural_interaction) +
1.96*std.err.freshproduce.rural.interaction)
r.est.exp.freshproduce.rural <- cbind(
  exp(r.est.freshproduce.rural.interaction[, c("Estimate", "Robust SE",
"LL", "UL")]),
  'Pr(>|z|)' = r.est.freshproduce.rural.interaction[, "Pr(>|z|)"]
)

get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.freshproduce.rural[,
"Pr(>|z|)"], get_significance)
print(significance_levels)

emm_freshproduce <- emmeans(freshproduce_rural_interaction,
~food_environment.f | Disadvantage_quintile)
emm_freshproduce_results <- pairs(emm_freshproduce, adjust =
"bonferroni")
summary_freshproduce <- summary(emm_freshproduce_results, infer =
FALSE)
summary_freshproduce$estimate <- exp(summary_freshproduce$estimate)
print(summary_freshproduce)

#SUPERMARKETS
supermarkets_interaction <- glm(Count_supermarkets ~
Disadvantage_quintile + Population + food_environment.f +
```

```
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_supermarkets_onlinevlocal_postcode)
summ(supermarkets_interaction, confint = TRUE, digits = 3)
#SIGNIFICANT INTERACTIONS in Quintile 4 and 5.

#Quasipoisson Model - no interaction
summ(supermarket_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(supermarket_quasipoisson, supermarkets_interaction, test =
"Chisq") #very significant, P<0.001

#using robust standard errors
cov.supermarkets.interaction <- vcovHC(supermarkets_interaction, type =
"HC0")
std.err.supermarkets.interaction <-
sqrt(diag(cov.supermarkets.interaction))
r.est.supermarkets.interaction <- cbind(Estimate =
coef(supermarkets_interaction), "Robust SE" =
std.err.supermarkets.interaction,
                                        "Pr(>|z|)" = 2 *
pnorm(abs(coef(supermarkets_interaction)/std.err.supermarkets.interacti
on), lower.tail = FALSE),
                                        LL =
coef(supermarkets_interaction) - 1.96
*std.err.supermarkets.interaction,
                                        UL =
coef(supermarkets_interaction) + 1.96*std.err.supermarkets.interaction)
r.est.supermarkets.interaction <- exp(r.est.supermarkets.interaction[,
-3])
r.est.supermarkets.interaction

#RURAL
supermarkets_rural_interaction <- glm(Count_supermarkets ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_supermarkets_onlinevlocal_postcode)
summ(supermarkets_rural_interaction, confint = TRUE, digits = 3)

cov.supermarkets.rural.interaction <-
vcovHC(supermarkets_rural_interaction, type = "HC0")
std.err.supermarkets.rural.interaction <-
sqrt(diag(cov.supermarkets.rural.interaction))
r.est.supermarkets.rural.interaction <- cbind(Estimate =
coef(supermarkets_rural_interaction), "Robust SE" =
std.err.supermarkets.rural.interaction,
                                              "Pr(>|z|)" = 2 *
pnorm(abs(coef(supermarkets_rural_interaction)/std.err.supermarkets.rur
al.interaction), lower.tail = FALSE),
                                              LL =
coef(supermarkets_rural_interaction) - 1.96
*std.err.supermarkets.rural.interaction,
                                              UL =
coef(supermarkets_rural_interaction) +
1.96*std.err.supermarkets.rural.interaction)
r.est.exp.supermarkets.rural <- cbind(
  exp(r.est.supermarkets.rural.interaction[, c("Estimate", "Robust SE",
"LL", "UL")]),
```

```
  'Pr(>|z|)' = r.est.supermarkets.rural.interaction[, "Pr(>|z|)"]
)

get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.supermarkets.rural[,
"Pr(>|z|)"], get_significance)
print(significance_levels)

emm_supermarkets <- emmeans(supermarkets_rural_interaction,
~food_environment.f | Disadvantage_quintile)
emm_supermarkets_results <- pairs(emm_supermarkets, adjust =
"bonferroni")
summary_supermarkets <- summary(emm_supermarkets_results, infer =
FALSE)
summary_supermarkets$estimate <- exp(summary_supermarkets$estimate)
print(summary_supermarkets)

#INDEPENDENT RESTAURANTS AND CAFES
independents_interaction <- glm(Count_independents ~
Disadvantage_quintile + Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_independents_onlinevlocal_postcode)
summ(independents_interaction, confint = TRUE, digits = 3)  #NO
SIGNIFICANT INTERACTIONS

#Quasipoisson Model - no interaction
summ(independent_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(independent_quasipoisson, independents_interaction, test =
"Chisq") #No significance

#using robust standard errors
cov.independents.interaction <- vcovHC(independents_interaction, type =
"HC0")
std.err.independents.interaction <-
sqrt(diag(cov.independents.interaction))
r.est.independents.interaction <- cbind(Estimate =
coef(independents_interaction), "Robust SE" =
std.err.independents.interaction,
                                        "Pr(>|z|)" = 2 *
pnorm(abs(coef(independents_interaction)/std.err.independents.interacti
on), lower.tail = FALSE),
                                        LL =
coef(independents_interaction) - 1.96
*std.err.independents.interaction,
```

```
                                          UL =
coef(independents_interaction) + 1.96*std.err.independents.interaction)
r.est.independents.interaction <- exp(r.est.independents.interaction[,
-3])
r.est.independents.interaction

#RURAL
independents_rural_interaction <- glm(Count_independents ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_independents_onlinevlocal_postcode)
summ(independents_rural_interaction, confint = TRUE, digits = 3)

cov.independents.rural.interaction <-
vcovHC(independents_rural_interaction, type = "HC0")
std.err.independents.rural.interaction <-
sqrt(diag(cov.independents.rural.interaction))
r.est.independents.rural.interaction <- cbind(Estimate =
coef(independents_rural_interaction), "Robust SE" =
std.err.independents.rural.interaction,
                                              "Pr(>|z|)" = 2 *
pnorm(abs(coef(independents_rural_interaction)/std.err.independents.rur
al.interaction), lower.tail = FALSE),
                                              LL =
coef(independents_rural_interaction) - 1.96
*std.err.independents.rural.interaction,
                                              UL =
coef(independents_rural_interaction) +
1.96*std.err.independents.rural.interaction)
r.est.exp.independents.rural <- cbind(
  exp(r.est.independents.rural.interaction[, c("Estimate", "Robust SE",
"LL", "UL")]),
  'Pr(>|z|)' = r.est.independents.rural.interaction[, "Pr(>|z|)"]
)

get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.independents.rural[,
"Pr(>|z|)"], get_significance)
print(significance_levels)

emm_independents <- emmeans(independents_rural_interaction,
~food_environment.f | Disadvantage_quintile)
emm_independents_results <- pairs(emm_independents, adjust =
"bonferroni")
summary_independents <- summary(emm_independents_results, infer =
FALSE)
summary_independents$estimate <- exp(summary_independents$estimate)
```

```
print(summary_independents)

#SANDWICH SHOPS AND SALAD BARS
sandwich_interaction <- glm(Count_sandwichsalad ~ Disadvantage_quintile
+ Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_sandwichsalad_onlinevlocal_postcode)
summ(sandwich_interaction, confint = TRUE, digits = 3)  #NO SIGNIFICANT
INTERACTIONS

#Quasipoisson Model - no interaction
summ(sandwich_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(sandwich_quasipoisson, sandwich_interaction, test = "Chisq") #No
significance

#using robust standard errors
cov.sandwich.interaction <- vcovHC(sandwich_interaction, type = "HC0")
std.err.sandwich.interaction <- sqrt(diag(cov.sandwich.interaction))
r.est.sandwich.interaction <- cbind(Estimate =
coef(sandwich_interaction), "Robust SE" = std.err.sandwich.interaction,
                                    "Pr(>|z|)" = 2 *
pnorm(abs(coef(sandwich_interaction)/std.err.sandwich.interaction),
lower.tail = FALSE),
                                    LL = coef(sandwich_interaction)
- 1.96 *std.err.sandwich.interaction,
                                    UL = coef(sandwich_interaction)
+ 1.96*std.err.sandwich.interaction)
r.est.sandwich.interaction <- exp(r.est.sandwich.interaction[, -3])
r.est.sandwich.interaction

#RURAL
sandwich_rural_interaction <- glm(Count_sandwichsalad ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_sandwichsalad_onlinevlocal_postcode)
summ(sandwich_rural_interaction, confint = TRUE, digits = 3)

cov.sandwich.rural.interaction <- vcovHC(sandwich_rural_interaction,
type = "HC0")
std.err.sandwich.rural.interaction <-
sqrt(diag(cov.sandwich.rural.interaction))
r.est.sandwich.rural.interaction <- cbind(Estimate =
coef(sandwich_rural_interaction), "Robust SE" =
std.err.sandwich.rural.interaction,
                                          "Pr(>|z|)" = 2 *
pnorm(abs(coef(sandwich_rural_interaction)/std.err.sandwich.rural.inter
action), lower.tail = FALSE),
                                          LL =
coef(sandwich_rural_interaction) - 1.96
*std.err.sandwich.rural.interaction,
                                          UL =
coef(sandwich_rural_interaction) +
1.96*std.err.sandwich.rural.interaction)
r.est.exp.sandwich.rural <- cbind(
  exp(r.est.sandwich.rural.interaction[, c("Estimate", "Robust SE",
"LL", "UL")]),
```

```
  'Pr(>|z|)' = r.est.sandwich.rural.interaction[, "Pr(>|z|)"]
)

get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.sandwich.rural[, "Pr(>|z|)"],
get_significance)
print(significance_levels)

emm_sandwich <- emmeans(sandwich_rural_interaction, ~food_environment.f
| Disadvantage_quintile)
emm_sandwich_results <- pairs(emm_sandwich,adjust = "bonferroni")
summary_sandwich <- summary(emm_sandwich_results, infer = FALSE)
summary_sandwich$estimate <- exp(summary_sandwich$estimate)
print(summary_sandwich)

