"Turning mirrors into windows": A study of participatory dynamic simulation modelling to inform health policy decisions

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“TURNING MIRRORS INTO WINDOWS”:
A STUDY OF PARTICIPATORY DYNAMIC SIMULATION MODELLING TO INFORM HEALTH POLICY DECISIONS

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BSc (Hons)
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Submitted in fulfillment of the requirements for the degree of

Doctor of Philosophy

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“Most people are mirrors, reflecting the moods and emotions of the times; few are windows, bringing light to bear on the dark corners where troubles fester. The whole purpose of education is to turn mirrors into windows.”

— Sydney Harris

This quote, attributed to journalist Sydney Harris, inspired the title of this thesis. For this thesis, “Turning mirrors into windows” reflects the transition achieved through the participatory model development approach. Participants work collaboratively to ensure their combined knowledge and expertise is reflected in the structure and logic of the model developed (the mirror). The learning achieved both through the collaborative process, and by using the resulting dynamic simulation models provides beneficial insights and forecasts the impact of intervention options to inform decision making for complex and contested issues (the window).
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Abstract

Introduction:

Achieving evidence-based public health policy is challenging. There is increasing recognition that more sophisticated, system-science, analytic methods, such as dynamic simulation modelling (DSM), are needed to better understand the dynamic, interacting and interrelated elements within complex public health systems. This thesis explored the implementation, feasibility and value of a novel participatory DSM approach as a tool for knowledge mobilisation and decision support in Australian health policy settings. An in-depth case study of participatory modelling of Diabetes in Pregnancy (DIP) in the Australian Capital Territory (2016-2018) was conducted. Two additional modelling case studies focusing on prevention of childhood overweight and obesity and alcohol-related harms in New South Wales provided supplementary data across different settings.

Methods:

A multidisciplinary stakeholder group, including researchers, clinicians, public health practitioners, policy makers, and simulation modelling experts, was convened to co-produce a pioneering, multi-method DSM to inform DIP health service policy and planning. Using participatory action research methods, interviews with participants, recordings from model development workshops and meetings, participatory research field notes and other documents were analysed to determine the feasibility and value of the participatory model development process. The analysis explored the deliberations, challenges, opportunities and decisions involved. Interviews with end-user participants for the primary and additional case studies explored their perceptions of the utility and value of this approach in applied settings.

Results:

Participatory DSM builds on elements of best practice in knowledge mobilisation, including embedding deliberative methods to build shared understanding. The methods enabled a collaborative, co-production approach to evidence-informed practice that moved beyond evidence synthesis to provide dynamic decision support. The participatory process was iterative, with key decisions re-visited and refined throughout the process. It facilitated a
significant, interdisciplinary knowledge base, built understanding of the modelling process, and established trust in the model to inform policy decisions. Key insights relating to the prevention and management of DIP were gained. The importance of implementing and maintaining population interventions promoting healthy weight for children and young adults was demonstrated. The unique benefits of simulation modelling most valued by health sector decision makers were its capacity to explore risk factor interactions, compare the outcomes of alternative intervention combinations, and consider the impacts of scaling-up. Participants also valued simulating new interventions prior to implementation, and mapping evidence gaps to prioritise future research.

Discussion:

Using a participatory approach to DSM for health policy is feasible and enhances the value of models as knowledge mobilisation and health policy decision support tools. The detailed analysis in this thesis revealed the socio-technical opportunities and challenges of implementing these interdisciplinary methods at the intersection of systems science, knowledge mobilisation and public health policy, and the key elements required for successful implementation in applied health policy settings.
Candidate’s declaration

I, Louise Freebairn, hereby declare that the work described in this thesis is my own. I am the principal researcher of all work contained in this thesis, including work conducted in association with my PhD supervisors and other co-authors. This thesis does not contain written or published materials prepared by others except where acknowledged within the text and has not been submitted to any other university or institution as a part or whole requirement for any higher degree.

Louise Freebairn

Date: 23 February 2019
List of publications and presentations

Professor Lucie Rychetnik was my primary supervisor and Associate Professor Jo-Atkinson and Professor Paul Kelly were my associate supervisors. They made conceptual and editorial contributions to the work contained in this thesis and are co-authors on the resulting publications. Several chapters in this thesis (Chapters 3, 4, 5, 6 and 7) contain material that is published or under review for publication, with the following citation details:


The specific contributions of the co-authors of these manuscripts are as follows: LF wrote the first and all subsequent drafts for all manuscripts. LR, JA and PK made conceptual and editorial contributions to all papers. GM made conceptual contributions to papers (1) and (4) and editorial contributions to other publications. NO made conceptual and editorial contributions to papers (4) and (5). YQ, CN and AK made conceptual and editorial contributions to paper (5). NR, CW and SR made editorial contributions to paper (2). Further details of author contributions to each paper are included in the author statements within the individual papers.

Presentations

During my candidature, I have made several oral presentations that draw on material from this thesis. The presentation details are as follows:

Freebairn L. Harnessing advances in simulation modelling to explore the complex issue of diabetes in pregnancy. Invited speaker at: Diabetes and obesity in pregnancy: understanding the problem and networking for solutions. Symposium hosted by ACT Health and University of Canberra. 17 August 2018, Canberra

Freebairn L, Atkinson JA, Kelly PM and Rychetnik L. Participatory dynamic simulation modelling for knowledge mobilisation in public health policy. Sax Institute Knowledge Mobilisation Conference. 4-5 July 2018. Sydney

Freebairn, L. Diabetes in Pregnancy: Simulation modelling to explore diabetes in pregnancy in the ACT. Presentation at Dynamic simulation modelling symposium: A what-if tool for prevention policy, planning and evaluation a satellite event of the Public Health Association of Australia conference hosted by The Australian Prevention Partnership Centre. 4 May 2018. Sydney


The final editorial authority remains my own.

Louise Freebairn ............................................................ Date: 23 Feb 2019

Lucie Rychetnik ............................................................ Date: 23 Feb 2019

Jo-An Atkinson ............................................................. Date: 25 Feb 2019

Paul Kelly ................................................................. Date: 25 Feb 2019
During my candidature I also contributed to the following publications on topics related to my research.


My contributions to the additional publications listed above are as follows. I wrote the first and subsequent drafts of paper (a). I made conceptual and editorial contributions to the other publications.
Acknowledgements

I am grateful for the financial support I received from the Australian National Health and Medical Research Council, the University of Notre Dame, Australia, and the Australian Prevention Partnership Centre through scholarships and project funding.

Thank you to my supervisors Professor Lucie Rychetnik, Associate Professor Jo-An Atkinson and Professor Paul Kelly for your excellent guidance. Thank you also to my “quasi-supervisors”, Professor Chris Nolan, Professor Alison Kent, and Dr Geoff McDonnell. The generosity you have all demonstrated in sharing your wisdom and experience; your perpetual encouragement and enthusiasm for my research; and the friendship and support you have offered me have been very much appreciated during my PhD journey. I feel extremely grateful to have had the opportunity to work with you and look forward to ongoing contact and collaboration.

Thank you to the computer scientists, particularly Professor Nathaniel Osgood, for sharing your tremendous knowledge and for supporting this work. It was indeed a privilege to work with you. Thank you also to simulation modelling staff and students at the University of Saskatchewan: Yang Qin, Anahita Safarishahrbijari, Allen McLean and Winchell Qian, for your valuable contribution to the diabetes in pregnancy model.

I am very grateful to the project participants for generously contributing their time and expertise to my research. This includes the participants who engaged in the model development processes for the three case studies and the end-user decision makers I interviewed, who were forthright and open in their assessment of the feasibility and value of participatory modelling. I was impressed by their dedication to improving health policy decision making and I am very appreciative of their support for this work.

It has been a delight to work with the staff from The Australian Prevention Partnership Centre (TAPPC) and the Sax Institute. In particular, I would like to thank project officers, Jacqueline Davison, Nick Roberts, Christine Whittall, Eloise O’Donnell, Nick Barker-Pendree, Sonia Wutzke, Emma Slaytor and Andrew Wilson for their support in funding, organising, implementing, observing and reflecting on the participatory meetings and workshops. I would also like to thank the communications team, Marge Overs, Helen Signy and Ainsley Burgess, for identifying and facilitating opportunities to promote my research.
I would also like to acknowledge my work colleagues, for their interest and enthusiasm in my research, and my employer, the Population Health Division within ACT Health, for supporting me to undertake this study.

This journey would not have been possible without the support of my family. Thank you to my parents, Marcia and Robert Skidmore, for your practical support for me to undertake this research while raising three children, and for proofreading the final version of this thesis. Thank you to my partner, Andrew, and my children Clare, Oliver and Hamish for all the encouragement and support you have given me during my doctoral studies. Thank you for listening and encouraging me at those times when I was excited and proud of my work, but also at those other times when I was anxious or frustrated. It has been quite a journey, and I’m glad to have shared it with you.
List of special terms and abbreviations

ACT Health: Australian Capital Territory Government, Health Directorate.

ADIPS: Australian Diabetes In Pregnancy Society.

Ageing chain: A stock and flow structure used in system dynamics to represent the ageing of the population.

Agent: Agents in agent-based modelling represent an individual object. Agents can represent virtually any individual object, for example, they may represent people, vehicles, projects, products or countries [1].

Agent-based modelling (ABM): A computer modelling method that simulates the actions and interactions of agents (i.e. individuals or collective entities such as organisations or groups) to assess their impacts on the system as a whole [2]. This method is useful for capturing heterogeneity in risk and in impacts of interventions and capturing social network influences.

Agent journey: This term was used to refer to the changes and events that occur to an agent throughout the simulation. For example, an agent will transition between states. In the model developed for the primary case study an agent will experience increases and decreases in weight status, insulin sensitivity, glycemia and diabetes status. These changes are tracked within the model and can be analysed.

Antenatal: The period covering conception up to the time of birth.

Birthweight: The first weight of the baby (stillborn or live born) obtained after birth (usually measured to the nearest 5 grams, and obtained within 1 hour of birth) [3].

Budding: Budding is a technique used in hybrid modelling where agents of particular interest are “budded” or created from the system dynamics components and become individuals in the agent-based modelling components.
**Calibration**: A process for tuning some parameters of the model so that the model’s behaviour matches a known (historical) pattern ([https://help.anylogic.com/index.jsp](https://help.anylogic.com/index.jsp)).

**Diabetes mellitus (diabetes)**: A chronic condition in which the body cannot properly use its main energy source, carbohydrates. This is due to a relative or absolute deficiency in insulin, a hormone that is produced by the pancreas and helps glucose enter the body’s cells from the bloodstream and then be processed by them. Diabetes is marked by an abnormal build-up of glucose in the blood, and it can have serious short- and long-term effects [3]. The three main types of diabetes are type 1 diabetes, type 2 diabetes and gestational diabetes.

**Diabetes in pregnancy (DIP)**: Diabetes in pregnancy (DIP) is a complication of pregnancy that is defined as carbohydrate intolerance resulting in hyperglycaemia (abnormally high blood sugar) [4]. Diabetes in pregnancy includes both gestational diabetes and pre-existing Type 1 or Type 2 diabetes.

**Discrete event modelling**: A modelling method that analyses processes and optimisation of resource allocation for service delivery (e.g. patient flows through an emergency department) [1].

**Dynamic simulation modelling (DSM)**: Dynamic simulation modelling is a systems science method that can be used to explore and understand problems that appear in the real-world using computer simulations [1, 5-7]. Common methods include system dynamics modelling, agent-based modelling, and discrete event simulation.

**Flows**: Flows are components used in system dynamics modelling. Flows are the rates at which the stocks (or system states) change. Flows are typically measurements of quantities in a given time period such as clients per month, dollars per year or incidence of disease during a defined period [2].

**Gestational age**: Duration of pregnancy in completed weeks, calculated from the date of the first day of a woman’s last menstrual period and her baby’s date of birth, or calculated via ultrasound, or derived from clinical assessment during pregnancy or from examination of the baby after birth [3].
**Gestational diabetes mellitus (GDM):** A complication of pregnancy that is defined as carbohydrate intolerance resulting in hyperglycaemia (abnormally high blood sugar) [4]. GDM occurs when the disease is first detected and diagnosed during pregnancy (gestation). It might resolve after pregnancy but signals a high risk of diabetes occurring later on [3].

**Incidence:** The number of new cases (of an illness or event, and so on) occurring during a given period.

**Initialisation:** The set of parameter values used at the start of the simulation.

**Insulin:** A hormone produced in the pancreas that helps glucose to enter body cells for energy metabolism.

**Model structure:** The manner in which the elements of a system are represented in the model; the building blocks of the model, including statecharts, stock and flow diagrams and process diagrams.

**NHMRC:** National Health and Medical Research Council

**NSW Health:** New South Wales Government, Ministry of Health

**Parameter:** Parameters are used for quantifying characteristics of the modelled objects and relationships between them. A parameter is normally a constant in a single simulation and is changed only when the model behaviour needs to be adjusted (https://help.anylogic.com/index.jsp).

**Parameterisation:** The implementation of parameters to quantify the model structure.

**Sensitivity analysis:** Sensitivity analysis is used to explore how sensitive the simulation results are to changes of the model parameters. The analysis runs the model multiple times varying one of the parameters and shows how the simulation output is impacted by the variation (https://help.anylogic.com/index.jsp).

**State:** Represents the “state” of the agent e.g. the agent is either in a pregnant state or not pregnant state. States are mutually exclusive and agents transition between states according to the statechart rules [1].
**Statechart**: A visual construct that allows the modeller to define the behaviour of agents using rules [1].

**Stocks**: Stocks are components used in system dynamics modelling. They are accumulations and characterise the system state. Stocks are usually expressed in quantities such as people, inventory levels, money, or knowledge [2].

**System dynamics**: System dynamics is a method for understanding how systems change. It models the relationships between elements in a system and how these relationships influence the behaviour of the system over time [1, 5, 8, 9]. Important elements of system dynamic models include feedback loops (the circular causality in the system), stocks and flows.

**TAPPC**: The Australian Prevention Partnership Centre.

**Transition**: Transitions determine agent movements between states in a statechart. Transitions have triggers, such as a message, a condition, or a timeout that determine the agent state will change [1].

**Type 1 diabetes**: A form of diabetes mostly arising among children or younger adults, marked by a complete lack of insulin and needing insulin replacement to survive [3].

**Type 2 diabetes**: The most common form of diabetes, occurring mostly in people aged 40 and over, related to lifestyle risk factors, and marked by reduced or less effective insulin [3].


Chapter 1: Introduction

This thesis explored the novel use of participatory DSM as an integrated decision support and knowledge mobilisation tool in Australian health policy settings. A participatory action research framework [1, 2] was utilised to study and evaluate the implementation of a participatory approach to DSM in a case study focused on prevention and management of diabetes in pregnancy in the Australian Capital Territory (ACT). Diabetes in pregnancy (DIP) was identified as a priority focus topic as incidence is increasing significantly in the ACT, nationally and internationally, resulting in increasing pressure on services to meet demand [3]. DIP impacted on 16% of pregnancies in the ACT in 2016 (increasing from 5% in 2006) and decision makers require tools to support effective decision making. DSM provided an opportunity to explore and compare the implications of health intervention options for diabetes in pregnancy services in the ACT and inform policy and program decision making (Chapter 3). Key findings related to the participatory modelling approach from the DIP case study were triangulated with supplementary data drawn from two additional case studies based in the neighbouring state of New South Wales (NSW). One applied participatory DSM to explore strategies to reduce alcohol related harm, and the other to examine the type and scale of interventions necessary to achieve the NSW Premier’s target to reduce childhood overweight and obesity by 5% by 2025. The three case studies are described in detail in Chapters 4 and 6.