#SWEETS AND DESSERTS
sweets_interaction <- glm(Count_sweetsdesserts ~ Disadvantage_quintile
+ Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_sweetsdesserts_onlinevlocal_postcode)
summ(sweets_interaction, confint = TRUE, digits = 3)  #NO SIGNIFICANT
INTERACTIONS

#Quasipoisson Model - no interaction
summ(sweets_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(sweets_quasipoisson, sweets_interaction, test = "Chisq") #No
significance

#using robust standard errors
cov.sweets.interaction <- vcovHC(sweets_interaction, type = "HC0")
std.err.sweets.interaction <- sqrt(diag(cov.sweets.interaction))
r.est.sweets.interaction <- cbind(Estimate = coef(sweets_interaction),
"Robust SE" = std.err.sweets.interaction,
                                  "Pr(>|z|)" = 2 *
pnorm(abs(coef(sweets_interaction)/std.err.sweets.interaction),
lower.tail = FALSE),
                                  LL = coef(sweets_interaction) -
1.96 *std.err.sweets.interaction,
                                  UL = coef(sweets_interaction) +
1.96*std.err.sweets.interaction)
r.est.sweets.interaction <- exp(r.est.sweets.interaction[, -3])
r.est.sweets.interaction

#RURAL
```

```
sweets_rural_interaction <- glm(Count_sweetsdesserts ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_sweetsdesserts_onlinevlocal_postcode)
summ(sweets_rural_interaction, confint = TRUE, digits = 3)

cov.sweets.rural.interaction <- vcovHC(sweets_rural_interaction, type =
"HC0")
std.err.sweets.rural.interaction <-
sqrt(diag(cov.sweets.rural.interaction))
r.est.sweets.rural.interaction <- cbind(Estimate =
coef(sweets_rural_interaction), "Robust SE" =
std.err.sweets.rural.interaction,
                                        "Pr(>|z|)" = 2 *
pnorm(abs(coef(sweets_rural_interaction)/std.err.sweets.rural.interacti
on), lower.tail = FALSE),
                                        LL =
coef(sweets_rural_interaction) - 1.96
*std.err.sweets.rural.interaction,
                                        UL =
coef(sweets_rural_interaction) + 1.96*std.err.sweets.rural.interaction)
r.est.exp.sweets.rural <- cbind(
  exp(r.est.sweets.rural.interaction[, c("Estimate", "Robust SE", "LL",
"UL")]),
  'Pr(>|z|)' = r.est.sweets.rural.interaction[, "Pr(>|z|)"]
)

get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.sweets.rural[, "Pr(>|z|)"],
get_significance)
print(significance_levels)

emm_sweets <- emmeans(sweets_rural_interaction, ~food_environment.f |
Disadvantage_quintile)
emm_sweets_results <- pairs(emm_sweets, adjust = "bonferroni")
summary_sweets <- summary(emm_sweets_results, infer = FALSE)
summary_sweets$estimate <- exp(summary_sweets$estimate)
print(summary_sweets)

#INDEPENDENT TAKEAWAYS
takeaways_interaction <- glm(Count_takeaways ~ Disadvantage_quintile +
Population + food_environment.f +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_takeaways_onlinevlocal_postcode)
summ(takeaways_interaction, confint = TRUE, digits = 3)  #NO
SIGNIFICANT INTERACTIONS
```

```
#Quasipoisson Model - no interaction
summ(takeaway_quasipoisson, confint = TRUE, digits = 3)

#Compare models
anova(takeaway_quasipoisson, takeaways_interaction, test = "Chisq") #No
significance

#using robust standard errors
cov.takeaways.interaction <- vcovHC(takeaways_interaction, type =
"HC0")
std.err.takeaways.interaction <- sqrt(diag(cov.takeaways.interaction))
r.est.takeaways.interaction <- cbind(Estimate =
coef(takeaways_interaction), "Robust SE" =
std.err.takeaways.interaction,
                                     "Pr(>|z|)" = 2 *
pnorm(abs(coef(takeaways_interaction)/std.err.takeaways.interaction),
lower.tail = FALSE),
                                     LL = coef(takeaways_interaction) -
1.96 *std.err.takeaways.interaction,
                                     UL = coef(takeaways_interaction) +
1.96*std.err.takeaways.interaction)
r.est.takeaways.interaction <- exp(r.est.takeaways.interaction[, -3])
r.est.takeaways.interaction

#RURAL
takeaways_rural_interaction <- glm(Count_takeaways ~
Disadvantage_quintile + Population + food_environment.f + Remoteness +
food_environment.f*Disadvantage_quintile, family = quasipoisson, data =
summary_data_takeaways_onlinevlocal_postcode)
summ(takeaways_rural_interaction, confint = TRUE, digits = 3)

cov.takeaways.rural.interaction <- vcovHC(takeaways_rural_interaction,
type = "HC0")
std.err.takeaways.rural.interaction <-
sqrt(diag(cov.takeaways.rural.interaction))
r.est.takeaways.rural.interaction <- cbind(Estimate =
coef(takeaways_rural_interaction), "Robust SE" =
std.err.takeaways.rural.interaction,
                                           "Pr(>|z|)" = 2 *
pnorm(abs(coef(takeaways_rural_interaction)/std.err.takeaways.rural.int
eraction), lower.tail = FALSE),
                                           LL =
coef(takeaways_rural_interaction) - 1.96
*std.err.takeaways.rural.interaction,
                                           UL =
coef(takeaways_rural_interaction) +
1.96*std.err.takeaways.rural.interaction)
r.est.exp.takeaways.rural <- cbind(
  exp(r.est.takeaways.rural.interaction[, c("Estimate", "Robust SE",
"LL", "UL")]),
  'Pr(>|z|)' = r.est.takeaways.rural.interaction[, "Pr(>|z|)"]
)

get_significance <- function(p) {
  if (p < 0.001) {
    return("***")
  } else if (p < 0.01) {
    return("**")
```

```
  } else if (p < 0.05) {
    return("*")
  } else {
    return("")
  }
}

significance_levels <- sapply(r.est.exp.takeaways.rural[, "Pr(>|z|)"],
get_significance)
print(significance_levels)

print(r.est.exp.takeaways.rural)

emm_takeaways <- emmeans(takeaways_rural_interaction,
~food_environment.f | Disadvantage_quintile)
emm_takeaways_results <- pairs(emm_takeaways, adjust = "bonferroni")
summary_takeaways <- summary(emm_takeaways_results, infer = FALSE)
summary_takeaways$estimate <- exp(summary_takeaways$estimate)
print(summary_takeaways)

#OUTPUT OF ALL INTERACTION MODELS
r.est.exp.alcohol.rural
r.est.exp.fastfood.rural
r.est.exp.healthyfood.rural
r.est.exp.freshproduce.rural
r.est.exp.supermarkets.rural
r.est.exp.independents.rural
r.est.exp.sandwich.rural
r.est.exp.takeaways.rural
r.est.exp.sweets.rural


  #Section 7: PLOT GENERATION----------------------------------------
-----
#INTERACTION PLOTS
#Creating plots and arranging them
#Create a list of plots
plot_list <- list()

#alcohol
p1 <- plot_model(alcohol_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(alcohol_rural_interaction, terms = c("Disadvantage_quintile",
"food_environment.f"))

p1 <- p1 +
  labs(x = "", y = "Predicted count (n)", title = "Alcohol Retailers",
       color = "Food Environment") +
  scale_y_continuous(breaks = seq(0,16, by = 2)) +
  theme(legend.position = "bottom")

plot_list[[1]] <- p1

#fastfood
p2 <- plot_model(fastfood_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(fastfood_rural_interaction, terms =
c("Disadvantage_quintile", "food_environment.f"))
```

```
p2 <- p2 +
  labs(x = "", y = "Predicted count (n)", title = "Fast Food Outlets",
       color = "Food Environment") +
  theme(legend.position = "none")

plot_list[[2]] <- p2

#healthyfood
p3 <- plot_model(healthyfood_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(healthyfood_rural_interaction, terms =
c("Disadvantage_quintile", "food_environment.f"))

p3 <- p3 +
  labs(x = "", y = "Predicted count (n)", title = "Healthy Food
Franchises",
       color = "Food Environment") +
  theme(legend.position = "none")

plot_list[[3]] <- p3

#freshproduce
p4 <- plot_model(freshproduce_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(freshproduce_rural_interaction, terms =
c("Disadvantage_quintile", "food_environment.f"))

p4 <- p4 +
  labs(x = "", y = "Predicted count (n)", title = "Fresh Produce
Outlets",
       color = "Food Environment") +
  theme(legend.position = "none")

plot_list[[4]] <- p4

#supermarkets
p5 <- plot_model(supermarkets_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(supermarkets_rural_interaction, terms =
c("Disadvantage_quintile", "food_environment.f"))

p5 <- p5 +
  labs(x = "", y = "Predicted count (n)", title = "Supermarkets",
       color = "Food Environment") +
  scale_y_continuous(breaks = seq(0,10, by = 2)) +
  theme(legend.position = "none")

plot_list[[5]] <- p5

#independent restaurants
p6 <- plot_model(independents_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(independents_rural_interaction, terms =
c("Disadvantage_quintile", "food_environment.f"))

p6 <- p6 +
```

```
  labs(x = "", y = "Predicted count (n)", title = "Independent
Restaurants/Cafes",
       color = "Food Environment") +
  theme(legend.position = "none")

plot_list[[6]] <- p6

#sandwich
p7 <- plot_model(sandwich_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(sandwich_rural_interaction, terms =
c("Disadvantage_quintile", "food_environment.f"))

p7 <- p7 +
  labs(x = "", y = "Predicted count (n)", title = "Sandwich/Salad
Shops",
       color = "Food Environment") +
  theme(legend.position = "none")

plot_list[[7]] <- p7

#takeaways
p8 <- plot_model(takeaways_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(takeaways_rural_interaction, terms =
c("Disadvantage_quintile", "food_environment.f"))

p8 <- p8 +
  labs(x = "", y = "Predicted count (n)", title = "Takeaways",
       color = "Food Environment") +
  theme(legend.position = "none")

plot_list[[8]] <- p8

#sweets
p9 <- plot_model(sweets_rural_interaction, type = "pred", terms =
c("Disadvantage_quintile", "food_environment.f"))
ggpredict(sweets_rural_interaction, terms = c("Disadvantage_quintile",
"food_environment.f"))

p9 <- p9 +
  labs(x = "", y = "Predicted count (n)", title = "Sweets/Dessert
Shops",
       color = "Food Environment") +
  theme(legend.position = "none")

plot_list[[9]] <- p9


#Create a common legend
common_legend <- ggplot(summary_data_alcohol_onlinevlocal_postcode,
aes(x = Disadvantage_quintile, y = Count_alcohol_retailers, fill =
food_environment.f)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(y = "Count", color = "Food Environment") +
  theme(legend.position = "bottom")