1.1. Origin of the thesis

My interest in decision support methods and knowledge mobilisation stemmed from over 20 years working in the health sector in a range of roles including clinical psychology and health service planning, but predominantly in maternal and child epidemiology working
with clinicians and policy makers to facilitate the use of evidence to inform policy and program decisions. Over this time, I observed that, despite an abundance of information and data being available for many priority topics, it was not available in a form that addressed the most frequent question in policy advice “What should we do about this?”

The reliance in health services research on traditional statistical analytic techniques, such as regression analysis and aetiological fractions, has provided substantial knowledge about diseases and their aetiology, however these methods can provide only limited understanding of the complex adaptive systems within which public health policy decisions are made [4, 5]. Complex adaptive systems are characterised by feedbacks, interrelations among components, self-organisation and adaptation, and time delays between cause and effects [4]. I was interested in exploring the potential value of more sophisticated analytical tools that could accommodate the dynamics of complex systems e.g. temporal dynamics, and the interrelationships between elements of the system such as feedback, and system responses to interventions for health policy settings. Tools, such as DSM, used in other sectors such as environmental sciences, manufacturing and business to synthesise, integrate information and forecast likely outcomes of policy and guide decisions [6-8] were not often considered as a method to support health policy decision making [9, 10]. I was interested to explore and assess the feasibility and value of using a participatory approach with this method for a priority public health issue, in this case gestational diabetes mellitus, in our local health service, ACT Health, in the Australian Capital Territory.

I focused on the participatory approach because I valued the expertise of my clinical and policy colleagues and wanted to collaborate closely with them to integrate their significant knowledge and other forms of evidence to develop a DSM for this priority health issue. My initial reviews of the literature indicated that the research on stakeholder participation in model development had primarily occurred in the environmental modelling field, with a
rich history of community-based model development, for example the work of Peter Hovmand, Peter Senge and Alexey Voinov [7, 11, 12]. There had been limited exploration of participatory modelling in the health sector and when DSM projects had been undertaken for health topics, they rarely involved end-user decision makers in the model development [13]. However, end-user involvement is a key factor in increasing trust in model outputs and facilitating their use to support decision making [10]. There were no studies of end-user experiences and perceptions of the participatory process and DSM as a health policy decision support tool.

My research interests aligned well with the principles of The Australian Prevention Partnership Centre (TAPPC), who funded my PhD research. TAPPC is a partnership centre in which research is co-produced by academic researchers, systems practitioners and policy makers across Australia. TAPPC aims to identify systems, strategies and structures to inform better decisions for improving the prevention of lifestyle-related chronic disease in Australia [14]. My employer, ACT Health, was a founding funding partner of TAPPC along with the National Health and Medical Research Council, NSW Health, the Australian Department of Health and a private health insurance funder. The study setting is described further in Chapter 3.

1.2. Rationale for the thesis

Achieving evidence-based policy for complex public health issues is challenging [15-17]. The challenges include misalignment of research activities and policy questions in terms of focus topic, timing and knowledge dissemination methods [18-20]. The knowledge mobilisation field has evolved in response to these challenges and encompasses a diverse range of activities and frameworks which aim to address the evidence policy gap [21]. Systems thinking and systems science approaches are increasingly being utilised to
understand and mobilise knowledge for complex issues such as those encountered in public health [22]. Dynamic simulation modelling is a systems science approach that can be used to develop understanding about complex problems using computer simulation [23, 24]. By involving end-user stakeholders in the model development, participatory DSM can facilitate the adoption and use of the models to inform decision making [10, 25]. The detailed literature analysis underlying this rationale is described in Chapter 2.

Important gaps in knowledge remain regarding: the feasibility of using participatory approaches in DSM to facilitate evidence informed decision making in Australian public health settings; how the involvement of stakeholders as participants in DSM projects impacts on the quality, trustworthiness and ultimately the use of model outputs for decision making; and the perceived value of participatory simulation modelling as an evidence synthesis and decision support method. These gaps in knowledge are explored in detail in the research protocol presented in Chapter 3.

This thesis contributes new knowledge by exploring the novel use of participatory simulation modelling as an integrated decision support and knowledge mobilisation tool in Australian health policy settings. The thesis explores the processes involved in, and the feasibility and value of, the participatory modelling approach. It describes the experiences of end-user decision makers engaged in the case study processes, and their perceptions of the value and utility of DSM and the likely impacts on policy and program decision making.

1.3. Overarching theoretical framework and research approach

A Participatory Action Research (PAR) methodology was chosen as it encapsulates the theoretical framework for this research to address the identified gaps in knowledge described above. The PAR framework was chosen as it closely aligns with the active, collaborative, iterative process of participatory DSM development and the involvement of
researchers as participants in the process. The framework also aligns well with the principles of partnership and co-production underpinning TAPPC and their remit to develop the information, tools and actions needed for effective systems-level prevention of chronic disease [14]. I completed the research for this thesis as the project lead for the primary DIP modelling case-study, and as an embedded researcher with TAPPC and ACT Health responsible for facilitating and studying the participatory modelling process.

There are many definitions of PAR that reflect wide ranging views, however most definitions agree that PAR is inquiry that is done by or with insiders to an organisation or community [26]. It is a reflective process that is deliberately and systematically undertaken, and requires that conclusions and recommendations be supported by evidence produced from the research [1, 26]. PAR is oriented to actions or cycles of actions that address a particular problematic situation [1, 26]. PAR embeds the research in the context. The research is planned and implemented, the effects observed and reflected on to determine next steps all within the context of the organisation or community of focus [1, 27].

The key features of action research include its collaborative nature and its emphasis on taking unified action on an issue [28]. It involves genuine partnership between researchers and decision makers, who work directly with the identified issue, across each stage of the research project, from identifying the problem to disseminating the results [2, 28]. This partnership involves shared control of the research agenda and commitment to mutual learning in the research process to improve researchers’ and research partners’ understanding of one another’s positions and contributions [28]. The case studies in this thesis were highly collaborative. The modelling teams and key policy partners worked collaboratively to negotiate the focus topics for the case studies, co-produced the DSMs and prioritised interventions to be tested.
An important qualitative element of PAR is how people are drawn into the processes of inquiry and action and how they participate and collaborate [27]. The goal of PAR is to make action more effective while simultaneously building up a body of scientific knowledge [2, 27, 28]. The goal of PAR in the context of this thesis was the co-production of knowledge that was useful, valid, descriptive, and informative of how practice and policy interventions may have a positive impact on public health issues.

PAR comprises iterative cycles of gathering data, analysing the data, planning action, taking action and evaluating, leading to further data gathering and so on. The PAR spiral [2] is presented in Figure 1 and shows the main steps of planning, acting, observing and reflecting.

*Figure 1: Participatory Action Research Spiral*

1.4. Application of the participatory action research framework to the research objectives

In participatory action research projects, there are two action research cycles operating in parallel [27, 29]. One is the action research spiral of plan, act, observe and reflect, described above, in relation to the applied research project. This is referred to as the core action research cycle [29]. In this research the development of three DSMs using a participatory process is the core action research cycle. This cycle relates to Research objective 1 (below).

The second is a reflection cycle which is an action research cycle that is undertaken alongside the core action research cycle. At the same time as the researcher is engaging in the project or core action research cycles, they are diagnosing, planning, taking action and evaluating about how the action research project itself is working and what is being learned [27, 29]. This secondary process of reflection has also been referred to as the ‘thesis’ action research cycle [29]. However, I haven’t adopted this term here to avoid confusion with my PhD thesis; which comprises of both the ‘core action research’ and ‘reflection action research’ cycles (Figure 2).

In this research, the reflection cycle involves the examination of the participatory process itself, investigating what worked well, what could be improved, how the participatory process contributed to the development of the models and what the experience was like for participants. This cycle relates to Research objective 2.
The action research cycles and their relationship to the research objectives are represented diagrammatically in Figure 2. The overall research objectives for this thesis were:

1. To pilot DSM to optimise the use of evidence to inform policy and program decision-making by synthesising and integrating diverse evidence sources into a decision support tool for diabetes in pregnancy using a participatory modelling approach. (Core action research cycle)

2. Investigate the perceived value and efficacy of participatory simulation modelling methods as an evidence synthesis and decision support method in an applied health sector context. (Reflection action research cycle)

These research objectives were investigated using a case study approach with three applied health policy and program examples. The primary focus and core case study for this research was the modelling project to inform prevention and management of diabetes in pregnancy in the ACT (Case Study 1). Two other case study modelling projects were used as sources of supplementary data to triangulate the findings for Research Objective 2, and
as comparison to see whether and how the findings from Case Study 1 are reflected in other settings. The research objectives and research questions are described further in the published research protocol included in Chapter 3.

1.5. Overview of thesis structure

This thesis is organised into eight chapters, five of which include peer-reviewed journal articles (four have been published, and one is undergoing review). All papers were prepared during my doctoral candidature with the University of Notre Dame. These papers, as well as each chapter, contain their own reference lists. Supplementary material related to ethics approval, study methods, and accompanying the published papers is included in the relevant chapters and in the Appendices.

Chapter 2: Literature Review

This chapter provides an in-depth analysis of the various literatures that are relevant to this thesis, including the broader challenges of achieving evidence informed decision making in the health sector. It explores the synergies between system science and knowledge mobilisation methods and outlines how these approaches were combined in the thesis. DSM is introduced as a system science approach that can be applied to complex public health issues to facilitate the use of evidence to inform policies and programs. Also included is an explanation of the key DSM concepts, and the main methods, their history and application are described. The motivations for using DSM over traditional statistical techniques is explained and the application of participatory processes in DSM is outlined. Chapter 2 also identifies the gaps in knowledge that are explored in more detail in Chapter 3.
Chapter 3: Study methods

Chapter 3 includes the published protocol for this research. This paper describes and discusses in further detail the current gaps in knowledge, which include the feasibility of using DSM in “real world” health policy settings, and the value and effectiveness of using participatory methods in model development. This paper also presents a detailed rationale and research protocol for the primary case study investigating diabetes in pregnancy in the Australian Capital Territory (ACT). The second part of the chapter outlines how the research methods evolved following the publication, in 2016, of the research protocol and explains my role in the research.

Chapter 4: Results Part 1: Mobilising Knowledge for Policy Development: implementing systems approaches through participatory dynamic simulation modelling

The published paper included in this chapter reviews knowledge mobilisation best practice and describes how the participatory DSM examined in this research built on these elements. It reports on the participatory modelling workshops from three policy settings, including the primary case study in the Australian Capital Territory (ACT), and two additional case studies from New South Wales (NSW), which were used as supplementary data sources to explore and compare the feasibility and value of participatory DSM in different settings. The reported findings from across the three case studies are reviewed and presented with reflections on the lessons learned from the participatory simulation modelling experience across policy settings, together with discussion of the benefits and challenges of this approach.
Chapter 5: Results Part 2: Turning conceptual systems maps into dynamic simulation models: revealing the analytical deliberations and decisions of participatory dynamic simulation modelling

The published paper in this chapter focuses on the processes, decisions, interactions and activities that were required to convert the qualitative, conceptual map developed by participants in the participatory workshops (described in Chapter 4) into a quantitative DSM. This paper presents a qualitative, empirical analysis of the core processes, stakeholder interactions and decisions, and practical strategies to develop a rigorous and policy relevant model, which occurred outside the formal participatory workshops at the interface between end-user participants and modellers. The implications for future participatory modelling research and practice are considered.

Chapter 6: Results Part 3: Decision makers’ experience of participatory dynamic simulation modelling methods for public health policy

The published paper included in this chapter reports on a qualitative analysis of the perspectives of end-user decision makers from the three case studies. It examines their views on the value of participatory simulation modelling to inform health policy and program decision making, and their experiences of engaging in the participatory process. The paper discusses interviewees’ motivations for contributing to the modelling projects, and their perceptions about the key elements of the participatory process. The unique benefits of participatory DSM for policy decision making processes are discussed. Also included are a list of recommended implementation strategies based on reflections from the three case study settings.
Chapter 7: Results Part 4: ‘Turning the tide’ on diabetes in pregnancy: Insights from advanced dynamic simulation modelling

The paper included in this chapter presents the DIP model that was developed in case study 1, presented here in the final draft format that is undergoing wider clinical review prior to journal submission. It describes the current challenges for the prevention and management of diabetes in pregnancy, provides an overview of the DIP model structure, logic, parameter inputs, assumptions and model outputs. The implications for DIP prevention and management are also discussed. Associated communication products prepared to facilitate knowledge dissemination to a non-technical audience and model documentation to accompany the manuscript are included in this chapter.

Chapter 8: Discussion and conclusions

The overall key findings of the research and their implications are presented in Chapter 8. These are discussed as a body of work in the context of participatory action research, knowledge mobilisation and the policy and practice implications of using DSM. The importance of using participatory methods to engage key stakeholders to co-produce models for policy decision support and the benefits and challenges of interdisciplinary research are reviewed and discussed. A framework proposed for reporting participatory DSM projects in the environmental sciences field is applied to the primary case study and extended based on the findings from this thesis. This chapter reflects on the strengths and limitations of this real-world research and makes recommendations for the implementation of future participatory modelling projects and for future research.

Appendices

Additional relevant information is provided in a series of appendices. Each appendix is referenced in the text of the Thesis.
References


Chapter 2: Literature review

This chapter includes a detailed analysis of the literature underlying the rationale for this thesis. It is divided into seven sections describing: the challenges of evidence-informed decision making; how the knowledge mobilisation field has developed to facilitate evidence-informed policy; how systems science methods can be applied to public health issues; the limitations of traditional statistical methods to analyse complex public health problems; the core concepts and methods of dynamic simulation modelling (DSM); how participatory methods can be applied to DSM and the important gaps in knowledge to be addressed.

2.1 Challenges of evidence-informed decision making

Government and public policies have profound impact on the lives and health status of populations, and therefore it is important to ensure that policies are cost effective and mitigate the likelihood of negative outcomes \([1, 2]\). Ensuring that policies align with research evidence is likely to result in higher quality and effectiveness \([3]\). However, challenges in the use of evidence to inform policy remain \([1, 3-7]\) and these are explored below.

Evidence-informed decision making is defined as the process of distilling and disseminating the best available evidence from research, context, and experience (political, organisational) and using that evidence to inform and improve public health practice and policy \([2]\). The barriers to evidence-informed policy include issues relating to the relevance...
and reliability of research findings, policy makers' skills in interpreting research evidence, costs of conducting research and poor alignment between the focus and timing of research results and the answers required for policy [7-9]. Key questions chosen by researchers may not align with the information priorities of decision makers, nor are the findings always presented in a form that is useful for or relevant to the decisions at hand [5]. A traditional investigator-driven approach to research that fails to adequately engage key stakeholders within health care systems is a known barrier to translating research into real-world settings [10]. Institutional characteristics, including the perceived importance and priority placed on research evidence, the availability and access to research, and the training of policy officers to engage with, assess and use research evidence have also been identified as important barriers to the use of evidence [2, 7, 8, 11, 12]

A frequently identified facilitator for the use of evidence in policy is the quality of relationships and collaborations between researchers and policymakers [7, 13]. Interaction and exchange between researchers and policy makers can facilitate the use of evidence in policy, however mechanisms and processes to promote these interactions are needed to extend the exchanges beyond familiar networks and existing relationships [9].

Consideration of research evidence within the context in which it will be used is also essential for effective policymaking and practice. The social and political context and the many forces at work in the policy environment provide challenges to integrating research evidence into policy and practice [9, 14]. The decision-making processes for researchers and policymakers are significantly different, both in terms of the “real-world” steps in decision making and also the factors that drive decisions [1]. Researchers rely on experimental and observational scientific studies to test specific hypotheses in a systematic
way and their influence is based on their specialised knowledge. On the other hand, policymaking is built on a complex combination of competing priorities including the political environment, history of related policies, demands from advocates and stakeholders, resource constraints and public perceptions of the value of the policy alternatives [1, 9, 14-16]. Decisions are often the result of compromise [1]. Even when based on sound scientific data, some decisions may not be considered ready for policy action due to lack of public support or competing policy issues [1].

Evidence provided to decision makers is often not in a form that is most useful for them [13]. Policymakers are looking for evidence that is timely, synthesised, contextualised for their local environment, demonstrates priority for an issue over many others, illustrates the policy implications of research findings, contrasts policy options and personalises the issue [1, 2, 11-13, 17]. Evidence dissemination preferences also vary between researchers and policymakers, with researchers ranking publication in peer review journals as their first preference for dissemination, whereas policymakers ranked seminars, webinars and workshops as their most preferred way of learning about research evidence [2].

2.2 Knowledge mobilisation to facilitate evidence-informed policy

A range of terms, including evidence-based policy/practice, knowledge translation, knowledge exchange, knowledge to action and knowledge mobilisation have been used to describe activities associated with facilitating the creation and sharing of research-informed knowledge to guide policy development [3]. Many of these terms are overlapping and are used interchangeably [18]. Some have been used as nouns to describe the process as a whole that results in the use of knowledge by decision makers whereas others are
used as verbs to represent actions or specific strategies taken to facilitate the uptake of research evidence [18]. The term knowledge mobilisation has been identified as encompassing the broadest range of activities and reflecting the non-linear, complexity of the process [3] and has been adopted for this research.

Best and Holmes have described three generations of knowledge mobilisation models: linear, relationship, and systems models [19]. The linear model involves a one-way process in which researchers produce new knowledge, which is disseminated to end users, and then incorporated into practice and policy [4]. In this model, knowledge is seen as a product that is supplied to users, can be generalised across contexts, and whose use is dependent on effective communication of results [19]. The relationship model incorporates the flow of information using principles from the linear model, however focuses on linkages and exchanges between the researchers and users of the information [3]. In the relationship model, knowledge generation is seen as a social and situational process arising from multiple sources (research, theory, policy, and practice), and not solely from the researcher [19]. In this model the use of evidence is seen to be dependent on effective relationships and processes [19].

The third-generation systems model builds on the linear and relational models and acknowledges that public health issues are often best understood as complex systems. They are dynamic and constantly changing, involve interdependent systems (e.g. individual, organisation, and community), have feedback effects and intervening in one part of the system can have unexpected ripple effect on other parts of the system [19-21]. Complex adaptive systems self-organise and adapt based on experience, meaning that from the
same starting point, an intervention can potentially have several different outcomes [22, 23].

Many models, theories and frameworks have been developed for knowledge mobilisation [24]. Twenty five key frameworks were identified in a recent comprehensive review of knowledge mobilisation in the United Kingdom [3], however previous reviews identified up to 60 frameworks in use [18]. There is overlap among the frameworks and common aims, phases or domains can be identified [3, 18, 24]. These phases vary from project to project but frequently include: clarifying the issue that needs to be addressed; negotiating the purpose and goals for the knowledge mobilisation activity; identifying, reviewing and selecting the knowledge that is relevant to the problem (e.g. new research findings, knowledge synthesis or knowledge tools such as practice guidelines); considering the connections and relationships that need to be established; identifying the people and positions who should be involved; developing action plans and resources needed to operationalise the knowledge mobilisation; and considering the potentially facilitating or inhibiting effects of the local context on knowledge mobilisation efforts [3, 18].

Systems approaches are well suited to address current, complex public health issues and systems [2, 25] and can be used to analyse both complex health issues as well as the context within which they emerge. Systems approaches, such as participatory DSM, can extend and build upon key elements of knowledge mobilisation including the synthesis of diverse knowledge and evidence, investigation of dynamic and non-linear relationships within systems and exploration of adaptive, emergent behaviour of the system in response to policy interventions. The details of the synergies between systems approaches and
knowledge mobilisation are explored further in Chapters 3 and 4 and therefore not repeated here.

2.3 Systems science methods and public health

Public health issues are complex, with individual heterogeneity embedded in multilevel social and environmental contexts [26]. There are intricate networks of factors, including the physical, biological, ecological, technical, economic, social, and political, that impact on public health [22, 23]. This complexity can hinder both the generation of knowledge and the implementation of evidence-based health policies [23]. For most public health problems there are many interacting risk factors that need to be considered as important contributors to the issue [27]. However, the interactions between these risk factors and delays between exposure and outcome make it difficult to identify which risk factors are most important to target and to forecast the likely impact of policy interventions [23, 27]. Changes in behaviour also occur naturally, and continuously, as people within the system acquire new information that alters their understanding. Planned change in such a system is difficult because of these dynamic characteristics: nothing stands still while the intervention is being implemented [4].

“Systems science” is a broad term referring to a family of analytic approaches that aim to uncover the behaviour of complex systems and inform policy and program interventions [26]. Complex systems are made up of interconnected and interdependent parts. The behaviour and characteristics of a whole system cannot be anticipated, and often differs from, the behaviour and characteristics of any one element in that system when these are considered separately [22, 26, 28, 29]. Characteristics that distinguish complex systems
from more simple ones include: the presence of many interrelated components of the system, bidirectional relationships between components (also known as feedback loops), non-linear relationships among components, self-organisation or adaptation of the system in response to interventions (policy resistance), delayed effects from exposure to outcome within the system, and changes in the system behaviour over time (temporal dynamics) [22, 23, 26, 30].

In public health, such complexity is common and can be a significant challenge for the design of public health policies and interventions. The interconnected dynamics of complex systems can result in potential synergies, which may be overlooked in traditional methods of policy design [23, 31]. Tipping points, where small actions can lead to large change, are important levers that can be identified and utilised in policy decision making [32]. However, policy responses should also consider that successful interventions in one part of the system may be counteracted by negative responses elsewhere [23, 31]. Sophisticated methodological and analytic tools, such as DSM, are useful to explore policy and program scenarios, such as whether an intervention works as intended, for whom, under what conditions, at what cost, how soon, and for how long [22, 23, 26, 27, 33].

2.4 Limitations of traditional statistical methods to analyse complex public health issues

Traditional epidemiological statistical techniques have contributed substantial knowledge in health research, however their inherent assumptions and characteristics result in important limitations when applied to complex systems, like those in public health policy. These limitations include reductionism, assumptions of independent associations between
attributes and effects, reliance on methods that assume linear relationships and an inability to accommodate time related dynamics of the system. These limitations and their impact on the policy decision making discourse are discussed in detail below.

Complexities within disease prevention science have commonly been dealt with by employing reductionist analytic approaches that focus on reliably estimating each component of a system [26] and reducing the system to a series of isolated and independent associational effects from which causal processes are inferred [22, 34]. Invaluable knowledge has been gained with these reductionist empirical approaches, including the discovery of the link between smoking tobacco and lung cancer and asbestos exposure and mesothelioma [22]. However, sole reliance on them may result in failure to achieve adequate understanding of broader system behaviour shaping some of the most pressing public health and disease prevention problems [22, 26, 33].

Traditional research methods such as randomised control trials may be viewed as the most rigorous scientific design for evaluating intervention effectiveness, however they also have limitations for real-world, policy-relevant research, when the exposure (i.e. policy issue) cannot be randomised, may be subject to time delays or may emerge over time as the system adapts and changes [1, 26]. For example, obesity is an important public health issue which is impacted by multiple interdependent systems eg. biological, behavioural, social and environmental [33]. Exposure to risk factors for obesity, such as family history or built environment, cannot be randomised and may occur many years before the onset of the condition e.g. dietary habits established in infancy and early childhood may result in the onset of obesity in adolescence or early adulthood. Reliance on reductionist methods, that attempt to isolate causal relationships between risk exposure and development of disease,
may hinder insights about these complex systems that could be important for effective intervention design or management of systems within which interventions are delivered [26].

Multilevel statistical analyses are often used to summarise data and estimate “independent” associations with individual-level outcomes to test hypotheses [35]. These techniques apply statistical controls for individual attributes, e.g. age or education status, believed to be simultaneously related to a health outcome of interest, e.g. development of diabetes mellitus, to isolate and investigate the impact of an independent variable e.g. obesity. However, these regression-based approaches necessarily simplify complex interrelations [36]. The focus is on decomposition of variability and estimating “independent” effects and this necessarily isolates elements from each other and ignores feedback loops e.g. the reinforcing feedback loop that results in increases in bodyweight associated with increasing age [35, 37].

Regression approaches are, therefore, not equipped to investigate the processes embedded in complex systems characterised by dynamic interactions between heterogeneous individuals and between individuals and their environment with multiple feedback loops and adaptation [27, 35]. By attempting to isolate the effect of changing a single factor while holding all the other features of the system constant, the context of dynamic interactions and feedback loops is excluded. This results in findings that may not be generalisable to other contexts, i.e. the effects of changing a single factor may be contingent on, or influenced by, dynamic relationships within the context of the system [35].
Another frequently used statistical approach is the attributable fraction, that estimates the comparative burden each risk factor contributes in a given population and the proportion of that condition that could be averted by targeting specific prioritised risk factors [38]. Attributable fractions are often used as a static measure that considers a fixed scenario, for a specific point of time, and assumes a risk distribution that remains unchanged over time [39]. The assumptions underpinning the attributable fraction are that exposure variables are independent, and relationships between exposures and outcomes are unidirectional, linear and constant through time [36, 38]. This can result in overestimation of the potential effect of an intervention, for example Page et. al. compared an attributable fraction approach with system dynamics modelling to assess the impact of suicide prevention interventions [36]. The authors demonstrated that, by artificially assuming that the population prevalence and incidence of suicidal ideation remained constant over time, the use of attributable fractions inflated the estimated effectiveness of the suicide prevention programs. In contrast, the system dynamics modelling approach allowed for dynamic movement of people in and out of states of suicidal ideation over time and this impacted on the assessment of intervention effectiveness [36].

Effective policy decision making requires approaches that combine mechanisms and explore their interactions, as no one relationship or mechanism is independently able to completely explain all important aspects of the issue [31, 33]. Disease systems involve complex relationships between causes and outcomes [23, 34]. Adaptivity means that individual and population behaviour can evolve based on past history and feedback loops and causal effects can be magnified (i.e., positive feedback) or dampened (i.e., negative feedback) as disease processes progress or social systems adapt [31, 40]. Contextual effects
mean that health outcomes are shaped by specific social, economic, and political contexts and have a high degree of sensitivity to initial conditions of the system [34].

These traditional analytic methods yield few insights into both the dynamic processes of systems, particularly when they involve feedback loops and adaptation, and the strength of associations between risk factors [22, 27]. Temporal dynamics are also important but not captured well using traditional epidemiological approaches [22, 26]. For example, time from an exposure to disease, and time from a given intervention to its impact on disease, are not considered in standard statistical techniques, such as attributable fraction estimates [36]. Understanding these complex processes and temporal dynamics is important for predicting the effects of the intervention under other scenarios and for identifying alternate interventions that may achieve the desired effect [22, 33, 35, 36, 41].

The limitations of these statistical techniques are often acknowledged in epidemiological papers, however may not be made explicit in the communication of results, and in managing expectations of intervention effectiveness, among stakeholders and policy planners [36]. This is important from a policy planning and resourcing perspective, as policy makers need to have confidence in the statistics intended to inform policy decisions [1, 27]. They also need guidance regarding the length of time that an intervention will take to have an effect, how long the effect might last, the impact of behavioural aspects of uptake and participation in the intervention, potential intervention implementation issues and impact of scaling up interventions - and this information is not commonly provided by traditional statistical techniques [36, 42].

These methodological challenges also limit the ability to explore complex causal factors and evaluate “up-stream” policies that target social determinants of health [22]. This can result
in the development of multi-sectoral, comprehensive strategies to tackle complex public health problems in the hope that if more risk factors are targeted in strategies for prevention, they are more likely to be effective [27]. However, comprehensive strategies may not represent the most efficient or effective approach to reducing disease burden at the population level. Rather, they may spread finite resources less intensively over a greater number of programs and initiatives, resulting in a reduced “dose” effect and diluting the potential impact of the investment [27]. For example, “Get Healthy Philly” was introduced in Philadelphia as a multisectoral initiative targeting healthy food access and affordability, tobacco control, built environment facilitators of physical activity, in multiple settings including workplaces, schools and other childcare settings [33]. It involved a range of approaches including partnerships with business, public health messaging and increasing walkability and rideability [33]. Using traditional methods of evaluation, it was not possible to determine which interventions included in the initiative were producing significant effects and which were having minimal or no effect [33]. Yet this would be important information to guide future intervention planning.

Failure to recognise the dynamics and feedbacks of the system, and the way the system adapts and responds, can lead to or exacerbate policy resistance as policy makers persistently react to the problem situation, intervening at low leverage points and triggering delayed and distant, but powerful feedbacks [32, 43]. As a problem intensifies, pulling the same policy levers can trigger a vicious cycle moving the system response further from rather than closer to our goals [43].

Systems science methods seek to “put the pieces back together” so as to understand characteristic system behaviour, not only at the level of the smallest components, but to
also provide insight into the system as a whole [26], helping decision makers understand how multiple variables, factors and interventions interact [44]. Dynamic simulation modelling methods can be used to explore the dynamic complexity that characterises many public health issues and provide guidance on when and how to intervene and likely unanticipated consequences of policy decisions [22, 44, 45].

The ability to test the potential impact of programs and policies in the “safety” of a virtual environment before they are implemented, saves time, effort, costs and resources [44, 46]. Systems science methods can capture “emergent behaviours” of the system, that is, system-wide behaviour that is observed but cannot be attributed to the behaviour of any individual component [22, 26].

2.5 Dynamic simulation modelling

Dynamic simulation modelling is a systems science method that can be used to explore and understand problems that appear in the real world using computer simulations [23, 30, 46, 47]. Dynamic simulation modelling can provide a mechanism to represent a complex system in a simpler form that is more accessible for direct study and experimentation [48]. Complex systems are often counterintuitive, with causes and effects separated in both time and space, and modelling allows experiments to be conducted to see how a system behaves under different conditions and scenarios [23, 47]. DSMs can account for temporal dynamics in estimating the likely population-level impacts of interventions over time [22, 36].
Once the model is built or even during the process of building, it can be used to explore and test our understanding of the behaviour of the system [23, 26, 32, 43, 47, 49, 50]. In many situations we are unable to use real-world experimentation to compare alternative solutions to problems because it would be unethical, too expensive, dangerous or impossible, and in these situations, models of the real system can be used to facilitate understanding [23, 30, 46, 47].

Models should not be viewed as “crystal balls” that can precisely predict the future but as tools that can enhance learning about complex issues and forecast likely outcomes for defined scenarios [20, 47, 50]. Dynamic models can help us more quickly identify inconsistencies between our understanding of the issue and the empirical evidence [50]. Models can also guide future data collection, raise new questions and hypotheses, facilitate the identification of important leverage points in a system and bring scientific rigour to thinking about an issue [23, 32, 43, 47, 51].