#combined plots
```

```
combined_plot <- (p1 + p2 + p3 + p4 + p5 + p6 + p7 + p8 + p9) +
  plot_layout(ncol = 3, widths = c(10,10,10)) +
  theme(legend.position = "none")

#add in common legend
final_plot <- combined_plot + plot_layout(ncol = 3, guides = "collect")
& theme(legend.position = "bottom")
print(final_plot)

#With labels
combined_plot <- (p1 | p2 | p3) / (p4 | p5 | p6) / (p7 | p8 | p9) +
  plot_annotation(tag_levels = 'A') +
  plot_layout(guides = "collect") & theme(legend.position = "bottom")

print(combined_plot)
```

APPENDIX E

E.1 Full Medline Search Strategy

1.	((food* or meal*) adj1 deliver*).tw.
2.	(online food* adj2 (order* or purchas* or shop*)).tw.
3.	(Uber eat* or menulog* or just eat* or doorDash* or deliveroo or meituan or grubhub or zomato or foodpanda or swiggy or faaso's).mp.
4.	(online food deliver* adj1 (service* or platform* or app*)).mp.
5.	1 or 2 or 3 or 4
6.	Fast Foods/ or food*.mp.

7.	Restaurant*.mp.
8.	exp Meals/
9.	Meal*.mp.
10.	Food outlet*.mp.
11.	"out of home food*".tw.
12.	(Take away food* or takeaway food* or take out*).mp.
13.	6 or 7 or 8 or 9 or 10 or 11 or 12
14.	5 and 13
15.	Accessibility.mp.
16.	Food Labeling/
17.	Pricing.mp.
18.	(Food Label* or Nutrition* Qualit* or nutrition polic*).mp.
19.	((Kilojoule* or Calorie*) adj1 (information* or label*)).mp.
20.	(food market* or food promot* or food advertis*).mp.
21.	Geograph*.mp.
22.	availabilit*.mp.
23.	Spatial distribution*.mp.
24.	Food pric*.mp.
25.	"Costs and Cost Analysis"/
26.	"Costs and Cost Analysis".tw.
27.	affordab*.mp.
28.	15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 or 27
29.	14 and 28

E.2 PRISMA-ScR Checklist

Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
TITLE			
Title	1	Identify the report as a scoping review.	1
ABSTRACT			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	2
INTRODUCTION			

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	6
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	6
METHODS			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	7
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale.	7
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	8
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	Supplementary Table 1
Selection of sources of evidence†	9	State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review.	8-9
Data charting process‡	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	9
Data items	11	List and define all variables for which data were sought and any assumptions and simplifications made.	9
Critical appraisal of individual sources of evidence§	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate).	N/A
Synthesis of results	13	Describe the methods of handling and summarizing the data that were charted.	9
RESULTS			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	9
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data were charted and provide the citations.	11

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12).	N/A
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives.	12
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	10-26
DISCUSSION			
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	27
Limitations	20	Discuss the limitations of the scoping review process.	32-33
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	33-34
FUNDING			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review.	35

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.
* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.
† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).
‡ The frameworks by Arksey and O'Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting.
§ The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).

From: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med. 2018;169:467–473. doi: 10.7326/M18-0850.

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Benchmarking online food delivery applications against menu labelling laws: a cross-sectional observational analysis

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Abstract

Objective: It is unknown how well menu labelling schemes that enforce the display of kilojoule (kJ) labelling at point-of-sale have been implemented on online food delivery (OFD) services in Australia. This study aimed to examine the prevalence of kJ labelling on the online menus of large food outlets with more than twenty locations in the state or fifty locations nationally. A secondary aim was to evaluate the nutritional quality of menu items on OFD from mid-sized outlets that have fewer locations than what is specified in the current scheme.

Design: Cross-sectional analysis. Prevalence of kJ labelling by large food outlets on OFD from August to September 2022 was examined. Proportion of discretionary ('junk food') items on menus from mid-sized outlets was assessed.

Setting: Forty-three unique large food outlets on company (e.g. MyMacca's) and third party OFD (Uber Eats, Menulog, Deliveroo) within Sydney, Australia. Ninety-two mid-sized food outlets were analysed.

Participants: N/A.

Results: On company OFD apps, 35 % (7/23) had complete kJ labelling for each menu item. In comparison, only 4·8 % (2/42), 5·3 % (2/38) and 3·6 % (1/28) of large outlets on Uber Eats, Menulog and Deliveroo had complete kJ labelling at all locations, respectively. Over three-quarters, 76·3 % (345/452) of menu items from mid-sized outlets were classified as discretionary.

Conclusions: Kilojoule labelling was absent or incomplete on a high proportion of online menus. Mid-sized outlets have abundant discretionary choices and yet escape criteria for mandatory menu labelling laws. Our findings show the need to further monitor the implementation of nutrition policies on OFD.

Keywords
Food environment
Online food delivery
Menu labelling
Nutrition policy
Energy labelling
Calorie labelling

In 2017, overweight and obesity affected 25 % of children and adolescents and 67 % of adults living in Australia[1]. Obesity is associated with poor health outcomes and higher risk of non-communicable diseases such as CVD, diabetes and some cancers[2,3]. The development of overweight and obesity is attributed to multiple individual and environmental factors, including the availability of energy-dense foods, abundant food supply and appealing marketing of unhealthy foods and drinks[3]. A key dietary risk factor for obesity and chronic diseases is the excess consumption of discretionary foods, which are energy-dense and nutrient-poor foods that are not essential for health and yet high in saturated fat, added sugars, Na or alcohol as defined by the Australian Dietary Guidelines[4]. In 2018, discretionary foods contributed a third of total daily energy intake for Australians[5] and findings from Australia's Household Expenditure Survey in 2015–2016 showed that meals-out and fast foods accounted for, on average, 34 % of weekly budgets for foods and beverages[6]. Research has shown

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that a high consumption of takeaway foods is associated with poorer diet quality and higher prevalence of abdominal obesity in young adults[7].

The digitalisation of the food environment is changing the way individuals order and access foods, with potentially harmful implications for public health[8]. Online food delivery (OFD) services are websites or applications that allow consumers to order food and beverages to be picked up or delivered by couriers[9]. OFD connect consumers to a wide range of food outlets and can include a food outlet's company apps (e.g. McDonald's 'MyMacca's' app) or third-party platforms such as Uber Eats[9]. Globally, OFD were used by over 1·8 billion people in 2022[10] and are expected to grow to 2·64 billion users by 2027[9]. In Australia, the market-leading third-party OFD include Uber Eats, Menulog and Deliveroo accounting for 59·7 %, 17·5 % and 12·1 % of the market share, respectively[11]. The OFD usage has grown rapidly, with new research showing that on average over seven million Australians aged 14 years and over are using this service in a 3-month period, up from 3·6 million in early 2020[12]. Within Australia, Sydney has the highest proportion of users (41 %)[12]. In 2022, two-fifths of people living in Australian capital cities were using this service and the primary users were millennials (born between 1981 and 1996) and Gen Z (born between 1997 and 2012)[12,13]. A 72 % increase in usage of OFD over 5 years in Australia was found to be driven by adults with a high income who seek convenience[14]. This is also supported by emerging evidence from the UK, showing least deprived areas had greater access to food outlets on OFD[15]. The 2019 coronavirus (COVID-19) pandemic may have further driven usage, as a report published in 2021 showed Australian consumers were spending three times more on OFD compared to pre-pandemic periods[16]. With easier access and more choice, there is a potential risk of increased consumption of takeaway meals that are high in saturated fat, salt, added sugars and have excessively large portion sizes[7]. Studies have shown that a high proportion of meals offered on OFD are poor in nutritional quality. A cross-sectional observational study in Australia and New Zealand found 86 % of popular menu items offered on the market-leading OFD platform were discretionary[17]. A similar study found twelve outlets available on four of the leading OFD platforms in Canada had low diet quality scores (HEI-2015) ranging from 19·95 to 50·78 out of a maximum score of 100 and did not meet healthy eating recommendations[18].

Given the large proportion of unhealthy menu items offered on OFD, it is critical that consumers are provided with nutritional information such as kilojoule labelling. In New South Wales (NSW) – the most populous state in Australia with over 8·1 million people, a Menu Labelling Scheme was introduced in 2011, to raise awareness and assist consumers to make healthier choices. It mandates food outlets in NSW with more than twenty locations in NSW or more than fifty locations nationally, to display nutrition information on menus at point-of-sale, including the average energy content in kilojoules (kJs) of food items for sale and the reference statement *'the average adult daily energy intake is 8700 kJ'*[19]. An initial evaluation of the scheme targeted at 18–24-year-olds found menu labelling enhanced consumers' understanding of average daily energy intake and led to a 519 kJ reduction in energy purchased[19]. A study in Australia found that compared to those without nutrition information, consumers who were provided with information selected meals with a significantly lower energy content[20]. In addition, a systematic review and meta-analysis further supported this, finding menu labelling to be effective in a real-world research setting, with a 420 kJ reduction in energy consumed and 325 kJ reduction in energy ordered[21].