**Methods in dynamic simulation modelling**

The models that were developed in the participatory simulation modelling case studies examined in this thesis applied three commonly used methods in DSM: System Dynamics (SD), Agent-Based Modelling (ABM) and Discrete Event Simulation (DES). Each method was chosen as the most appropriate tool to capture the mechanism being modelled. With advances in modelling software the methods can be used in combination within a single model and this opportunity was leveraged in this research with “hybrid” models utilising multiple modelling methods being developed. These methods, their history and application are outlined below.
System Dynamics

System dynamics is a method for understanding how systems change. It models the relationships between elements in a system and how these relationships influence the behaviour of the system over time [23, 29, 30, 51]. Important elements of system dynamic models include feedback loops, stocks and flows. Feedback loops represent the circular causality in a system i.e. how elements in the system have positive or negative reinforcing effects on other elements [23, 30, 52]. Causal loop diagrams are used to conceptualise the system, identify key variables and important feedback loops [52].

System dynamics is considered a strategic modelling method where the system is modelled at an aggregate level [30, 52]. In this modelling method individuals, for example, people or products, do not appear in the model as individuals, they are represented in “stocks” or accumulations. Individual events, such as decisions or recovery from a disease, are similarly not considered, they are aggregated in “flows” [23, 30, 52].

Jay Forrester created the system dynamics method in the 1950’s. His first dynamic model explained the large fluctuations in production, inventories, headcount and profit in the appliance division of General Electric. Towards the end of the 1960s, his work increasingly turned to public policy issues and the more general term “System Dynamics” replaced “Industrial Dynamics” [53].

The combination of the field’s three defining elements, namely feedback, computer simulation, and engagement with mental models, facilitated the adoption of system dynamics across a wide range of applications [53]. For the first element, feedback, Forrester placed prime importance on patterns of behaviour of feedback systems and the
policies that produced them. He identified that decisions in different parts of an organisation created repercussions elsewhere and that those repercussions eventually fed back to impact on the originator [53].

The second element, computer simulation, brought Forrester’s theory to practical realisation [43, 53]. The “what if” analysis capability of computer simulation brought scientific rigour to policy makers and managers considering the effects of decisions and facilitated the identification of leverage points [32, 43]. As mentioned previously, leverage points are those places in the system where a small shift in one element can produce large changes in other parts of the system [32]. System dynamics practitioners have argued that many policies debated in corporations or government are low leverage and unlikely to result in significant impact or, where leverage points have been intuitively identified, without a systems approach, then actions taken may in fact impact on the leverage point in the opposite direction to that required [32, 43, 53].

Forrester also valued the importance of engaging with the mental models of managers and decision-makers. Mental models are our cognitive understanding of a system [52]; people rely on mental models to understand and manage situations ranging from simple every day decisions, like what to cook for dinner, to developing a high level strategy for a complex policy issue [20, 52]. The purpose of computer simulation is not to provide “the answer” but to create a process through which stakeholders interact with a model to learn about the complex dynamics of the systems in which they were embedded, improve their intuition and create a new mental model which can then become the shared basis for action [20, 52, 53].
The system dynamics approach has two main advantages relative to other policy informatics approaches. First, by emphasising feedback, system dynamics can identify and highlight potential areas of policy resistance [43]. Models illustrate how policy actions can trigger reactions, which can be delayed and unanticipated, that feed back to undermine original policy objectives and even exacerbate original problems [23, 32, 43]. An understanding of the sources of policy resistance is essential for the design of improved public policies.

Second, the feedback approach enables system dynamics models to capture complex dynamics with minimum detail. In contrast to other modelling techniques that generate complexity from detailed depictions of individual agents, the system dynamics approach allows modelers to isolate those dynamics generated by the broader feedback structure of systems [23, 32]. This approach can produce models that are small enough to easily communicate core insights to policy makers, yet sophisticated enough to replicate counterintuitive behaviours [54].

**Discrete Event Simulation**

Discrete Event Simulation (or Discrete Event Modelling) models systems as processes and can be used to explore the impact of policy and program decisions for constrained and non-constrained resource systems [55]. The core concepts of discrete event simulation (DES) are entities, attributes, events, resources, queues, and time.

Entities are objects that have attributes, experience events, consume resources, and enter queues over time as they move through the model [30, 55]. In health care applications, entities are often people with a disease or patients in a service.
Attributes are features specific to each entity that allow it to carry information and, in a health context, could include age, sex, ethnicity, health status, past events, and accumulated costs [55]. These values may be used to determine how an entity responds to a given set of circumstances, for example, the timing and type of past events may influence the likelihood and timing of subsequent events [55]. Attribute values may be modified at any time during the simulation, aggregated with those of other entities, or analysed further outside the simulation (e.g., to estimate mean cost and effect) [30, 55].

Events are generally defined as things that can happen to an entity or the environment. An event can be the occurrence of clinical conditions such as onset of a condition, a diagnostic test result, or progression of a disease to a new stage; resource use (e.g., outpatient clinic visit or admission to hospital); clinical decision (e.g., change in dose); or even experiences outside of health care (e.g., failure to show up at work) [55]. Events can occur, and recur, in any logical sequence.

A resource is an object that provides a service to an entity. DES represents resource availability at relevant points in time (e.g., an emergency department with resourcing for six beds can treat people more quickly than one with resourcing for two beds). In representing resources, DES can capture spatial factors, such as the number of available consulting rooms or distance between a ward and an operating theatre [30]. Queues are an important concept in DES and occur when several entities compete for a specific resource for which there is a constraint [41]. When a resource is “occupied” it cannot be accessed by an entity and the entity must wait, forming a queue [30, 55]. The simulation can be used to identify the utilisation of resources, the time spent in the system or part of the system,
waiting times, queue lengths, system throughputs, bottlenecks and costs of entity processing [30, 55].

Time is also an important component of DES. An explicit simulation clock (initiated at the start of the model run) keeps track of time making it possible to track periods between events (e.g., hospital length of stay, time spent with symptoms, survival) [55]. In health care, events occurring to an individual and how that individual interacts with others, the health care system, and the general environment can be modelled in DES simultaneously [55]. The term “discrete” refers to the fact that DES moves forward in time at discrete intervals (i.e., the model jumps from the time of one event to the time of the next) and that the events are discrete (mutually exclusive) [55]. DES operations can include delays, services provided by different resources, and choices between process branches [30, 41].

The level of abstraction for DES is much lower than for system dynamics. The process diagrams reflect the physical steps that happen in the real-world system. Entities and resources are passive in DES, that is, they have no behaviour of their own, they just carry data. Anything that happens to them is defined by the process flowchart [30, 55].

DES was first used in the 1950’s in manufacturing companies to assist in the improvement of production processes [56]. In 1961, IBM engineer Geoffrey Gordon developed the GPSS (General Purpose Simulation System) which is considered the first software implementation of discrete event simulation [30]. A time-consuming feature of early DES was designing, writing and de-bugging the model's code [56]. From the earliest days of simulation, there has been interest in creating the means to make this more rapid and more reliable and with advances in technology this has been realised [30, 56].
DES is widely used in business, logistics and manufacturing. It is one of the more common modelling methods used in healthcare to model health services. A recent umbrella review of systematic reviews found 586 papers published for health care applications of DES compared with 103 for system dynamics, 47 for agent-based modelling and 1 for hybrid modelling [57]. DES has been used to model biologic processes [58], emergency department flows [40, 59], health system performance [60], and economic impact of changes to population health screening methods [61].

Agent-based modelling

Agent-based modelling (ABM) is the most recently developed of the three modelling methods. In ABM, system-level phenomena are observed through explicit modelling of an individual, their behaviours and their interactions with each other and with the environment [62]. The models can be used to uncover complex causal effects, identify underlying mechanisms behind complex systems, and make sense of large amounts of existing evidence and data [63]. The adoption of ABM by simulation practitioners increased from the early 2000’s, triggered by computer science led advances in modelling technology, rapid growth in computing power and memory and a motivation to gain deeper insights into systems that could not be well captured by other modelling methods [30].

In an ABM, actors in a system are represented as autonomous individuals. They are given a starting configuration and rules that govern their behaviour, including adaptation, and interaction with each other and with their environment through time [62, 64]. The ABM then simulates both individual trajectories and population-level patterns or outcomes, which are generated from the bottom up by the actions and interactions of the agents. This
modelling method provides mechanistic mapping from individual-level assumptions to evolving population-level dynamics [62]. Assumptions can be informed by data or theory, and outcomes at both the individual and population levels can be compared statistically. ABM allows enormous flexibility in assumptions, and agents can be modelled at any level (or multiple levels) of scale. [64]

Agents can represent virtually anything in agent-based modelling [30]. For example, agents can be people, vehicles, equipment, health services, projects, investments or products. Agents may or may not interact in a social context and they may be active or passive within the model. Agents may be positioned in a spatial context (or not), may or may not interact with each other and may be very many or very few [30, 63]. The characteristics of agents may be defined in the model or they may emerge from the model dynamics and stochastics [62-64].

By modelling populations of individuals, ABM can also capture the interaction of actors with each other and with their evolving environments. This type of interaction and feedback between individual and social levels of scale is important for the study of such phenomena as interacting social influence and social selection processes, strategic social marketing, and the bidirectional influence of social norms and individual behaviour [30, 62, 64].

The level of abstraction in an ABM is also flexible and is determined by the level of abstraction of the “agents”. If agents are individuals, then the ABM will be more detailed, however if the agents are developed at a high level of abstraction e.g. Projects, companies or concepts, then the model will also be at a high level of abstraction [30]. ABM allows for multiple levels of aggregation to coexist within a given model or to be modified easily if
necessary. ABM can be useful when the appropriate level of complexity or abstraction is not known ahead of time and requires exploration during model development [62].

An important benefit of ABM is that it can be used to explore emergent phenomena which results from the interactions of individual entities [62]. Stochasticity can be applied to the agents’ behaviour with sources of randomness incorporated where appropriate, as opposed to a noise term added more or less arbitrarily to an aggregate equation in other modelling methods [62].

ABM is of use when describing the system from the bottom up, that is, from the perspective of the individual agents’ activities. It is useful when the behaviour of individuals is complex and cannot be clearly defined in an aggregated form and when activities rather than processes are a natural way of describing the system [62]. Experts can easily ‘connect’ to the model facilitating the crucial process of validating and calibrating the model through expert judgement [62]. ABMs strive to represent detailed reality by including individual behaviour, social networks and interactions, geographies, environmental variations, and evolution. Thus, the computational model underlying a “realistic” ABM might contain thousands of rules and model parameters [65].

ABMs allow us to generate hypotheses that articulate complex causal pathways which may include latent variables. Therefore, the ways variables are instantiated (represented) differ from those of other statistical approaches [65]. Good modelling practices suggest instantiating the model parameters with empirical data whenever possible. When such data are not available, models may be parameterised based on values derived from subject matter experts. As a last resort, the parameters for which there are no data or even expert opinion may be derived through calibration [65]. The relative importance of quantifying
unspecified parameters can be assessed using sensitivity analysis of simulation data, which demonstrates the magnitude of the impact the missing information is likely to have on the model outcomes of interest [62, 65]. Moreover, ABM and other systems science methodologies are capable of handling bidirectional relationships and feedback loops; non-linear, networked relationships; and heterogeneity, which are difficult to handle using statistical methods [65].

An early example of ABM was the Schelling model of segregation [66]. This was an abstract study of the interactive dynamics of discriminatory individual choices. Schelling demonstrated, using models of racial dynamics in neighbourhoods, that individual members of two recognisable groups distributing themselves in accordance with a preference that one’s neighbours be members of the same group as themselves or even a preference for a mixture, but “only to some limit”, led to complete segregation. Once the minority share (or number of people in the opposite group) in a neighbourhood reached the “tipping point”, then the existing residents moved away, and more minority group members moved into the neighbourhood. This model demonstrated that the behaviour at an individual level (micro-behaviour) was different to the population level (macro-behaviour). For example, even when individuals had only a 60% preference to have neighbours who were like them the resulting segregation at the population level was 100%.

Other early applications of ABM included the study of evacuation, traffic and customer flows; market behaviour including stock markets, internet service provider business models, and shopbots (online price comparison software); operational risk management and organisational design; and how individuals are influenced by their social context [62]. More recent examples of health applications in ABM include models of obesity [31],
tobacco use [64], diabetes [63], cardiovascular disease [61] and for the reduction of alcohol related harms [67, 68].

Multimethod modelling

Advances in simulation modelling software now allow the modelling methods described above to be combined into multi-scale hybrid models. This means that different components of the system can be modelled at the appropriate level of abstraction [30]. For example, in the model developed for diabetes in pregnancy in this thesis, agents have individual differences, including age, weight status and ethnicity. They can interact with health services represented by process (DES) components and system dynamics occur within an agent to represent the physiological dynamics underlying the development of impaired glucose regulation.

This flexibility is advantageous for several reasons: it allows each of the methods to be chosen and implemented when they are best suited in terms of level of abstraction [30]; it facilitates stakeholder understanding and learning [50, 69] and it can maximise computational efficiency [50].

The involvement of stakeholders in the model development process can facilitate the mobilisation of model-based learning into policy and program decision making. Policy modelling is likely to be of limited value if done without strong and iterative engagement with the users of the model outputs, i.e. decision makers [46, 69, 70]. Modellers must engage with users in a meaningful, ethically informed and iterative way. This is introduced briefly below and explored in detail in Chapters 3 to 6.
2.6 Participatory simulation modelling

The process of participatory simulation modelling involves engaging multidisciplinary stakeholders in a group model-building process and can be used in conjunction with multiple modelling methods including system dynamics, discrete event simulation and agent-based modelling [49, 52, 71, 72]. Various terms have been used to describe these activities including: participatory modelling, group model building, companion modelling (ComMod), and participatory simulation [72]. The tools and methods used in these different approaches may differ, however the underlying principles are in essence very similar, and subscribe to the same basic aim, to engage end-users and other stakeholders actively in model development to increase the robustness, validity, utility of and trust in the models and facilitate their use to support decision-making processes [50, 52, 69, 71-73]. The term participatory modelling has been adopted in this research. Participatory modelling has been an important method in system dynamics modelling almost since its inception [71] and has been widely adopted in environmental modelling projects [52, 73-78].

Osgood (2017) describes the history of stakeholder engagement in modelling projects as being divided into two eras, with a third era just starting to emerge [50]. In the first era “Bring us your problem, and we’ll tell you what decision is best”, modelling projects were mostly conducted inside academic or specialist organisations, with the primary outcome delivered to stakeholders being findings from model explorations conducted in isolation by such specialists. This was replaced by a second era in which models were often delivered to the stakeholder team for use, but generally as a “black box” [50]. Stakeholders were able to interact with the model (for example, through a web-based or desktop interface), but only
for pre-defined scenarios and with constrained outputs. Within this second era of modelling, the internals of the model, including the assumptions made, typically remained invisible to end users, and were unable to be modified by them [50]. Even in those cases in which the modeller was embedded within the end user team, requests to evolve the model, even for modest changes to the assumptions, or to add certain outputs or new types of scenarios, had to be referred to the modeller for action [50].

Advances in modelling technologies allow more transparency and a third era of participatory modelling is developing which is increasingly being undertaken within interdisciplinary teams [49, 50]. Although modelling experts are still required, modelling is no longer restricted to computer science experts, and models are being designed to be broadly accessible across team members [63]. Team members are able to proactively inspect and critique the assumptions of a model, locally modify those assumptions, run the model, and increasingly to supplement previously defined model outputs with those that they develop themselves [50]. Such broader access to models can support faster model evolution and learning, particularly in identifying discrepancies between model results and empirical observations or knowledge concerning the world, and in helping to refine mental models across the team [20, 23, 43, 52].

It is difficult to understand and forecast in advance the impact of policy decisions on system behaviour as a whole [23, 32]; however, an unambiguous model specified on a computer can play out the logical implications of the assumptions captured within that model [50]. From this perspective, the discovery of an inconsistency between what the model suggests in simulation results and empirical knowledge is not a failure of the model, but a success of the modelling process to facilitate learning, in that the process helps refine that
understanding, making it more robust [49, 50, 77]. Within this third era of modelling, embedded transparent models within teams helps harness the knowledge across the breadth of the team and can enhance their ability to identify areas where their knowledge falls short, and contribute to making it more robust [50].

Principles and functions of participatory modelling

Many frameworks, guidelines and principles for participatory modelling have been developed within the environmental sciences field where it has been widely acknowledged that sustainability issues involve social processes and stakeholder engagement is necessary to support effective action [69, 70, 72, 79, 80]. Frameworks and guidelines for participatory modelling have ranged from highly prescriptive scripts used for Group Model Building associated with system dynamics modelling [52, 71, 73, 81-83] to more general guidelines and considerations [20, 49, 69, 72, 84].

Participatory modelling projects are diverse and flexible principles guiding the conduct of participatory processes that are also easily modifiable and applicable across sectors have been proposed as a practical approach to inform existing and future practice [69, 72]. The following principles have been emphasised:

Planning stakeholder engagement - There should be careful consideration of the selection of stakeholders to include as participants, what their level of involvement and function will be in the participatory model development and at what phases of the project they will be involved [69, 84]. The specific skills, knowledge and domains of influence that each stakeholder or group of stakeholders bring to the process also need to be taken into
account, including the skills and knowledge of the modelling team, to ensure the right mix is available to guide model development [85].

**Being aware of social and group dynamics, special interests, power and hierarchies** - A participatory modelling process should always consider the reasons and intentions of stakeholders in becoming involved as well as the reasons and intentions of modellers (and other professionals) in proposing the involvement of stakeholders [49]. The social dynamics within the participant group need to be considered, including, for example, how powerful stakeholders might permit, facilitate, or encourage other actors to participate, or alternatively, how they might prevent them from participating [49].

**Flexibility** - Participants are involved in the process from the very beginning, having a say in the goals of the study, and also in the choice of methods, models and scenarios, and the scope of the study [49, 72]. In many cases the participation in the study becomes the most important and productive part of the project. Unexpected changes in goals and priorities (particularly those that arise from learning from the model) should be expected and accommodated within the process [49, 72]. Stakeholder motivation is important for the success of projects, and stakeholders may be demotivated if they are forced into a predefined protocol or procedure [72].

**Openness and transparency** – being open both scientifically and socially. Learning to work with stakeholders throughout the whole project, and providing tools that they require, they choose, and they are willing to use is necessary to encourage stakeholders to use the models to inform decision making [72]. It may not be possible to identify which tools will be needed at the start of a project, the decision-making process itself needs to be collaborative, and that in this process a range of models and modelling methods may be
needed [72]. Existing models need to be tested, documented, and archived in such a way that would make them available if stakeholders require them, and the models should be kept open so that they can be easily modified if such modifications are needed [72].

**Iterating and refining** - participatory modelling needs to be collaborative, iterative and agile [46, 49, 72]. This approach facilitates a sense of ownership of the model and encourages commitment from users about what they may come to see as ‘their’ model, rather than some black box that someone else is imposing on them [46]. Participant input also helps to prevent modellers making naive assumptions about the focus topic for the model, which is easy to do if one is not a domain expert [46].

**Accepting uncertainty and encouraging learning** - In participatory modelling, the model is always evolving, and uncertainty is an important consideration and discussion point [49, 72]. Through collaboration, the modellers are educated about the complexities of the system they are trying to represent, but equally, the users are educated about the capabilities, limitations and uncertainty in the model that they are helping to develop [46]. Active engagement of stakeholders can help parameterise and check the logical consistency of models, even where ‘hard’ data is sparse [46]. Lack of data should not be used to justify a decision not to model, but the approach needs moderation [46]. An iterative, participative approach to modelling allows data needs to be identified and ways of addressing these developed [46, 49, 72]. Rather than being viewed as “crystal balls” that are assessed as either being accurate and successful or flawed and a failure, models have significant potential to assist learning through the participatory process by bringing together best evidence, data and knowledge and consolidating and testing a shared hypothesis [20, 50].
A recent review of participatory modelling projects identified a number of functions enabled by the engagement of stakeholders in model development processes [69]. The most frequently reported function was gaining access to specific domain knowledge, followed by facilitating group processes and social learning, and yielding socially robust solutions (i.e., those that are accepted by decision makers and the general public) [69]. Joint problem framing so that real-world problems are addressed, developing scenarios and indicators to capture the relevant concepts from both science and practice perspectives, gaining access to and informing decision makers about state-of-the-art science; presenting results and facilitating use of the model results to inform decisions were also identified as important functions of participatory model development processes [69].

2.7 Important gaps in knowledge

The advances in technology described in the preceding sections are leading to increased adoption of tools and methods capable of integrating diverse evidence sources and exploring the dynamics of complex systems to inform policy decision making [83, 86]. However, most participatory modelling projects do not explicitly reflect on the participatory process component of the project [69]. Therefore, many of the challenges in aligning these technological advances with real-life policy making had not been examined in detail and were unresolved [69]. Questions also remained regarding how to facilitate participatory processes effectively and encourage the acceptance of participatory modelling processes [46, 72]. Exploration of different participatory modelling methods have been needed to produce more detailed understanding of what motivates stakeholder participation, in both the short and long term, with particular emphasis applied to understanding the value (or lack thereof) participants obtain from participation, and how
participatory model building and model-based reasoning can result in improvements to decision making [87]. No standard template for participatory modelling processes has emerged [69] and the literature is mostly theoretical [88]. It has been argued that lessons to improve participatory modelling approaches will likely come from “craft knowledge”, gained from experience [46].

Many participatory simulation modelling projects have been conducted in the environmental science field. Therefore rigorous evaluation of the acceptability, perceived value and utility of these methods and tools in the health sector has been required if their adoption to support evidence-informed policy and planning is to be achieved [41, 89]. To date, while DSM has been applied to health sector issues, the potential of participatory DSM in the health sector has not been adequately explored. In particular, stakeholder engagement and involvement of end-users in health-related simulation model development has been lacking [86, 90] or, when engagement has occurred, the participatory process has not been analysed and reported [91].

These gaps in knowledge and resulting research questions are described in more detail in the research protocol presented in Chapter 3.
References


Chapter 3: Research methods

Section 3.1 in this chapter presents the published research protocol. This paper also explored the challenges associated with achieving evidence-based health policy making, and how system science applications to knowledge mobilisation, such as participatory DSM, have potential to overcome these challenges. Important gaps in knowledge are identified, including firstly, whether it is feasible to use a participatory approach to dynamic simulation modelling as a method for evidence synthesis and decision support in “real-world” public health settings. Secondly, what are the perceived value and efficacy of participatory simulation modelling methods from the perspective of end users.

Section 3.2 describes how the research methods evolved following publication of the research protocol. Section 3.3 describes my role in the primary DIP case study and the two supplementary case studies to examine the participatory DSM approach. Also included in Section 3.3 is a summary of the research questions, and their relationship to the study objectives, data sources, and the other chapters in thesis. Section 3.4 provides the relevant information about the ethics approvals for this research.

3.1 Paper 1: Simulation modelling as a tool for knowledge mobilisation in health policy settings: a case study protocol

Simulation modelling as a tool for knowledge mobilisation in health policy settings: a case study protocol

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Abstract

Background: Evidence-informed decision-making is essential to ensure that health programs and services are effective and offer value for money; however, barriers to the use of evidence persist. Emerging systems science approaches and advances in technology are providing new methods and tools to facilitate evidence-based decision-making. Simulation modelling offers a unique tool for synthesising and leveraging existing evidence, data and expert local knowledge to examine, in a robust, low risk and low cost way, the likely impact of alternative policy and service provision scenarios. This case study will evaluate participatory simulation modelling to inform the prevention and management of gestational diabetes mellitus (GDM). The risks associated with GDM are well recognised; however, debate remains regarding diagnostic thresholds and whether screening and treatment to reduce maternal glucose levels reduce the associated risks. A diagnosis of GDM may provide a leverage point for multidisciplinary lifestyle modification interventions. This research will apply and evaluate a simulation modelling approach to understand the complex interrelation of factors that drive GDM rates, test options for screening and interventions, and optimise the use of evidence to inform policy and program decision-making.

Methods/Design: The study design will use mixed methods to achieve the objectives. Policy, clinical practice and research experts will work collaboratively to develop, test and validate a simulation model of GDM in the Australian Capital Territory (ACT). The model will be applied to support evidence-informed policy dialogues with diverse stakeholders for the management of GDM in the ACT. Qualitative methods will be used to evaluate simulation modelling as an evidence synthesis tool to support evidence-based decision-making. Interviews and analysis of workshop recordings will focus on the participants’ engagement in the modelling process; perceived value of the participatory process, perceived commitment, influence and confidence of stakeholders in implementing policy and program decisions identified in the modelling process; and the impact of the process in terms of policy and program change.

Discussion: The study will generate empirical evidence on the feasibility and potential value of simulation modelling to support knowledge mobilisation and consensus building in health settings.

Keywords: Health systems, Participatory simulation modelling, Gestational diabetes mellitus, Group model building, Evaluation, Knowledge mobilisation

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Background
Health systems are under continual pressure to provide accessible and effective health services within limited slow growing or reducing budgets. In this context, decisions regarding the best investment of health funds need to be well informed, reviewed regularly and aimed at achieving the greatest health gain for the investment.

The divide between research and health system actions has been frequently recognised [1–3]. Knowledge derived from research and experience will be of little benefit unless it is utilised and its success monitored [1]. There is a need to bridge the gap between the increasingly sophisticated research on using evidence and practitioner knowledge to inform practice and policy and the pragmatic nature of agency decision-making for strategies and actions [2]. Advances in technology have led to increased adoption of tools and methods aimed at integrating diverse evidence sources to inform decision-making [4, 5]. However, rigorous assessment of the value and utility of these methods and tools is required prior to them being more generally adopted for evidence-based decision support. The application of systems science and simulation modelling to the decision-making process is an innovative area with great potential value for those responsible for allocating scarce resources [6].

What are the challenges of evidence-informed policymaking?
Evidence-informed policy decisions are essential to ensure that health intervention programs and service plans are likely to be effective and offer value for money. However, barriers to the use of evidence to inform decision-making remain [7] and the use of published research to inform policy development is often limited [8]. Descriptive evidence and analytical studies are used to describe issues and inform priorities; however, evidence on the implementation and impact of interventions is less commonly used to inform program planning decisions and strategic actions [7]. In some cases, program decision-making can be driven by “informed guesswork, expert hunches, political and other imperatives” [9].

To address this, evidence provided to policymakers needs to be in a form that is useful to them [10–12]. Policymakers require synthesised and localised data that contrasts and prioritises policy options, demonstrates effectiveness of interventions, demonstrates the need for a policy response, demonstrates cost effectiveness of actions, reflects the level of public support for a particular issue and personalises the problem [12, 13]. In addition, policy and program decision-making processes are rarely linear. They are frequently iterative processes and are influenced by a range of inputs such as political environment, budget constraints, resources, values, available expertise and ethics [7, 12, 14, 15].

Even when research evidence is considered, as in public health policy development for the prevention of chronic disease [2], this evidence often points to a large range of risk factors that contribute to the problem, including broader social determinants of health. Our lack of understanding about how these risk factors interact, and which are the most important, have resulted in the development of more comprehensive, cross-sectoral strategies to tackle complex or ‘wicked’ problems [5]. However, this approach may not represent the most efficient or effective approach to reducing disease burden at the population level. Rather, it may act to spread finite resources less intensively over a greater number of programs and initiatives, diluting the potential impact of investment [5].

Knowledge mobilisation to support evidence-based decision-making
The term knowledge mobilisation (KM) is used to refer to a range of active approaches deployed to encourage the creation and sharing of research-informed knowledge [2]. The number of terms used to describe KM activities is large [16] and have been widely debated. These terms include knowledge translation, knowledge transfer, knowledge to action, knowledge exchange, knowledge interaction, etc. [2]. This multiplicity of terms can be a barrier to clear communication in this field [2]. In this research, the term KM is preferred as it reflects that the process of producing and applying knowledge in the health sector is non-linear and iterative. KM can involve a number of activities, including capacity building, advocacy, implementation, research and evaluation [17]. Not all of these activities are applied in every KM project [17] and they can be applied in different orders; however, they share the common function of generating and sharing research-informed knowledge [2].

KM strategies have been applied to a range of issues, including the quality and effectiveness of health services, addressing policy questions (for example, mapping health inequity and healthcare disparities), and addressing managerial and organisational issues such as the composition of multidisciplinary teams and the costs and consequences of different service models [2, 18]. A key strategy of KM is the production of good quality, synthesised evidence [9] such as scoping reviews, systematic reviews, meta analyses and research summaries highlighting key findings for decision-makers [9, 10].

Traditional methods of KM via evidence synthesis have made a valuable contribution; however, they have a number of characteristics that limit their utility as decision support methods for complex policy questions. Firstly, systematic reviews and meta-analyses focus on clear and specific questions and therefore have a narrow focus of investigation and limited potential to examine complex questions [11, 19]. Secondly, these methods frequently exclude
qualitative evidence, and when qualitative evidence is included it is not used to answer the primary research question but only to answer supportive questions such as whether an intervention was acceptable to consumers [19]. Thirdly, these methods produce static overviews of the evidence and policy options that are passively provided to decision-makers, leaving them to interpret that evidence in their localised context and to navigate complexity and uncertainty as they weigh up options for responding to the problem [20].

While there are many KM approaches and techniques, the evaluation of their use is still in its infancy [2, 21]. The limited focus on evaluation of the effectiveness of KM methods, including systems-based ones, has been attributed to the challenges associated with the evaluation task [2], including the methodological challenges of conducting rigorous evaluations. It can be difficult to measure impact, to attribute impact to different strands of the activity in a complex environment, and to minimise the evaluation reporting burden on stakeholders [2].

**Systems approaches to knowledge mobilisation**

There are acknowledged synergies between KM and systems science [21]. Systems science methods have emerged as an effective analytical approach with the capacity to examine both complex health problems and the context in which they are embedded [6, 22, 23]. Systems science can be used to map health system components and their interactions; synthesise evidence, examine and compare the potential outcomes of interventions; and guide more efficient investment and conscientious disinvestment of resources [5]. As practical systems-based KM tools and strategies emerge, their efficacy needs to be evaluated and this knowledge to be shared [2, 21].

Systems approaches recognise the highly contextualised nature of health services and communities and, therefore, evidence to inform decision-makers is unlikely to be in the form of prescriptive statements of ‘what works’ [24]. Rather, evidence from a systems-thinking perspective will suggest the range of strategies that will have different types of effects for different groups under certain conditions. Building this type of evidence base will involve undertaking diverse methodologies, including the use of case studies investigating the efficacy of using systems techniques to inform decision-making [24].