The increased demand and usage of food delivery services have led to a growing number of food outlets partnering with OFD[17]. However, it is unknown how well menu labelling is implemented by these online platforms. To our knowledge, there are no public health policies or nutritional labelling requirements that specifically apply to OFD platforms in Australia[22]. It is of further concern that food outlets with multiple locations that have fewer than twenty locations in NSW or fifty locations nationally are also likely serving energy-dense and nutrient-poor discretionary foods, and yet are exempt from the NSW Menu Labelling Scheme.

Thus, the primary aim of this study was to examine the prevalence of kJ labelling by large food outlets onto their company and third-party OFD apps in Sydney, Australia. A secondary aim was to evaluate the nutritional quality of menu items from mid-sized food outlets that do not meet the criteria for the NSW Menu Labelling Scheme.

Methods

Study design

This cross-sectional observational study was conducted in Sydney, Australia to assess the prevalence of kJ labelling and the nutritional quality of menu items from food outlets on OFD.

Sample selection

Selection of geographical location

As millennials (born between 1981 and 1996) and Gen Z (born between 1997 and 2012) are the primary users of OFD in Sydney[12,13], the top ten Local Government Areas (LGA) with the highest population of 15–44-year-olds were identified. This was achieved through a search of publicly available population-level Australian Bureau of Statistics census data[23]. Research has shown there is an uneven distribution of food outlets across the various suburbs by their Socio-Economic Indexes for Areas (SEIFA). SEIFA ranks areas in Australia based on their relative socio-economic advantage and disadvantage[24], with

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unhealthiest food outlets concentrating in most disadvantaged suburbs[17]. Suburbs in an Australian context refer to smaller residential communities outside but close to large cities and can also include inner city and central business district areas[25].

As such, from the ten LGA identified for the study, suburbs were grouped into SEIFA Index of Relative Socioeconomic Disadvantage (IRSD) to obtain an area-based measure of socio-economic status[26]. IRSD summarises information about the economic and social conditions of suburbs including income, educational attainment, unemployment and occupation of residents. The lower an area's IRSD score, the greater disadvantaged residents in that area are compared with residents in other areas[26]. Using Microsoft Excel (version 16.66) random number generator, suburbs were randomly selected within each SEIFA decile to ensure a representative spread across Sydney. The suburbs in order of SEIFA deciles, with most disadvantaged (decile 1) to least disadvantaged (decile 10), were Fairfield, Granville, Burwood, Woodpark, Kogarah, Chifley, Dulwich Hill, Ryde, Cremorne Point and Bondi, respectively. These suburbs were used as the location for delivery to identify large and mid-sized food outlets within the third-party OFD.

Identification of online food delivery and food outlets

OFD assessed in this study included company and third-party ordering apps. The third-party OFD apps selected in this study were Uber Eats, Menulog and Deliveroo, as these were the most used apps by consumers in Australia[11,12]. In this study, the definitions of 'large' and 'mid-sized' food outlets were guided by the criteria for 'standard food outlets' defined by the Food Act 2003 and Food Regulation 2015[27]. Large food outlets were defined as those outlets with twenty or more locations in NSW or fifty or more locations in Australia, which currently are required to comply with the scheme. Mid-sized outlets were defined as those with five to nineteen locations within NSW and are yet to meet the criteria for the scheme. All food outlets identified on OFD were manually searched online for the number of locations across NSW and Australia to classify them as 'large' or 'mid-sized'. This was cross-checked against an existing list of large food outlets from a NSW Food Authority evaluation report[19]. Company apps of these large food outlets were subsequently identified – for example, McDonald's as a large food outlet has a separate 'MyMacca's' app and Domino's has a separate 'Domino's' app.

Data extraction

A standardised protocol was used to collect data from large and mid-sized food outlets on third-party OFD apps. Company apps of large food outlets were only assessed for kJ labelling. Two researchers with dietetic training (SC, AJ) conducted searches for the ten suburbs on each of the three OFD apps. Researchers were logged out of personal accounts to avoid possible user bias introduced by prior usage and to ensure only publicly accessible data were collected. Searches were conducted over a 3-week period from 24th August to 14th September 2022. The time window for the search was set between 18.00 and 21.00, to reduce variability of menu items offered at different times. For consistency across apps, only the name of the suburb was searched for delivery. If the app requested researchers to pin a location, the top search result was selected, which is the location that automatically appears when the suburb name is entered. If a food outlet appeared more than once in a suburb search, data from only one location were extracted. For example, when a search in a suburb (e.g. Granville) on Uber Eats showed multiple McDonald's locations nearby, one location was randomly selected and assessed. Duplicate outlet locations within the same third-party app were excluded. For example, 'Pizza Hut Fairfield' was assessed once even though it was present in both searches for the suburbs of Fairfield and Woodpark on Deliveroo.

Outcome measures

The primary outcome of this study was the prevalence of kJ labelling of menu items offered from large food outlets on their company and third-party OFD apps. The secondary outcome was the nutritional quality of menu items from mid-sized outlets and prevalence of kJ labelling of these outlets on third-party OFD.

Kilojoule labelling by large food outlets

For the whole menu of large food outlets, researchers observed the number of menu items with and without kJ labelling and whether it displayed the reference statement, *'the average adult daily energy intake is 8700 kJ'* – an additional mandatory component of the NSW Menu Labelling Scheme. All large outlets in each search were assessed, irrespective of store opening hours at time of data extraction, as menus were available for viewing. From the data collected, the proportion of menu labelling was calculated by dividing the number of menu items with kJ labelling by the total number of menu items on the menu for that location and that third party app. The prevalence of kJ labelling by large food outlets on company and third-party OFD was determined, and this was compared within and across OFD. The data were further analysed by food outlet locations. Descriptive statistical analysis was performed using Microsoft Excel (Version 16.66).

Nutritional quality of menu items from mid-sized food outlets

To get a better representation of what consumers could order during store opening hours, data were only collected from mid-sized food outlets that were taking orders at the time of extraction. The data collected included menu item names, pictures and descriptions. A sample of five menu

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items from each outlet was identified using the 'picked for you' section on Uber Eats which is in a prominent position at the top of the screen or webpage. Similarly, the first five menu items in the 'popular menu section' were collected on either Menulog or Deliveroo. These items were chosen as they are the most salient to consumers and may have increased likelihoods of being ordered, as the principles of nudging suggest[28]. Researchers also noted whether mid-sized food outlets had voluntarily included kJ labelling of menu items on the OFD.

Menu items collected from mid-sized outlets were classified into food and beverage categories published by Chan and colleagues[29]. These categories have been previously used to classify menu items on online delivery platforms[30]. The food and beverage categories in this classification system aligned with the food and beverage types in the Australian Dietary Guidelines classification of Five Food Groups (FFG) and Discretionary items[4]. Thus, the menu items could then be classified as either FFG or Discretionary.

FFG items were foods or food combinations from the five food groups: (i) vegetables and legumes/beans, (ii) fruit, (iii) grain (cereal foods), (iv) lean meats and poultry, fish, eggs, tofu, nuts and seeds and legumes/beans and (v) milk, yoghurt, cheese and their alternatives[4]. Discretionary food items are those that are higher in saturated fat and/or added sugars, added salt or alcohol, generally more energy dense and low in fibre[4]. Mixed meals or bundle meals with discretionary components were classified based on their major ingredient or item, in its respective discretionary category. For example, a burger with bacon and a burger bundle meal with chips were classified as discretionary cereal-based mixed meals.

When menu items lacked information for classification, it was classified as 'not further defined'. Researchers (SC, AJ) cross-checked 20 % of the classification and differences were resolved by group consensus. The proportion of menu items in each category was calculated and the proportion of total discretionary items was determined.

Results

The prevalence of kilojoule labelling by large food outlets

Kilojoule labelling within each online food delivery app

A total of forty-three unique large food outlets were identified from the ten suburb searches across each of the three third-party apps. Of these unique outlets, twenty-three had a company app, forty-two were present on Uber Eats, thirty-eight on Menulog and twenty-eight on Deliveroo. A total of twenty-three menus from food outlets on company apps and 482 menus from food outlets on third-party OFD were assessed as shown in Figure 1. The menu of a food outlet franchise was assessed at each different location as food outlets had more than one