Research methods in prevention science have traditionally employed a reductionist approach focusing on the detail of each component of the system. For example, many studies focus on the design, measurement and analysis of specific interventions for specific target groups. These studies have contributed and will continue to contribute significantly to understanding the effectiveness of prevention interventions, gaining knowledge about direct causal relationships and understanding components of complex systems [6, 25]. However, this approach can result in a failure to achieve understanding of the broader system behaviour influencing prevention problems and can hinder insights that may be critical for effective policy and program decision-making [25]. Traditional statistical methods have difficulty accounting for delays between cause and effect, non-linear relationships and unanticipated consequences of interventions [23].

Applying a systems approach through dynamic simulation modelling can provide a method to map, visualise and quantify a complex system, to promote discussion among stakeholders [26], and to identify points of high leverage for intervening. Leverage points are those places in a system where a small shift can create a large impact [27]. Leverage points are difficult to identify in complex systems using traditional reductionist research methods which examine relationships between specific elements of the system in isolation [28–30]. It is also difficult to identify the direction of shift required to obtain the desired outcome without comprehensive analysis and understanding of the system and its behaviour [27, 31]. Unanticipated consequences of interventions can have profound and negative impacts [31, 32], and can lead to policy resistance in which the intended positive impact of the intervention is counteracted by system responses to the intervention itself [32].

Dynamic simulation models allow for rapid integration and use of new evidence for policy analysis, make trade-offs of policy options explicit, and act as a vehicle for advancing controversial, contested and value-laden debates [5, 31, 33]. Their use to explore the implications of policy options can give rise to policy scenarios that have not previously been considered [5].

System dynamics modelling has been used as a tool to represent disease prevalence, risk factors and local context and to simulate the health outcomes of interventions, thus facilitating the alignment of prevention efforts by a range of community stakeholders [34]. For example, Loyo et al. [35] used a stakeholder engagement process to develop a system dynamics model to simulate the impact of various interventions in chronic disease outcomes. The model was used to illustrate which interventions were most effective leverage points in the local context/system and therefore to align and mobilise prevention efforts of community stakeholders [35].

Participatory modelling processes, such as the one described by Loyo et al. [35], provide an opportunity to understand and develop efficient solutions in the health sector [36, 37]. Participatory modelling, firstly, helps community stakeholders understand how multiple variables, factors and interventions interact. Secondly, simulation modelling can test the potential impact of programs and policies in the ‘safety’ of a virtual environment before they are implemented, saving time, effort, costs and resources. Thirdly, modelling demonstrates potential secondary and
tertiary effects (and even unintended consequences) of intervention strategies. Fourthly, modelling can guide and prioritise data collection and facilitate dialogue among stakeholders [36].

The process of participatory simulation modelling involves engaging multidisciplinary stakeholders in a group model-building process and can be used in conjunction with a number of modelling methods [31, 37, 38]. The value of this engagement is the development of a shared mental model of the causal pathways and potential intervention points in the system [39]. A participatory modelling approach enhances stakeholder knowledge and understanding of the system and its dynamics in varying conditions. It identifies and clarifies complex and contested real world problems [33] and the impact of solutions, therefore facilitating the development of action statements based on the evidence [39, 40]. The involvement of key decision-makers in the model development and validation increases their sense of ownership and confidence that the model is valid for their local context. They are therefore more likely to draw on the outputs to inform decisions about priority interventions and policies [23, 37, 39, 41].

Important gaps in knowledge

The application of systems thinking to health improvement is acknowledged as an ongoing challenge [42, 43]. Stakeholder engagement and involvement in the modelling process has been particularly lacking, resulting in unsuccessful projects [42] and a reluctance from ‘non-researchers’ to use models as a decision support tool [33]. A systematic review of the use of simulation modelling to inform surgical patient flow processes found that only half of publications stated that they had produced a model to inform policymakers and health service managers and only 26% actually included policymakers and health service managers in the simulation modelling process [44]. Where policymakers have been included in the simulation modelling process there remains an absence of rigorous analysis of their perspectives on the utility of the model, their learning relating to the development and use of the model, and their commitment to implement the findings of the model [5, 37].

Relationships and collaborations are routinely identified as a key factor in systems approaches [45] and this is particularly true for participatory modelling processes. Important elements for implementing successful systems thinking to address complex issues include the formation of networks and teams, distributed leadership, and strong and effective communication and feedback mechanisms [17]. Understanding the role of participants within the system as well as in the participatory modelling process and bridging professional cultures [45] is key to understanding the factors that will impact on the uptake of simulation modelling as an evidence synthesis tool. Participatory modelling approaches aim to combine multidisciplinary stakeholder perspectives to tackle the social complexity of problems and recognise that different types of knowledge contribute alternative and valuable perspectives to the problem discourse [33].

Evaluation of the participatory simulation modelling process in the health sector has been lacking [5, 41] despite assessment of its efficacy being essential to inform decision-making [5, 37]. Understanding the intricacies of the participatory process [33] and evaluating methods and tools to facilitate participatory modelling is necessary to improve modelling outcomes [4, 31, 37] and further research is required to develop and refine rigorous evaluation methods [39]. The Challenge and Reconstruct Learning (CHaRL) Framework has been proposed by Smajgl and Ward [46] to evaluate participatory modelling processes. This framework can be used for deliberative approaches [47] and involves assessing formalised and facilitated learning among decision-makers and decision influencers at varied policy levels. The key component of the CHaRL framework is the change in perception or belief about assumed causality within the system. In other words, participants’ mental models are challenged by the presentation of different perspectives, scientific evidence and system interactions through the modelling process. The change in mental model can be measured using individual value and attitude/belief orientations recorded by participants pre- and post- the modelling process [46].

Study objectives

The objectives of the research are to apply and evaluate a simulation modelling approach, using gestational diabetes as a case study to:

1. Pilot simulation modelling to optimise the use of evidence to inform policy and program decision-making by synthesising and integrating diverse evidence sources into a dynamic simulation model of gestational diabetes using a participatory modelling approach. The model will be used to understand the complex interrelation of factors that drive gestational diabetes mellitus (GDM) rates and test options for interventions.

2. Investigate the perceived value and efficacy of participatory simulation modelling methods as an evidence synthesis and decision support method in an applied health sector context.

Using GDM as a case study

GDM is a complication of pregnancy that is defined as carbohydrate intolerance resulting in hyperglycaemia (abnormally high blood sugar) of variable severity with onset or first recognition during pregnancy [48]. GDM defined in this way includes women with undiagnosed pre-existing diabetes, as well as those for whom the first onset is during
pregnancy (especially during the third trimester of pregnancy). The prevalence of GDM is increasing both in Australia and internationally [49].

Identified risk factors for GDM include maternal body mass index of at least 30 kg/m² [50–52], increasing maternal age [52], physical inactivity [50, 52], increasing parity, and ethnicity [53]. Women are also at increased risk if they have a history of GDM [52], previously had a macrosomic baby (birthweight greater than 4000 g), a family history of diabetes [52], polycystic ovary syndrome [52], or a diet low in fibre [54, 55].

Perinatal risks associated with GDM include macrosomia, shoulder dystocia, other birth injuries, hypoglycaemia and perinatal mortality [53, 56]. Long-term risks for the infant from GDM include sustained impairment of glucose tolerance [57], subsequent obesity [58] (although not when adjusted for size) [59], and impaired intellectual achievement [60]. For women, gestational diabetes is a strong risk factor for the development of diabetes later in life [61, 62].

Although the risks associated with gestational diabetes are well recognised, debate remains as to whether screening and treatment to reduce maternal glucose levels reduce these risks [53, 63]. Given this uncertainty, professional groups disagree on whether to recommend routine screening, selective screening based on risk factors for gestational diabetes, or no screening [53]. There is also debate over the efficacy of using a single raised blood glucose result to diagnose GDM [63].

The Australian diagnostic threshold for GDM was changed to be consistent with WHO criteria from January 1, 2015. The WHO report from which the criteria were obtained acknowledges that the evidence for the threshold chosen is weak. However, they argue that the benefits of treatment, i.e. reduction of risk for macrosomia, shoulder dystocia and pre-eclampsia is sufficient justification. Treatment of gestational diabetes once diagnosed is generally medicalised (insulin treatment) and involves intense use of health services, mostly in the third trimester. Investigations of the cost implications of using the lowered diagnostic threshold concluded that cost effectiveness will only be achieved if treatment reduces the risk of caesarean section birth and developing Type 2 diabetes mellitus [64, 65].

Pregnancy has been identified as a point in the life cycle where individuals have increased motivation to commit to health improving behaviours, for example, in smoking cessation [66]. A diagnosis of GDM (or even a glucose tolerance test result that approaches the diagnostic cut-off) may provide a powerful leverage point for multidisciplinary health interventions promoting lifestyle change to reduce the risk of developing diabetes later in life. Almost all women (95%) with a diagnosis of borderline GDM in an Australian study identified that managing their borderline GDM was important or very important for the health of their baby and themselves [67]. Enablers identified by women to implement lifestyle change during pregnancy include family support [66, 67], physical access to programs, knowledge (about diet, exercise and GDM), and motivation levels [67].

Previous models of GDM developed to investigate the cost effectiveness of screening and treatment regimens [64, 65, 68, 69] have provided valuable evidence to inform decision-making. However, these models focussed on an economic evaluation of specific treatments and did not analyse the wider outcomes of policy and program decisions, including the intended and unintended consequences and resource implications of interventions delivered in the health system [70]. Dynamic simulation modelling has been used to investigate the intergenerational impact of GDM on the development of Type 2 diabetes mellitus among First Nations and other population groups in Canada [71]. This model included representations of factors contributing to the development of diabetes mellitus, including changes in behaviour regarding diet and physical activity over time and found that GDM disproportionately contributed to the development of Type 2 diabetes mellitus in First Nations populations compared with other population groups [71].

Dynamic simulation modelling provides an opportunity to explore and compare the implications of health intervention options for GDM services in the Australian Capital Territory (ACT) and to inform policy and program decision-making. The simulations derived from the model can be used to explore the dynamic interaction of risk factors such as maternal weight and weight gain (pre and during pregnancy); the impact of screening earlier or later in pregnancy; the impact of universal or selective screening; the impact of lowering the diagnosis threshold on the number of women diagnosed, health outcomes and health system impacts; the implications of intervention options for prevention and treatment of GDM with different target groups and with different timings (e.g. at the start of pregnancy, during pregnancies, between pregnancies); GDM diagnosis and risk of later development of Type 2 diabetes in the ACT; and the short- and long-term outcomes for mother and baby following treatment for GDM.

The current research project will contribute to knowledge on the application of systems thinking to a localised health system case study by undertaking, validating and evaluating a participatory simulation modelling process focusing on GDM.

Methods/Design
Design overview
The study design will use mixed methods to achieve the research objectives. A participatory simulation modelling approach will be used to synthesise evidence and explore
strategies for GDM diagnosis, early intervention and management (Objective 1). Evaluation of the modelling process as a systems-based knowledge synthesis tool will incorporate both qualitative and quantitative methods (Objective 2).

Research questions
Simulation modelling will be used to answer the following research questions about GDM interventions in the ACT. Model simulations will explore:

- The dynamic interaction between risk factors such as pre-pregnancy maternal weight, maternal weight gain during pregnancy, GDM diagnosis and life-time risk of developing of Type 2 diabetes for mothers and babies in the ACT
- The short- and long-term outcomes for mother and baby following treatment for GDM in the ACT
- The impact of changing the diagnosis threshold on the number of women diagnosed, health outcomes and the health system impacts (including health economic analysis)
- Health outcomes achieved from priority interventions identified by participants
- Cost effectiveness of priority interventions identified by participants

This research will also explore the effectiveness of participatory simulation modelling methods to optimise the use of evidence to inform policy and program decision-making through qualitative and quantitative methods investigating the participatory modelling process and evidence of impact on decision-making (detailed further below). The specific questions to be answered by this research include:

- Whether simulation modelling is an effective tool to facilitate evidence-informed decision-making in an applied health setting
- The efficacy of applying a participatory approach to model development
- The benefits and limitations of using simulation modelling to explore potential outcomes from a range of policy and intervention options to inform decision-making

Study setting
The study is being conducted as part of an ongoing initiative of The Australian Prevention Partnership Centre to apply systems approaches to the prevention of chronic disease. The research will be carried out at the ACT Government Health Directorate, which provides publicly funded health services for a population of approximately 390,000 in the ACT and is the major health referral centre for the Greater Southern Region of NSW. The total catchment area population is over 600,000 people. Tertiary level maternity services are provided by Canberra Hospital at the Centenary Hospital for Women. There are two publicly funded hospitals and one private hospital in the ACT, providing maternity services.

The number of women giving birth in the ACT is over 6000 per year. Approximately 15% of these women are not ACT residents but access services in the ACT for high risk pregnancy complications (i.e. requiring tertiary level care). There a number of models of antenatal maternity care provided in the ACT including hospital-based outpatient care, tertiary level care, private midwifery care, and shared care (which is integrated with primary healthcare providers).

A specialist gestational diabetes service with satellite clinics in community health centres works with generalist maternity services to provide education and health services for women with gestational diabetes.

Participants
Purposive sampling will be used to recruit participants with a range of expertise such as endocrinology, obstetrics, neonatology, diabetes education, nursing, midwifery, policy, health economics, exercise physiology, pathology, public health, research, allied health, health service management, consumers (healthcare recipients) and the simulation modelling expert team. The anticipated number of participants is 10 to 15 to allow for wide engagement with influential leaders while maintaining a manageable dialogue with meaningful contributions from all members.

The inclusion criteria for participants is that they are recognised experts in providing care, planning services, undertaking research or developing policy for the diagnosis and management of GDM. Participants must also be willing to attend model development and application sessions and participate in the evaluation.

Participants in the group model building and model validation processes will be asked to provide written consent prior to participating.

Procedure
Objective 1 – Participatory model development

Model development This research will employ a participatory simulation modelling process, which will involve the following steps [4, 26, 31, 36]:

- Forming an expert sub-group of the participants listed above who will define the boundaries of the model. A model is not able to include in detail every possible factor, relationship and intervention, and therefore only those that are relevant to the policy and practice questions to be answered by the model should be included in the first instance. Engaging with the literature and collaborating with stakeholders
and researchers to understand the risk factors for GDM, options for GDM diagnosis and intervention, and reach agreement on the priority health and economic outcome indicators to be included in the model structure

- Identifying data sources and populating the model with data (parameterising the model)
- Deciding which local and/or national data on current practices and behaviours should be incorporated into the model
- Identifying potential intervention leverage points and mapping the mechanism by which interventions have their effect in the model
- Validating the model using accepted validation methods such as assessment of face validity, system behaviour reproduction, parameter estimation, sensitivity analysis and statistical testing [41]
- As the model develops into a functioning simulation tool, exploring possible scenarios and prediction of outcomes
- Ensuring the purpose, assumptions and limitations of the model are clearly stated
- Using the final model to explore the timing, frequency and combination of interventions that deliver optimal impact

The participatory model development process will identify the factors to be represented in the model. It is anticipated that a combination of high level aggregated, individual characteristics and interactions and event-based factors (e.g. service utilisation), will be identified. Therefore, a more flexible hybrid modelling approach will be adopted incorporating system dynamics, agent-based and discrete event modelling methods.

System dynamics modelling methods were created in the 1950s by Jay Forrester in the field of engineering. System dynamics modelling utilises feedback loops (causal loop diagrams) and stock (accumulations) and flow diagrams to represent complex systems [6, 23, 72]. This modelling method represents the dynamics of the system at a high level of abstraction [6], making them an efficient form of modelling in terms of computing resources. System dynamics simulates patterns and trends in system behaviour. Simulation experiments can be used to compare and contrast intervention alternatives to inform decision-making [70].

Agent-based modelling (ABM) methods have been developed more recently and allow for representation of individuals or agents within the system. The model can be built from the ground up by defining agents, their behaviours and their interactions [6, 72]. ABM is a computational method used to examine the actions of agents (e.g. individuals) situated in an environment (e.g. neighbourhood). ABMs specify decision rules controlling dynamics such as ‘If–Then’ statements and mechanistic interactions among agents. When the program is run, agents interact with one another and their environment, often resulting in counterintuitive insights about behaviour of agents and the system [23]. Incorporating ABM components allows flexibility to incorporate the dynamics of people making decisions affecting population health outcomes, and thus efficient planning of healthcare interventions [70].

Discrete event modelling methods represent the system as a process, namely, as a sequence of operations or events performed across entities [72]. For example, discrete event methods are frequently used to represent and improve efficiency of health services such as emergency departments. This modelling method represents complex systems at a low level of abstraction. The core concepts in discrete event simulation (DES) are events, entities, attributes and resources. An event happens at a certain time point in the environment and can affect resources and/or entities. Entities have attributes and consume resources while experiencing events, but consumption is not affected by individual-level behaviour. Attributes are features or characteristics unique to an entity. They can change over time or not. Resources are objects that provide a service to an entity. Queues are another important concept in DES and occur when several entities compete for a specific resource for which there is a constraint [70]. DES modelling is useful to analyse resource utilisation, throughput of services and the impact of varying policy decisions [70].

Advances in modelling software technology now enable multiple modelling methods to be integrated [72]. This allows for modellers to represent the many interacting components of a system and the complex interplay between individual behaviour and social connections across populations [6].

**Model application** Once the model develops into a functioning simulation tool it will be used to explore possible scenarios and prediction of outcomes. During this phase, a broader stakeholder group will be formed and engaged in policy/strategy dialogues facilitated by interaction with the model and explore the costs and benefits for a range of intervention options. The composition of the stakeholder group will include the full scope of disciplines and consumers outlined in the Participants section. The model application process aims to refine the model as well as to demonstrate the utility of the model to key decision-makers so as to inform policy action and program decisions.

The transdisciplinary simulation modelling process provides an opportunity to establish network relationships and analyse policy and program options based on outcomes simulated. An action statement regarding GDM diagnosis and treatment in the ACT based on the simulation
modelling work and synthesised evidence will be developed with the expert group.

**Data analysis** The model will be built using AnyLogic 7.2, St Petersburg, Russian Federation. AnyLogic software allows for multiple modelling methods to be integrated into a single hybrid model providing participants both flexibility and transparency in model design.

Model parameterisation involves populating the model with data and will evolve in accordance with the participatory modelling process. This will make use of the following:

- Secondary analysis of de-identified administrative data to inform transitions (hazard rates/probabilities/relationships between risk factors) within the model structure. For example, regression analyses may be conducted to determine the contribution of gestational diabetes in relation to other risk factors to perinatal outcomes such as birthweight.
- Published demographic information such as age and gender characteristics, age-specific fertility rates, population estimates of weight status categories.
- Published results from research on intervention effects such as the impact of targeted pregnancy weight management programs focused on nutrition or physical activity on the development of GDM.
- Local expert knowledge to supplement available data.
- Partitioned administrative and/or available survey data to calibrate the model.

Statistical analysis of administrative data will be conducted using IBM SPSS Statistics version 22, United States.

Data availability is a potential limitation to this study. It is proposed that, where data is not of high quality or is not available, placeholder values will be used and tested using the following methods. Firstly, the model simulations will be analysed against trends and patterns observed in historical data and, secondly, sensitivity testing will be conducted around the missing values to determine if the model outputs depend significantly on them. When parameters are identified that the model is sensitive too, this can be used to guide and prioritise future research activities to obtain these important pieces of data.

Assumptions surrounding the use of placeholder values will be made explicit in descriptions of the methods used to develop the model.

Validation of the model is necessary to assess the logic, soundness and utility of the model outputs [41]. Validation of the model can be conducted as part of the model development process by conducting tests and involving the model users in assessing the validity of the model [73].

The model will be validated using accepted validation methods such as assessment of face validity, system behaviour reproduction, parameter estimation, sensitivity analysis and statistical testing [41]. Expert participants in the model development process will be asked to assess whether the model and its behaviour and outputs are reasonable given their knowledge of the system [73]. The model behaviour will also be tested against historical data and model simulations over time will be assessed. Available data will be partitioned with a subset used to build the model and the remaining data used to determine (or test) whether the model replicates the historical system behaviour [73]. Parameter variability and sensitivity analyses will also be conducted to test model behaviour and to determine which parameters the model is most sensitive to. Those parameters that are sensitive, that is they cause significant changes in the model’s behaviour or output, should be made sufficiently accurate prior to using the model [73].

**Objective 2 – Evaluation of a participatory approach to dynamic simulation model building**

**Procedure** The case study methodology allows for investigation of the strengths, weaknesses and evaluation of participatory simulation modelling as a mechanism to influence policy and program decision-making and develop action statements [2]. Little is known about the value, strengths and limitations of simulation modelling as applied to ‘real world’ health policy decision-making. The key research questions addressed in this study include those relating to engagement of experts in the process; perceived commitment, influence and confidence of stakeholders in implementing policy and program decisions identified in the modelling process; and measuring the impact of the process in terms of policy and program change.

The evaluation of the participatory modelling process is informed by the CHaRL Framework proposed by Smaigl and Ward [46]. The CHaRL framework can be used for deliberative approaches and involves assessing formalised and facilitated learning among decision-makers and decision influencers at varied policy levels. The key component of the CHaRL framework is the change in perception or belief about assumed causality within the system. In other words, participants’ mental models are challenged by the presentation of different perspectives, scientific evidence and system interactions through the modelling process. The change in mental model can be measured using individual value and attitude/belief orientations recorded by participants before and after the modelling process [46].

Therefore, the evaluation methods to determine the effectiveness and impact of systems dynamic modelling will include investigating the:

- Participation in the process, e.g. response rate to invitations, attendance and retention at modelling sessions and subsequent deliberative forums.
Participants’ perceptions of the key factors that contribute to GDM and the best use of resources to diagnose and manage GDM through survey responses

Group interactions, contributions and engagement with the process by qualitative analysis of audio recordings of the model building and engagement sessions

Informant views via semi-structured interview on the:

- value of simulation modelling as an evidence synthesis tool
- strengths and limitations and intention to use simulation modelling in the future
- perceived enablers and barriers to the use of simulation modelling
- personal response to the participatory modelling process
- Follow-up environment scan to determine policy and program decisions that were informed by the modelling process and the model outputs

Data analysis

Quantitative analyses will include measuring and reporting the number of sessions attended, and analysing the responses recorded on the before and after forum surveys.

Participants will be asked to record their views on the main contributing factors to GDM, the optimal time for screening for GDM and how they would allocate resources to a hypothetical new service for women with GDM. They will also be asked to provide self-reported evaluation feedback reflecting on their learning and ways to improve the modelling sessions.

Qualitative analyses will include analysing the data collected during:

1. Model development sessions
2. Model application sessions
3. Semi-structured interviews (pre- and post-modelling workshops)
4. Notes and memos based on meetings and de-identified conversations with participants and the modelling team

The model development and application sessions will be audio recorded, primarily to allow the investigators to review content information and expert advice provided by participants relating to model development. The recordings, participant observations and field notes will be kept to highlight particularly valuable comments and analyse behaviours or interactions between participants. The analysis of field notes will be triangulated against the audio recordings and interview transcripts.

Semi-structured interviews will be conducted with participants of the model development and model application sessions. Participants will be purposively selected for interviews to provide a range of perspectives and interviews will be conducted face-to-face where possible.

The main domains to be covered will include participant’s perceptions or ‘mental model’ of GDM through the modelling process, value of simulation modelling as an evidence synthesis methodology to inform decision-making, and intention to use this method in the future. The proposed interview questions are contained in Box 1.

### Box 1 Semi-structured interview questions to obtain key informant views

**Prior to workshops**

Based on your experience, what are the current challenges that GDM services are facing? What do you think is driving these challenges? What changes do you think GDM services need to make to cope with these challenges? Which interventions would you prioritise to prevent and manage GDM?

Could you talk a little about your thoughts on evidence-based decision-making in the health policy context? To what extent do you think evidence is used to inform health policy and program decisions? What factors have you found to be useful to support its use? What are the main challenges?

Have you had experience using results of evidence synthesis methods such as systematic reviews, meta-analyses? Did they meet your needs for evidence to inform your decision-making? From your experience, what are the strengths and limitations of these methods? What other forms of evidence do you use in decision-making?

Have you participated in any form of simulation modelling process before? (If reply yes) Could you tell me about the modelling process and your experience of it? In your opinion, what are the benefits and limitations of simulation modelling as an evidence synthesis tool?

**Post workshops**

Could you tell me about your experience of participating in the simulation modelling process? What are the strengths and weaknesses of simulation modelling as an evidence synthesis tool?

Has/How has the modelling process influenced your opinion of the key factors that contribute to GDM? Has/How has the modelling process influenced your opinion of the best use of resources to screen for and treat GDM?

Will you use the outcomes of the gestational diabetes modelling process to guide your future decision-making? Why or why not?

Based on your experience would you say simulation modelling is worthwhile for health sector policy/practice settings? Why/why not?

Do you intend to use the outputs of this model or participate in other simulation modelling projects in the future? Why or why not?

In your opinion, what would you say are facilitators and barriers to the use of simulation modelling to synthesise evidence for decision-making?

Do you have any recommendations to improve the process for using simulation modelling as an evidence synthesis tool?
Field notes relating to meetings and informal discussions will be maintained by the researcher in a journal format and will be included in the qualitative data analysis.

Audio recordings will be transcribed and integrated with field notes and reflections. Transcriptions will be de-identified, collated and coded so that only general themes emerge.

Interview data will be independently coded by two investigators. Initial codes will be derived from the research aims and subsequently refined over two coding cycles. The two coders will compare and agree upon codes and emerging themes at the end of each cycle, resolving disagreement by consensus opinion or by the creation of new, mutually agreeable, codes/themes.

Data analysis will be iterative and begin with identifying central organising concepts, patterns and themes from the coded data. Thematic analysis will be reflective and revised by revisiting the coded and collated data to ensure that identified themes and subthemes are coherent, distinctive and relevant to the research question [74].

Common and repeated themes identified from the modelling sessions will be investigated through interviews to better understand informant views in relation to specific topics, and to assess the strength and importance of various themes. A comparative analysis will be conducted to understand the range of participant views in relation to their role perspective and level of power within their organisation, e.g. clinician, researcher, manager and policymaker views.

This research involves investigators who currently work within the local health sector. This provides some advantage as these investigators have good knowledge of the system and context; however, it also presents challenges and limitations. For example, the investigators’ willingness to identify and report on system limitations may be impacted by their professional affiliation with the organisation. The involvement of external co-investigators and the use of independent reporting mechanisms through The Australian Prevention Partnership Centre are mitigation strategies to be employed for this challenge. The use of voluntary recruitment processes and confidentialised analyses of individual input and participation will be employed to address perceptions of coercion or concerns of repercussion from either participating or declining to participate in this research.

A follow-up environment scan to determine policy and program decisions that were informed by the modelling process and the model outputs will be conducted three to 6 months after the model engagement workshops. This will involve interviews with end users and document analyses to determine the use of model outputs to inform decision-making.

Data storage and management
All audio-recorded data from the model development and model application sessions will be de-identified by using codes instead of names and removing any potentially identifying text from transcripts. Data will be stored securely on password protected computers or ACT Health secure servers and will only be accessible to the researchers.

Paper surveys will be anonymised and scanned to create an electronic file to be stored in secure folders on a secure server only accessible to the researchers. The paper surveys will then be securely destroyed. Clinical and administrative data to be used for the project will be de-identified prior to analysis.

Discussion
This project will apply systems science and simulation modelling to GDM in the ACT as a case study.

The outcomes will include, firstly, producing a model that will be a functioning simulation tool to explore possible scenarios and the impact of those scenarios on health outcomes for the mother and baby as well as service impacts for the health system; secondly, developing a joint commitment for policy action and program decisions through engagement with the stakeholder group and, thirdly, evaluating the use of simulation modelling to inform decision-making.

The participatory model-building process will be informed by a multidisciplinary expert stakeholder group. This provides an opportunity to ensure the model reflects the shared understanding of the causal pathways and potential intervention points in the system.

Simulation modelling methods will be used to explore and compare strategies for GDM diagnosis, early intervention and management. The modelling will include interaction between risk factors, the short- and long-term outcomes for mother and baby, and potential modes and timing of intervention.

Importantly, involving key decision-makers and experts in the model development and validation process increases the acceptability of the model for the local context. The model is therefore more likely to be useful to inform decisions about priority interventions and policies.

Systems science is emerging as an effective way to examine both complex health problems and their context. It can be used to synthesise evidence, examine and compare potential outcomes of policy options, and guide the best use of limited resources through methods such as simulation modelling. This research will contribute to existing knowledge, firstly, by applying a participatory process to simulation modelling in a local health setting; the participatory process will engage expert stakeholders in the development of a functioning model to inform decision-making. Secondly, by developing and incorporating evaluation methods to investigate the efficacy of simulation modelling as an evidence synthesis tool. Thirdly, by using quantitative data to develop a simulation model to inform health policy and program decisions.
Abbreviations

ABM: Agent-based modelling; ACT: Australian Capital Territory; ChAmRL: Challenge and Reconstruct Learning; DES: Discrete event simulation; GDM: Gestational diabetes mellitus; KM: Knowledge mobilisation

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- PhD top up scholarship (2015–18).

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Authors’ contributions

LF conceptualised the manuscript and wrote the first draft. All authors have made important intellectual contributions to multiple draft revisions. All authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

Ethics approval and consent to participate

This research has been reviewed and approved as low risk by the ACT Health Human Research Ethics Committee (ACTHLR.15.150) and the University of Notre Dame Human Research Ethics Committee (0151195).

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Chapter 3: Research methods

Section 3.1 in this chapter presents the published research protocol. This paper also explored the challenges associated with achieving evidence-based health policy making, and how system science applications to knowledge mobilisation, such as participatory DSM, have potential to overcome these challenges. Important gaps in knowledge are identified, including firstly, whether it is feasible to use a participatory approach to dynamic simulation modelling as a method for evidence synthesis and decision support in “real-world” public health settings. Secondly, what are the perceived value and efficacy of participatory simulation modelling methods from the perspective of end users.

Section 3.2 describes how the research methods evolved following publication of the research protocol. Section 3.3 describes my role in the primary DIP case study and the two supplementary case studies to examine the participatory DSM approach. Also included in Section 3.3 is a summary of the research questions, and their relationship to the study objectives, data sources, and the other chapters in thesis. Section 3.4 provides the relevant information about the ethics approvals for this research.