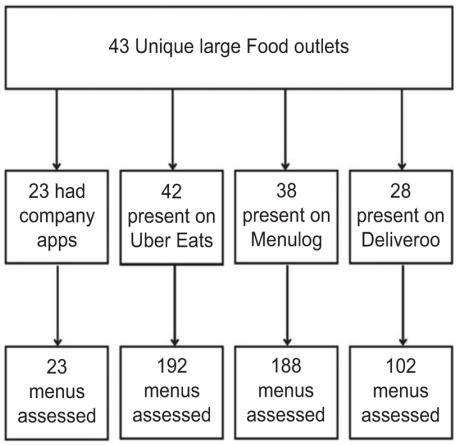

Fig. 1 Identification of menus on online food delivery (OFD) for kJ labelling assessment from forty-three unique large food outlets in Sydney, Australia. Large food outlets were defined as those outlets with twenty or more locations in NSW or fifty or more locations in Australia that are subject to menu labelling schemes. Ten suburbs were searched on third party apps to identify large food outlets, where the menu was assessed for kJ labelling. Large food outlets varied in presence across the three third-party OFD apps and/or company apps

location within one OFD platform and across the varying OFD. For example, McDonald's menu was assessed six times on Uber Eats due to the six different locations found. Overall, 192 menus from Uber Eats, 188 menus from Menulog and 102 menus from Deliveroo were assessed.

The median percentage of menus with kJ labelling across large food outlets on Uber Eats was 63 % (IQR: 89). Median percentage of menus with kJ labelling on Menulog was 61 % (IQR: 83). On Deliveroo, the median percentage of menus with kJ labelling was 22·5 % (IQR: 80). On company apps, the median percentage was much higher at 88 % (IQR: 27). Online supplementary material, Supplemental Table S1 provides a detailed overview of the proportion of kJ labelling across company apps and different outlet locations by each large food outlet assessed.

On company OFD apps, 35 % (8/23) of outlets had complete kJ labelling. In comparison, Uber Eats, Menulog and Deliveroo had 4·8 % (2/42), 5·3 % (2/38) and 3·6 % (1/28) of large outlets with complete kJ labelling at all locations, respectively. Online supplementary material, Supplemental Table S1 also shows that the proportion of menu items kJ labelled was inconsistent across different outlet locations within the same app, as the amount of menu items kJ labelled varied from 0 to 100 %. It was inconsistent for 55 % (23/42), 47 % (18/38) and 39 % (11/28) of large outlets on Uber Eats, Menulog and Deliveroo, respectively.

Kilojoule labelling across all online food delivery apps

Only one out of the 43 (2·3 %) large food outlets had complete kJ labelling across all locations and OFD apps on which it was present. In contrast, kJ labelling was completely absent on 23 % (10/43) of large outlets across all OFD apps. Of large outlets, another 23 % (10/43) had

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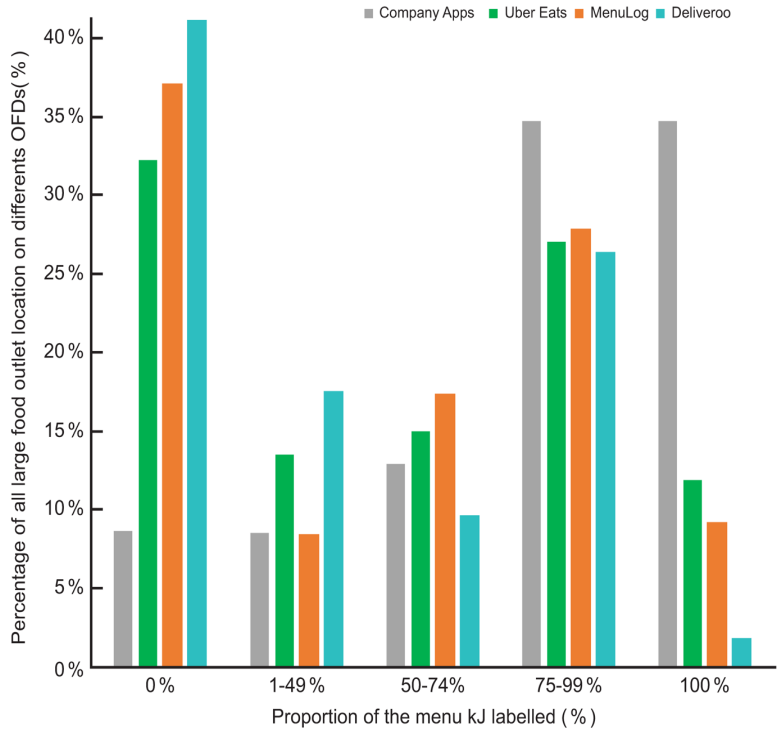

Fig. 2 The proportion of kilojoule labelling for all large food outlet locations on different online food delivery (OFD) apps. A total of twenty-three large food outlets had a company OFD app. The number of outlet locations menus assessed on Uber Eats, Menulog and Deliveroo was 192, 188 and 102, respectively. Food outlets were categorised based on the proportion of kJ labelling, into quartiles, with the exception of '1–49 %' as there was only a small percentage of outlets in this category. The proportion of menu labelling was calculated by dividing the number of menu items with kJ labelling by the total number of menu items on the menu for that location and that third party app

inconsistent kJ labelling across OFD, as they had menu items kJ labelled on some OFD apps but not on others.

Kilojoule labelling at different outlet locations

As large food outlets were found to have inconsistent kJ labelling within and across OFD apps, the data were further analysed by outlet locations. Figure 2 compares the proportion of kJ labelling by all large food outlet locations across their company and the three OFD apps. This figure shows that compared to company apps, where 35·0 % (8/23) of all large outlets had complete kJ labelling, only 12·0 % (23/192), 9·0 % (17/188) and 2·0 % (2/102) of outlet locations on Uber Eats, Menulog and Deliveroo, respectively, had complete kJ labelling. Two out of twenty-three outlet locations (8·7 %) did not have any form of kJ labelling on their company apps. In contrast, many more outlet locations on Uber Eats, Menulog and Deliveroo lacked any form of kJ labelling on their menu items. In respective order, kJ labelling was completely absent for 32·3 % (62/192), 37·2 % (70/188) and 41·2 % (42/102) of outlet locations on these OFD.

Large food outlets displaying the reference statement

Of the large food outlets that had a company app, 57·0 % (13/23) displayed the reference statement *'The average adult daily energy intake is 8700 kJ'*. On Uber Eats, Menulog and Deliveroo, the percentage of food outlets that displayed this reference statement at all locations was 0 %, 7·9 % (3/38) and 11 % (3/28), respectively.

Additional observations from large food outlets

On company ordering apps, one of the outlets that had incomplete kJ labelling provided a link to access allergen information. Once researchers accessed this link, additional nutritional information could be found. Similarly, two additional food outlets on Uber Eats had a direct link to access further nutritional information. Most food outlets with customisable menu items did not include kJ labelling for those items. However, it was found that one beverage outlet had displayed kJs for each customisable add-on, for example, adding confectionery or sweets into a drink. Furthermore, one food outlet on both Uber Eats and Menulog labelled all drinks and sauces flavours with the same kJ amount, for example, 'Coca-cola' and 'Coca-cola No Sugar' were both labelled with 730 kJ even though 'Coca-cola No Sugar' contains < 2 kJ/100 ml[31]. Additionally, one food outlet had kJ labelling for all menu items, except for bottled water.

Nutritional quality of menu items from mid-sized food outlets

A total of ninety-two mid-sized food outlets were identified across the three OFD apps. Five menu items from each

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Table 1 The proportion of mid-sized food outlets with menu items (*n* 452) in each category

Type of category	Food categories	*n*	%
Discretionary	Cereal-based mixed meal	104	23·0
	Meat or alternative-based mixed meal	90	19·9
	Milk-based beverages	40	8·8
	Baked good/dessert (homemade or similar)	32	7·1
	Fried potato (or similar)	26	5·8
	Iced confectionary and dairy-based desserts	26	5·8
	Vegetable-based mixed meal	17	3·8
	Sugar-sweetened beverages	10	2·2
	Total	345	76·3
Five food groups	Cereal-based mixed meal	70	15·5
	Vegetable-based mixed meal	11	2·4
	Meat or alternative-based mixed meal	9	2·0
	Meat and alternatives	8	1·8
	Beverages (juice, tea, milk/ milk alternative-based beverages)	5	1·1
	Other food (vegetables, soup, dairy and alternatives)	4	0·9
	Total	107	23·7

*Food and beverage categories are from a study published by Chan and colleagues[29] (*n* 20), two categories not shown in table: cereal-based mixed meal (not further defined) and meat or alternative-based mixed meal (not further defined) as they could not be categorised into Five Food Group or Discretionary according to the Australian Dietary Guidelines[4].
†Mixed meals or bundle meals with discretionary components were classified based on their major ingredient or item, in its respective discretionary category[4, 29]For example, a burger with bacon and a burger bundle meal with chips were classified as discretionary cereal-based mixed meals.

food outlet were assessed for nutritional quality. Menu items in the 'picked for you' section were extracted from ninety outlets on Uber Eats and menu items from the 'popular' section were extracted from two outlets on Menulog. Eight menu items that were classified as 'not further defined' due to insufficient description were excluded, resulting in a total of 452 menu items. The proportion of menu items in each category is shown in Table 1.

Discretionary items accounted for 76·3 % (345/452) of menu items. The majority of menu items were discretionary cereal-based mixed meals, which included pizzas, burgers, pasta, noodles or rice meals with discretionary components (e.g. fried chicken). The second largest discretionary item category was discretionary meat or alternative-based mixed meals. These included dishes such as fried chicken or meals with discretionary components such as meat curries made with cream.

Five food group items accounted for a total of 23·7 % (107/452) of menu items, with cereal-based mixed meals being the largest FFG category accounting for 15·5 % (70/452). These included dishes where the main component was pasta, noodles or rice without discretionary components.

Kilojoule labelling by mid-sized food outlets

A total of ninety-two mid-sized food outlets were identified across the three OFD apps. Mid-sized food outlets were analysed for whether they had displayed nutritional information on OFD. It was found that only two outlets – one each on Uber Eats and Menulog – had kJ labelling with 63 % and 55 % of their menu labelled, respectively.

Discussion

This study examined the prevalence of kJ labelling on OFD menus of large and mid-sized food outlets in NSW. This study found that on all three third-party OFD apps, less than 6 % of food outlets had complete kJ labelling on their menus. Additionally, the median percentage of menus with kJ labelling was higher on company apps (88 %) compared to third party OFD platforms. Our investigations also found over 75 % of 'picked for you' menu items from mid-sized outlets were in the discretionary category. Taken together, the findings of this study highlight that there is considerable room for improvement of kJ labelling on OFD to help consumers make informed choices.

A main finding of this study showed kJ labelling was incomplete or absent from most food outlets on OFD. While the NSW Menu Labelling Scheme requires large food outlets to provide kJ labelling at point-of-sale[19], it is evident that this information has been poorly provided on online food retail platforms. A recent study conducted in the USA similarly found more than half of restaurants offering children's meals via online platforms were not compliant with California's Healthy-By-Default Beverage Law (SB1192)[32]. This law requires restaurants that serve a children's meal with a beverage, to make the default beverage offered to be either water, unflavoured milk or non-dairy alternatives such as soy or almond milk. Likewise, another study from the USA found only 37 % of products sold across national online grocery retailers had provided nutrition and allergen information that is historically required on food product labels[33]. A recent randomised controlled study found calorie labelling resulted in fewer calories being purchased on OFD[34]. Furthermore, between 71 and 76 % of people involved in this study supported the idea of energy labelling[34]. As use of these online forms of food retail continues to increase in popularity, it is critical for these food policies to be upheld and maintained in digital settings.

Menus that are only partially labelled limit a consumer's ability to make informed choices. This study revealed inconsistencies in kJ labelling between different locations for the same franchise store and between the type of delivery service (whether through third-party couriers or company-owned). A study conducted in Canada also showed that energy labelling differed across various OFD services, with Uber Eats more likely to have provided calorie information than other platforms[35]. A recent Uber Eats article states that while Uber Eats are initially responsible for entering menus, once created, restaurants themselves can edit or add new menus on the app[36]. The ultimate responsibility of ensuring menu items have kJ labelling is therefore likely to be left to the food outlets. It is notable that Uber Eats currently does

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not allow menu edits to span multiple restaurant locations[37], hence menus for different locations need to be created and updated individually. This may therefore explain the inconsistent labelling between different outlet locations shown in our study. Our findings suggest that delineating the responsibilities that a meal delivery application or OFD service has compared to the food outlet offering the food and drink items may be helpful in the revision or creation of new menu labelling policies.

In this study, discretionary items accounted for over three-quarters of suggested menu items from mid-sized outlets. These findings align with a study conducted by Wang & Korai where 81 % of complete menus on independent takeaway outlets were discretionary foods, and these foods were likely to be offered as value bundles[30]. Although the Menu Labelling Scheme is currently only applied to standard food outlets with over twenty locations in the state or over fifty locations nationally[19], it may be beneficial to include these smaller 'mid-sized' franchise stores that do not currently meet the Scheme's definition. Research from the USA measured the energy content of popular independent and small-chain restaurants that were not mandated to display energy values[37]. Investigators noticed meals from these smaller-chain restaurants averaged 49 % higher in energy than meals from the largest national chain restaurants[37]. In addition, an Australian study showed that the majority of products from large food outlets were classified as unhealthy based on the study's criteria for total fat, saturated fat, sugar and Na[38]. Therefore, mid-sized outlets may be just as popular and nutritionally poor as larger outlets. Lowering the threshold to include mid-sized food outlets in the Scheme is a commonly suggested approach to extend the reach of menu labelling[40–42]. In the Australian Capital Territory, Australia, the threshold is lowered to include food outlets with seven or more locations within the territory[43]. Under a menu labelling scheme in the USA, this threshold includes franchises with at least twenty locations across the whole country[44]. It is evident that there is valid reasoning for the criteria of menu labelling schemes to be widened to include food outlets and franchises beyond an arbitrary number of locations.

Strengths and limitations

A key strength of this study is that kJ labelling was explored across multiple market leading OFD platforms as well as company OFD. However, as of 16th November 2022, Deliveroo had announced it would no longer operate in Australia[45]. Previous studies that investigated OFD were limited to only one platform[17,30]. Moreover, the results from this study could potentially be used to inform future policy guidelines on monitoring and implementing menu labelling for online platforms.

Despite this, limitations of this study must be acknowledged. Only ten suburbs in Sydney were included in the analysis and as such, a wider reach would be needed to capture all food outlets in NSW. This study additionally included customisable items in the percentage of total kJ labelling of the menu; however, as this is not a 'standard menu item', the percentage of mandatory labelling could be higher for some large food outlets. Furthermore, this study only looked at the nutritional quality of five menu items from each mid-sized food outlet; hence, the results cannot be generalised for the whole food outlet, although the positioning of menu items in prominent areas such can influence their selection[46].

As our study has shown there is a need for standardised approaches to menu labelling for menu boards and online platforms, other recommendations such as using the Health Star Rating or traffic light systems could similarly be adopted to provide more insight for consumers[47,48]. Investigation of other food outlet types such as supermarkets and convenience stores that sell products required to be kJ labelled under the scheme and can be delivered via OFD is indicated. Similar studies could also be conducted to analyse the prevalence of menus with kJ labelling in different states of Australia and world-wide.

Conclusion

The digital food environment is continuing to influence how we access foods, with potential adverse implications for population health. Kilojoule labelling was absent or incomplete on a high proportion of online menus, particularly on third-party OFD. The inconsistency of kJ labelling across different outlet locations on OFD demonstrates the need for clear guidance for the implementation of the NSW Menu Labelling Scheme on online food retail platforms, such that customers can make informed, and ideally healthier, choices. Mid-sized outlets that are currently exempt from menu labelling should be further considered, given the high proportion of discretionary food choices. The increased usage and accessibility to discretionary foods offered via online platforms highlight the need to update public health nutrition policies on menu labelling to include the digital food environment.

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Conflicts of interest

There are no conflicts of interest.

Authorship

S.C. and A.J.: data collection, data analysis and interpretation and writing – original draft preparation. S.J., S.R.P. and A.A.G.: conceptualisation. S.J., S.R.P., A.A.G. and M.A.A-F.: supervision. S.J., S.R.P., A.A.G., V.C., M.A.A-F., P.C.F. and P.P.: writing – review and editing.

Supplementary material

For supplementary material accompanying this paper visit https://doi.org/10.1017/S1368980024000673

Ethics of human subject participation

Not applicable.

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The Sydney Morning Herald

Lifestyle Health & wellness Nutrition

This loophole in your food delivery app may be a hazard to your health

Sarah Berry

April 15, 2024 — 5.00am

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In less than a decade, food delivery apps have gone from nonexistent to a multibillion-dollar industry, with Australians so hungry for their services that Uber Eats has been dubbed the "jewel in the crown" of its global operation.

By making junk foods more accessible than ever, food delivery apps have forever altered our food environment, leaving public health experts increasingly worried about the "new normal" that has been created.

Food labelling rules need an update. DIONNE GAIN

Back in 2011, when Uber Eats and many other platforms were but a twinkle in their founders' eyes, state governments around the country introduced menu labelling laws requiring large fast-food outlets to display both the average energy content (as kilojoules) on menu items and the reference statement, "The average daily energy intake is 8700 kJ" at point of sale.

Though single meals from fast food outlets contain up to 90 per cent of our total daily recommended energy intake, consumers greatly underestimate the energy content of fast foods.

The idea was that providing this information could help them limit their energy consumption, but a new review found labels were either absent or incomplete on in-house or third-party ordering apps.

The researchers looked at 43 large food outlets (franchises or chains with more than 20 locations in the state or 50 locations nationally) in NSW. They found less than 6 per cent of menus on food delivery apps such as Uber Eats, Menulog and the now defunct Deliveroo, had complete kilojoule labelling for all items listed.

Only 35 per cent of in-house apps for large fast-food chains, such as MyMacca's, had complete information.

“Meal delivery apps only really became popular around 2018-19 and then really picked up during COVID,” says lead author of the research, PhD candidate Sisi Jia, from the University of Sydney’s Charles Perkins Centre. “So I think the menu labelling scheme didn’t know what a third-party platform was back then. And it hasn’t been updated yet to include these other platforms.”

This loophole means food apps can get away with not providing the required information without fear of reprisal.

Separate research, including Jia’s own, has found people rarely use online food delivery services to purchase healthy foods, which comprise less than 20 per cent of the options available.

“[People are] ordering late on a Saturday night, they’re ordering typical unhealthy foods like burgers, pizza, fried chicken,” she says. “And they’re using a lot of promotions on these apps. So we know that they’re not good for our health, but they’re so accessible and so convenient.”

But, nutrition labels do encourage small improvements in the choices people make. This matters when overweight and obesity affects at least 25 per cent of Australian children and 67 per cent of adults.

An Uber Eats spokesperson said they would continue to expand their restaurant offerings – they currently have 50,000 – “while also using enhanced product design to help customers easily navigate to selections they’re interested in and to surface information that is important to them”.

The George Institute for Global Health food policy research fellow Damian Maganja said the findings are similar to the inconsistencies they have seen in online supermarkets.

Research has found people rarely use online food delivery services to purchase healthy foods.
EDWINA PICKLES

“Honest labelling can help people make informed decisions about the food they’re buying, but it’s not much use if that information isn’t easily visible or available at all,” said Maganja, who was not involved with the new study.

Jia and her colleagues advise people against using delivery services frequently (once a week or more) and say their findings highlight the need to update public health nutrition policies on menu labelling to include the digital food environment.

“The NSW Government is working hand in hand with all jurisdictions on a coordinated national approach to menu labelling,” said Tara Moriarty from the office of minister for agriculture.

“In November 2022, it was recognised by all states and territories that a national approach to menu labelling was required and agreed on the development of a policy guideline.

“Food Standards Australia New Zealand have been requested to prepare a proposal for a food regulatory measure for menu labelling under the Australia New Zealand Food Standards Code.”

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Food delivery apps leaving out nutritional info

By Sophia McCaughan
Updated April 15 2024 - 7:05am, first published 7:00am

Large food outlets leave out nutritional information on food delivery apps, a study has revealed. (Flavio Brancaleone/AAP PHOTOS)

Outdated NSW menu labelling laws are allowing large food outlets to leave out nutritional information on food delivery apps, a study has revealed.

The University of Sydney study shows that menu items for major food outlets such as McDonald's and KFC on food delivery apps are missing information on food that would help consumers make healthy choices.

The 2011 NSW Menu Labelling Scheme requires large fast-food outlets to display the average kilojoule content on menu items.

But the study's lead author SiSi Jia said that was not being done on online food delivery platforms.

"Just because it is online doesn't mean that the rules or regulations should be different," Ms Jia said.

She said the laws were written in a time when only traditional food environments were in mind, but since the pandemic the use of food delivery apps had increased.

"We need to update them, but we also need to make sure that they're well monitored and enforced," Ms Jia said.

According to market research company Roy Morgan, in 2022 around 40 per cent of people in Australian capital cities were using food delivery apps.

The defintion of large food outlets are franchises or chains with more than 20 locations in the state or 50 locations nationally.

The study reviewed 43 unique large food outlets with a total of 482 menus from UberEats, Menulog and Deliveroo included, with Deliveroo no longer in operation in the country.

Ms Jia told AAP that 94 per cent of menus of large food outlets had incomplete kilojoule labelling.

"We found that less than 6 per cent of menus on third party delivery apps had complete kilojoule labelling," she said.

The research found that there were also inconsistencies between different locations for the same franchise store and between the type of delivery service.

"Displaying the kilojoule content on a menu item is important to help people make more informed health choices," Ms Jia said.

"There are multiple studies that show menu labelling have real world impact."

NSW Agriculture Minister Tara Moriarty said the state government was working with other jurisdictions on a coordinated national approach to menu labelling.

"Food Standards Australia New Zealand (FSANZ) have been requested to prepare a proposal for a food regulatory measure for menu labelling under the Australia New Zealand Food Standards Code," she said in a statement.

Australian Associated Press

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Uber Eats discovery leaves 'ashamed' Aussies reeling: 'Refuse to look'

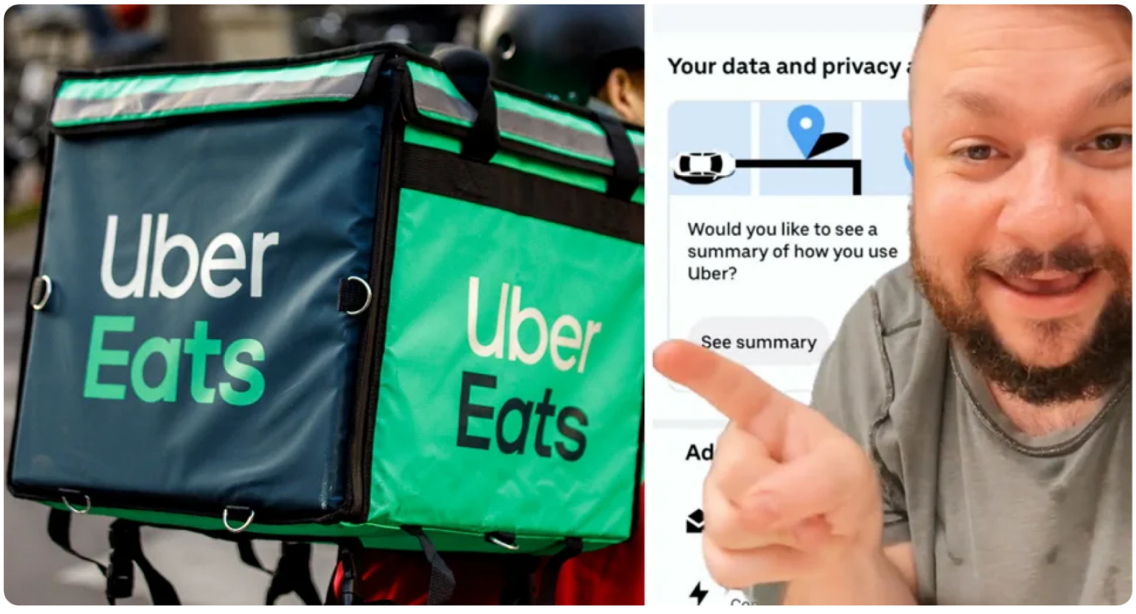
The find has been a big wake-up call to users of the popular food delivery service.

Amber Lowther

Updated 29 August 2023 · 3-min read

When cooking feels like too much of a chore, so many of us take the easy way out and turn to apps like Uber Eats without a second thought. But if you were to delve into your food ordering habits, you might be rattled by what you find.

Aussie TikToker Christian Hull did some digging earlier this week, and after making a mind-blowing discovery about his own penchant for Uber Eats, showed viewers how to check exactly how many times they've ordered through the app — sending fellow users into a spin.



Comedian Christian Hull has lifted the lid on a little-known feature of Uber Eats. Source: Getty, TikTok/@christianmhull

https://au.news.yahoo.com/uber-eats-discovery-leaves-ashamed-aussies-reeling-refuse-to-look-054751676.html

the following steps for tracking past Uber Eats orders:

1. Open the Uber or Uber Eats app and click on "Account"

2. Tap "Settings" (ignore this step if using the Uber Eats app)

3. Click on "Privacy"

4. Tap "Privacy Center"

5. Click on "See summary"

You'll then be shown how long you've been using the apps, how many trips you've taken, your rider rating and how many times you've ordered with Uber Eats. You can also see exactly what you've ordered and request to have detailed data emailed to you.

- Disturbing reason mayonnaise in man's burger 'started moving'
- McDonald's staff praise major move after employee's desperate plea
- CCTV shows HelloFresh customers targeted in 'recurring' problem

'Ashamed of my number'

Mr Hull spoke to Yahoo News Australia about discovering how many times he's ordered food through Uber Eats. "My podcast producer brought it up during recording my podcast Complete Drivel. I said 'I absolutely don't want to see that'. I don't cook and I'm not a very good cook. It's just so easy [to use Uber Eats]," the comedian said.

"I looked it up and I was very ashamed of my number. I have ordered Uber Eats 940 times, which is quite significant. And I've spent about $32,000 on Uber Eats, which is a lot of money. Maybe I should learn how to cook," he added.

Order history leaves Aussies reeling

Uber Eats users flooded the comment section on Mr Hull's video, with many shocked to learn they've ordered through the app hundreds or thousands of times. "1007, I deleted the app yesterday," wrote one embarrassed foodie. "I've ordered Uber Eats 1,229 times. Oops," commented another.

"Been with them for 2,857 days and in that time, I've ordered 641 times," claimed someone else, while others said they "refuse to look" out of fear the number would be higher than expected.

convenience" of food delivery apps.

"Our previous research tells us that over 85 per cent of popular menu items on these platforms are 'junk foods' — we know that too much of these foods can elevate our risk of obesity and associated chronic diseases like diabetes and heart disease," she told Yahoo.

Ms Jia also shared the following advice for users:

- Be mindful of how often you use meal delivery apps — using them once in a while is completely fine, in moderation.
- Choose healthier food options including meals abundant with vegetables, opt for grilled/steamed instead of deep-fried, and forego adding sugary drinks or fries to your order.

Do you have a story tip? Email: newsroomau@yahoonews.com.

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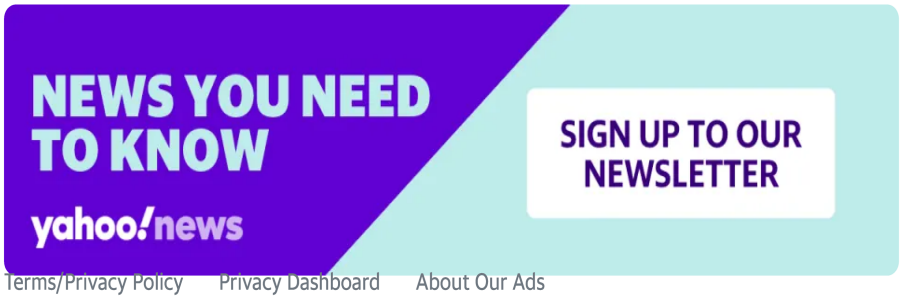

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Tips and shortcuts to help you eat well when you can't be bothered cooking after work

Sonia Nair

July 18, 2022

Pumpkin and chickpea casserole is a nutritional and affordable one-pot. WILLIAM MEPPEM

- Easy midweek meals with 12 ingredients or less
- Easy-to-prepare meals for fed up cooks
- 20 epic pasta bakes

Cooking can be hard. Particularly when you've come out of two years of intermittent lockdowns and are still living through one of the most severe health crises of our time. Which is perhaps why a tweet I haphazardly flung into the universe about not being able to summon the energy to cook after physically commuting into the office struck a chord with people. I received many tips and hacks, many more expressions of people experiencing the same struggle.

Anecdotal evidence isn't the only thing underlining our collective inability to cook at the moment. An UberEATS report from March 2021 revealed that Australians were spending 210 per cent more on food delivery than before the pandemic, even as in-venue dining returned.

This is at odds with the significant shift in how people fed themselves while in lockdown. Research showed that as people spent more time at home and less time doing everything else that a regular life entails – socialising, exercising, commuting to the office, recreational activities – their food consumption became more sustainable and healthier. They ate more fruit and vegetables, bought local, reduced their household food wastage, improved their culinary capabilities, and used online deliveries not for readymade food, but groceries.

This phenomenon certainly bore out in my own life. With a sudden surplus of time, I devised meal plans that I never would have followed in the past, repurposed leftover ingredients in improvised meals, and elevated the drudgery of the weekly grocery run into an occasion worth dressing up for.

So how do we get back to feeding ourselves in a sustainable and fulfilling manner? According to Sisi Jia, an accredited practising dietitian at The University of Sydney's School of Health Sciences, the odds are stacked against us.

The freezer is your best friend when you're simply too tired to even fry an egg.

"The cost of living is rising. Healthy groceries like fresh vegetables are at an unattainable price. The burden of preparing and cooking meals is dissuading people from feeding themselves in a rewarding way.

"Depending on where you go, the price points when you get takeout can be cheaper than fresh produce. In this food environment, it's easier to access unhealthier food than it is to access healthier food."

Jia's colleague Dr Stephanie Partridge, a Senior Research Fellow and an accredited practising dietitian, says people's inability to cook is a reflection of a "strange, new working environment".

"During lockdowns, we were working longer hours and this hasn't gone backwards. It's fine to be exhausted – an inability to cook is a reflection of the other parts of our lives. Ask yourself: can I cut back on work now that I'm commuting into the office and leave slightly earlier so I have more of the day to myself?"

Keep spinach in the freezer for stand-by meals such as this spinach and walnut pesto pasta WILLIAM MEPPEM

Tips and tricks to cook more

As the replies to my tweet attest, **the freezer is your best friend** when you're simply too tired to even fry an egg. **Bulk cooking** meals that freeze well – lasagne, pasta sauces, soups and stews – is a common tactic. The slow cooker was touted more than once as a life-saving appliance, particularly in winter.

Meal kit delivery services – like Marley Spoon, HelloFresh and Dinnerly – are a great option for people who don't have the ability or time to prepare meals, saving the time expended for meal planning and grocery shopping.

Partridge, who has studied meal kit delivery services, weighs up the nutritional properties and convenience of these meal kits.

'We've found they're pretty good with vegetables, carbs and protein per serve. They're generally healthy meals. These services are not for everyone, however, because it's costly per serve. It's often cheaper to buy these ingredients yourself and prepare them yourself, but the time saving is something you have to weigh up for your household."

Jia uses the weekend for meal planning and bulk cooking.
"On a Sunday afternoon, I'll make a **healthy pasta bake** with lots of vegies that will reheat well throughout the week. Another idea I have is a **shepherd's pie** – it's slightly involved so I make it on a Sunday, but it keeps for ages. Sometimes I'll also use the weekend to make a soup, keep it in the fridge and on weeknights, I'll add noodles and vegies," Jia says.

As for weeknights, Jia recommends **marinating meats** the night before you go to work and stir-frying them with seasonal vegetables and potatoes when you return from work. This tip can be extended to pre-preparing any meal the night before, from soups and pastas to risottos and fried rice. Partridge swears by **one-pan and one-pot meals.**

Stir-fries, such as Adam Liaw's chicken and broccoli hokkien noodles (WILLIAM MEPPEM

Many people swear by a few dependable recipes they can cook on autopilot in a pinch.

And keep it simple – store-bought pasta, **stir-fries**, eggs on toast with accompaniments, frozen chips and vegetables with sausages or chicken tenders, and build-your own burrito or poke bowls are a few of the common dishes people subsist on.
Avail yourself of pre-cut vegies or mixed bags of greens.

And feeding oneself takes a village when times are tough – cook meals for neighbours, family and friends when you're able to, and enjoy the reciprocity when you're unable to.

With cost of living increases impinging on household budgets, Jia and Partridge recommend **bulking up meals with frozen and canned vegetables** – which have the same nutritional properties as fresh vegetables – and canned pulses. Jia regularly adds **frozen spinach to her pasta sauces,** while Partridge often throws canned chickpeas into her one-pan meals.

When we return home from an arduous day at work and it'd take more time to order takeaway than cook, Jia says it's important to remember how rewarding cooking yourself a meal can be.

"One of the barriers is thinking or feeling like cooking is tiring or not worth the effort. But cooking can be enjoyable and should not be seen as a chore, but as a fulfilling or productive activity. Cooking is essential to our health."

Jia recommends some good old-fashioned bragging on Instagram to show off the fruits of your labour.

But implementing sustainable habits takes time, and Partridge's gentle reminder to take it easy on ourselves is an important one.

"Being fed and having food to consume is the most important thing. Don't be too hard on yourself. Try to do half a week to start off with, work on keeping that habit up and build on it slowly. Cook food you really enjoy the taste of."

MORE: Health and nutrition

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Appetite for convenience: how the surge in online food delivery could be harming our health

Published: August 13, 2021 3.35pm AEST

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With the simple touch of a smartphone, online food delivery services conveniently offer takeaway food straight to your door.

Contact-free delivery has surged in popularity as lockdowns have limited physical access to restaurants and food outlets. Industry reports suggest Australians are spending three times more on online food delivery than before the COVID-19 pandemic.

Globally, online food delivery is set to become a US$200 billion industry by 2025.

While these delivery apps provide easy access to a variety of foods, they may be harmful for our health.

Online food delivery services increase access to fast food

During January and February 2020, we analysed data from Uber Eats, the market-leading online food delivery service in Australia and New Zealand.

We focused on online food ordering in 233 suburbs in Sydney and 186 suburbs in Auckland with above-average populations of young people (aged 15-34). This age group represents the biggest consumers of online takeaway foods.

We evaluated 1,074 popular food outlets available on Uber Eats across Sydney and Auckland by type and nutritional quality.

A delivery man hands a paper bag to a woman at a front gate.

The use of food delivery apps has surged during the pandemic. Shutterstock

Results showed fast-food chains were the most popular food outlets. Fast-food chains accounted for 38% of the popular food outlets we looked at in Sydney and 54% in Auckland.

In Sydney, the most common fast-food chains were McDonald's (54 stores, 8.4%), Subway (52 stores, 7.6%), Oporto (42 stores, 6.2%) and Domino's (19 stores, 2.8%).

In Auckland, the most common fast-food chains were Subway (46 stores, 11.7%), McDonald's (40 stores, 10.2%), Burger King (24 stores, 6.1%) and Hell Pizza (20 stores, 5.1%).

These fast-food chains were all classified in the lowest healthiness category.

When The Conversation contacted Uber Eats for comment, their spokesperson pointed to their grocery category, which "[makes] fresh fruit and vegetables more accessible for thousands of Australians".

The spokesperson also said "quinoa, kale, bowls, brussel sprouts, edamame, acai, kombucha, hummus, poke and brown rice" all increased in popularity since June 2020. However according to our assessment, these items were not as popular or as well spruiked as the unhealthy menu items.

Read more: ***Want to be happier, healthier, save money? It's time to get cooking***

Independent outlets are rushing to join, but how healthy are their menus?

In Sydney, we found independent takeaway stores, like your local kebab shop or fish and chip shop, are the second most popular food outlet type (30% of all food outlets).

In a separate study, we analysed the menu items (13,841 in total) from 196 of Sydney's most popular independent takeaway stores on Uber Eats. We used a classification system of 38 different food and beverage categories based on the Australian Dietary Guidelines.

We found more than 80% of all the menu items were discretionary or "junk" foods. A large number of menu items (42%) were categorised as "discretionary cereal-based mixed meals", which includes foods such as pizzas, burgers, kebabs and pidés. Other types of junk foods could be battered fish or chicken schnitzel, and sugary drinks, among others.

Marketing tactics don't help

Both these studies demonstrate the abundance of unhealthy menu items available on these platforms. This, combined with in-app marketing tactics, can hinder consumers from making healthier choices.

We found unhealthier menu items were more than twice as likely to be categorised as "most popular" than healthier options on Uber Eats. In addition, unhealthy menu items were nearly one-and-a-half times more likely to include a photo, and over six times more likely to be offered as a value bundle compared with healthier items.

A young man sits on his bed eating pizza.

More than 80% of the menu items we looked at from independent takeaway stores on Uber Eats were junk foods. Shutterstock

In another study, we observed how online food delivery services have leveraged the pandemic to promote junk food on social media.

Our recently published digital marketing analysis on the Instagram accounts of nine online food delivery services across three regions (Australia/New Zealand, North America and the United Kingdom) found nearly 70% of all food advertised was junk food.

In 2020, 32% of posts referenced the pandemic. Most commonly, the messaging in these posts encouraged consumers to stay home and get food delivered to support local businesses.

While of course during lockdowns it's important to stay at home, and supporting local businesses is noble, worryingly, more than 97% of the food items featured in COVID-related Instagram posts from Australia and the UK were junk foods.

Read more: ***Combo meal deals and price discounts on fast food encourage us to eat more junk. It's time for policy action***

Can we promote healthier choices in the digital age?

Easy access to junk foods and drinks enabled by online food delivery presents a further challenge to the increasing rates of obesity. Australian data suggest 16% of 18 to 24-year-olds are obese. In New Zealand, around one in three people over 15 are obese.

The World Health Organization has acknowledged the growing impact of online food environments on people's diet choices. For the benefit of public health, it urges collective action by food industry, governments, policy makers and researchers.

In line with the WHO, we propose the following actions:

1. **include healthy online food environments in the National Obesity Strategy.** This is a ten-year strategy, currently under consultation, that will guide Australia's actions on the overweight and obesity epidemic. The public, particularly young people, have asked for supportive food environments that will enable them to make healthy food choices. This framework will be an important way to put the public health impact of online food delivery services on the agenda

2. **restrict junk food advertising on social media.** Online food delivery services need to be considered with the broader food industry in government policies restricting junk food advertising to young people

3. **generate clear public health messaging on health and environmental impacts.** Research has suggested convenient takeaway produces excessive amounts of waste. Combining the messaging may enhance potential for behaviour change.

Read more: ***Home-delivered food has a huge climate cost. So which cuisine is the worst culprit?***

In a world disrupted by COVID-19, the way we purchase and consume food is changing. The time is ripe to shape the online food environment to promote easy access to healthy and nutritious convenience food.

This article draws on research by former University of Sydney Masters students Andriana Korai and Celina Wang.

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