3.1 Paper 1: Simulation modelling as a tool for knowledge mobilisation in health policy settings: a case study protocol

3.2 Evolution of research methods following publication of the protocol

My overall study objectives, from the protocol paper above, were to:

1. Pilot simulation modelling to optimise the use of evidence to inform policy and program decision-making by synthesising and integrating diverse evidence sources into a DSM of gestational diabetes using a participatory modelling approach.
2. Investigate the perceived value and efficacy of participatory simulation modelling methods as an evidence synthesis and decision support method in an applied health sector context.

As the study progressed following the publication of the protocol paper, further developments to the study methods were implemented. These developments included modifications to the scope of the DIP case study model, and triangulation of data compiled about the value of PSM in this case study with additional data from two other modelling projects conducted under the auspices of the Australian Prevention Partnership Centre. These developments are described below.

3.2.1 Revised model scope for DIP case study (study objective 1)

The case study scope was expanded during the model development process from initially including only gestational diabetes mellitus to including all forms of diabetes in pregnancy. Diabetes in pregnancy includes both diabetes diagnosed during pregnancy, i.e. gestational diabetes mellitus (GDM), and pre-existing diabetes. While most women who experience diabetes in pregnancy have GDM, participants identified during the first model development workshop that the number of pregnant women presenting to services with pre-existing Type 2 diabetes is increasing, and that these women have more complex care needs. Therefore, as the model development progressed, the participants identified pre-existing Type 2 diabetes as a priority for inclusion in the model. Type 2 diabetes was also identified as being of interest from a broader public health perspective as many of the risk factors are amenable to lifestyle interventions.
3.2.2 Expanded perspective on the value of participatory dynamic simulation modelling - triangulation of data from other modelling projects (study objective 2)

The investigation into the value of participatory simulation modelling in health policy and program decision making (objective 2) was expanded to include the perspectives of participants from two other modelling projects (Table 1). These additional simulation modelling case-studies used the same participatory processes to develop DSMs for use in applied health policy settings under the auspices of The Australian Prevention Partnership Centre. However, only the primary DIP case-study was accompanied by a concurrent program of research to study the participatory modelling process – as reported in this thesis.

Triangulation is defined as the collection of information using more than one method, including more than one perspective and more than one sample [1]. Triangulation is used to increase the probability that alternative explanations for the phenomena being investigated are uncovered through the use multiple data collection methods, settings and participants [1, 2]. When the data converges, or triangulates, it produces more reliable insights than could be generated from a single method [2]. The decision to draw on participants’ experience from the two other modelling projects strengthened the research by allowing the triangulation of data collected in other Australian public health policy settings, and at different stages of model maturity.

My data collection methods for all three case studies included modelling workshop observations, field notes and interviews with the participants of the model development workshops. End-user participants from the three DSM projects (Table 1) were invited to participate in semi-structured interviews to discuss their experiences of the modelling workshops, and their perspectives on the application and impact of participatory simulation modelling on health policy and program decision making. My role in each project is described below in Section 3.3 and summarised in Table 2.
Table 1: Description of dynamic simulation modelling case studies and context. (modified from Chapter 4: Decision makers experience of participatory dynamic simulation modelling methods for public health policy paper)

<table>
<thead>
<tr>
<th>Topic area</th>
<th>Type of model</th>
<th>Model development period</th>
<th>Context</th>
<th>Application to decision making</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prevention and management of Diabetes in Pregnancy (DIP)</td>
<td>Tripartite model (system dynamics, agent based modelling and discrete event simulation)</td>
<td>2016 - 2018</td>
<td>Diabetes in pregnancy (DIP) is increasing in Australia, and diabetes services are having difficulty meeting demand with existing resources. This DSM focused on DIP from a local perspective. It considered the short, intermediate, and long-term implications of the increasing prevalence of risk factors for DIP. Prevention of risk factors was prioritised in the model as small delays in the development of diabetes will have implications for the longer-term burden of disease and costs to the health system.</td>
<td>The model informs the investments for intervention in DIP, including both clinical and population health interventions. Workload and resource use have been incorporated into the model to enable it to act as a resource allocation decision support tool.</td>
</tr>
<tr>
<td>Reduction of alcohol-related harms (Alcohol)</td>
<td>Agent based model</td>
<td>2015 - 2016</td>
<td>This project was implemented as a collaboration between The Australian Prevention Partnership Centre, a state department of health, local and national alcohol researchers, clinicians and program planners to inform strategies for reducing alcohol-related harms.</td>
<td>The model captures the heterogeneity of drinking behaviours across the state population, the dynamics of those drinking behaviours across the life course, the acute and chronic harms that arise and the differential effects of interventions across subgroups in the population.</td>
</tr>
<tr>
<td>Reduction of childhood overweight and obesity (Obesity)</td>
<td>System dynamics model</td>
<td>2016</td>
<td>In September 2015, an Australian State Premier unveiled an ambitious target to reduce childhood overweight and obesity in children by five per cent over 10 years. Based on population projections and the anticipated impact of enhancing the existing suite of interventions delivered, it was estimated that additional strategies, or combinations of strategies, would be required to achieve the Premier’s target. However, the complexity of the problem and uncertainty about where best to target resources and efforts presented a challenge to decision makers.</td>
<td>The model tests the likely impacts of a range of policies and programs and informs the combination of interventions that might achieve the Premier’s target.</td>
</tr>
</tbody>
</table>
3.3 Candidate’s role in research activities

Participatory action research is highly collaborative [2]. It involves extensive teamwork between researchers and partners throughout the research process; from identifying the problem to disseminating the results [3]. The modelling case studies included in this thesis involved the contribution of many people, however all of the research reported in the published papers that form the basis of this thesis was led by me. This section aims to distinguish and clarify my role in the implementation of the participatory process for each case study, the model development for the primary case study, and the qualitative data collection and analysis. My role in the case-study development, implementation, and associated research activities for the primary case study (DIP model), and in additional case studies, is summarised in Table 2. In summary, I led all of the work for the DIP case study, as well as the supplementary data collection and analysis of participants’ experiences in the two additional case studies focusing on childhood overweight and obesity and reducing alcohol related harms. A detailed overview of my study objectives, research questions and data sources is provided in Section 3.3.1. The details of my roles in the model development for diabetes in pregnancy, and the qualitative data collection and analysis are described below in Sections 3.3.3 and 3.3.4 respectively.

For the primary case study of DIP, I was the project lead and led all activities including: project conceptualisation and design, initial engagement with the lead domain experts; recruiting participants to the expert modelling consortium; planning, organising and facilitating workshops and meetings; managing stakeholder relationships; managing the core model development team (excluding technical supervision of the model programming). I also led the analysing of evidence and providing of relevant data to inform the model (Table 2). The core deliberative and analytical processes involved in the participatory approach are described in detail in Chapters 4 to 6 and are not repeated here.
Table 2: Candidate role in case study implementation and related research activities involved in the participatory modelling process for each of the case studies

<table>
<thead>
<tr>
<th>Case study implementation and research activity led by me</th>
<th>Prevention and management of Diabetes in Pregnancy (DIP)</th>
<th>Reduction of alcohol-related harms (Alcohol)</th>
<th>Reduction of childhood overweight and obesity (Obesity)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Project conception, design and planning (paper 1)</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workshop planning, organisation and facilitation</td>
<td>✔</td>
<td>Planning advice</td>
<td>Planning advice</td>
</tr>
<tr>
<td>Engaging / collaborating with lead domain expert (a)</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observational data collection, and advice on workshop implementation</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stakeholder coordination and management for expert modelling consortium (b)</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Core model development team (c) management</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data provision (including statistical analysis) to guide model development</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Participant observations, analysis of recordings and field notes from participatory modelling workshops (papers 2 and 3)</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Qualitative data collection and analysis of deliberations and decisions in model development process (paper 3)</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interviews with end-user participants - data collection and analysis (paper 4)</td>
<td>✔</td>
<td>✔</td>
<td></td>
</tr>
<tr>
<td>Translating outcomes of participatory model development process for technical programming of DIP model (paper 5)</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:  
(a) Domain expert – well-respected authority on the focus issue who can play a lead role in the project planning and workshop facilitation.  
(b) Modelling consortium – the broader group of expert participants who participated in the model development process. These were people with a range of expertise, including providing or planning health services, undertaking research or developing policy for the issue in focus.  
(c) Core model development team or group – a smaller core group of computer scientists, computer science students, research officers, public health practitioners, and medical specialists who met frequently with the project lead to progress the model.
3.3.1 Expanded summary of research questions and data sources

The overall objectives of this research were to examine the utility and feasibility of using participatory DSM in applied health sector contexts; and to investigate the perceived value and efficacy of the approach as an evidence synthesis and decision support method. I conducted an in-depth examination of the primary case study (DIP) and two additional case studies (alcohol and obesity) to determine the elements and strategies involved in successful implementation, the overall challenges and opportunities arising from the participatory approach, the nature of the analytic deliberations and decision-making processes, and the end user perspectives of its value and utility. The research questions that were examined to achieve the study objectives are outlined below and aligned with the reported findings in Chapters 4 to 7.

The primary research questions addressed in Chapter 4 were: “how does participatory DSM build on current knowledge mobilisation best practice?” and “How can participants be engaged actively to successfully contribute their expert knowledge to the participatory process?”. In this chapter, I examined and described the participatory activities and stakeholder engagement strategies utilised across the three case studies and related them to knowledge mobilisation principles and practice.

Chapter 5 focused on the primary case study (DIP) and explored the overall research questions: “what were the analytical processes involved in converting the qualitative conceptual map, developed collaboratively with participants, into a quantified DSM?”; and “what were the decision-making processes involved in developing a rigorous DSM to answer current policy and program questions for diabetes in pregnancy prevention and management?”. I analysed the workshop and meeting recordings, and triangulated this data with field notes and other documentation to uncover the deliberative methods and decisions involved.

I explored the value of participatory DSM from the perspectives of end-user decision-maker participants in Chapter 6. The paper in this chapter focused on the following research questions: “What was the experience of participating in the interactive model building
activities like for end-user participants?”, “What were the benefits and challenges of the approach from their perspective?”, “What did participants learn from engaging in the participatory model development process?” and “How were they using the DSMs to inform policy and program decisions?”. I interviewed participants from the DIP case study before and after the participatory modelling process, and the participants from the two additional case studies after their participatory process to gain their perspectives on the efficacy and value of the approach to inform decision making.

The DIP model and outputs are described in Chapter 7. This chapter addressed the research questions in relation to DIP as outlined in the protocol paper, and provides information about the many data sources used to inform the model. The research questions addressed by the model included: “How does the dynamic interaction between risk factors impact on DIP development”; “What are the short- and long-term outcomes for mother and baby following diabetes in pregnancy?”, and “What is the impact of prevention interventions prioritised by participants on incidence of DIP and individual health outcomes?”.

An overview of the research questions explored, the data sources used to answer them, and their relationship to each of the two study objectives is provided in Table 3. Further detail about the data collection and analyses is provided in Sections 3.3.3 to 3.3.5.
Table 3: Overview of research questions and data sources used to investigate the objectives

<table>
<thead>
<tr>
<th>Research questions and associated papers within this thesis:</th>
<th>Relates to objective:</th>
<th>Data sources:</th>
<th>Thesis Chapter</th>
</tr>
</thead>
<tbody>
<tr>
<td>How does participatory DSM build on knowledge mobilisation best practice? (paper 2)</td>
<td>1, 2</td>
<td>✔ ✔ ✔</td>
<td>4</td>
</tr>
<tr>
<td>How can participants be engaged to facilitate their expert knowledge contribution to the process? (paper 2)</td>
<td>1, 2</td>
<td>✔ ✔ ✔</td>
<td>4</td>
</tr>
<tr>
<td>What were the analytical processes involved in converting conceptual systems maps to quantified simulation models? (paper 3)</td>
<td>1, 2</td>
<td>✔ ✔</td>
<td>5</td>
</tr>
<tr>
<td>What were the decision-making processes involved in producing a rigorous DSM to answer health service and policy questions relating to diabetes in pregnancy? (paper 3)</td>
<td>1</td>
<td>✔ ✔ ✔</td>
<td>5, 7</td>
</tr>
<tr>
<td>What was the experience of participating in the interactive model building activities like for end-user participants? (paper 4)</td>
<td>1, 2</td>
<td>✔ ✔</td>
<td>6</td>
</tr>
<tr>
<td>What were the benefits and challenges of the approach from their perspective? (paper 4)</td>
<td>1, 2</td>
<td>✔ ✔</td>
<td>6</td>
</tr>
<tr>
<td>What did end-user participants learn from being involved? (paper 4)</td>
<td>1, 2</td>
<td>✔ ✔</td>
<td>6</td>
</tr>
<tr>
<td>How were the case study models being used to inform policy and program decisions? (paper 4)</td>
<td>1, 2</td>
<td>✔ ✔ ✔</td>
<td>6</td>
</tr>
<tr>
<td>How does the dynamic interaction between risk factors impact on development of DIP? (paper 5)</td>
<td>1</td>
<td>✔ ✔</td>
<td>7</td>
</tr>
<tr>
<td>What are the short- and long-term outcomes for mothers and babies following DIP? (paper 5)</td>
<td>1</td>
<td>✔ ✔</td>
<td>7</td>
</tr>
<tr>
<td>What is the impact of prioritised prevention interventions on DIP incidence and individual health outcomes? (paper 5)</td>
<td>1</td>
<td>✔ ✔</td>
<td>7</td>
</tr>
</tbody>
</table>
3.3.2 Search strategy and literature compilation

In addition to the comprehensive literature review presented in Chapter 2, each paper in this thesis includes a literature review section to provide an overview of current knowledge and to situate the research. A range of search terms were used to identify relevant research. These were utilised regularly to search PubMed, Google Scholar and Medline (OVID) databases. The list of terms here is not exhaustive and is included to provide an overview of the literature domains that informed this research. The main search terms included: “knowledge mobilisation”, “knowledge translation”, “knowledge transfer”, “participatory action research health”, “dynamic simulation”, “agent-based model”, “system dynamics”, “hybrid modelling”, “participatory modelling”, “group model building”, “co-production health”, “interdisciplinary research health”, “participatory research”, “diabetes and pregnancy”, “gestational diabetes”, “prevent* diabetes and pregnancy”, “collaborative research”, “population health modelling”, “health policy decision support”, “social policy decision support”, “epidemiologic methods”, “policy modelling”, “modelling guidelines”, “selecting modelling methods”, “systems science (thinking) and population health” and “evidence based policy health”. Notifications were set up in Google Scholar and ResearchGate to alert me to new published research on topics of interest using the search terms listed above. The identified literature was stored and categorised in Endnote version 9. Additional research was identified and recommended by my supervisors, other collaborators and colleagues, and from reference lists of the papers identified during database searches. The literature was reviewed and synthesised under “questions”, or topics, that were refined iteratively throughout this PhD research and eventually formed the literature review in Chapter 2.

3.3.3 Diabetes in pregnancy model development

The technical computer programming for the DIP model development process was undertaken in collaboration with the Computational Epidemiology and Public Health Informatics Laboratory (CEPHIL), Department of Computer Science, University of Saskatchewan. Under the supervision of Professor Nathaniel Osgood, three post graduate students took responsibility for implementing the technical development of the DIP model. I was the primary conduit between the technical modellers and the participatory modelling
consortium (the participant stakeholders). In addition to all communication with participants, I facilitated regular model development meetings and frequent communication with the technical modellers to contribute to and guide the model development. This often involved translating the technical modellers’ questions into the language of the DIP expert stakeholders, and in return translating the input from our expert stakeholder group back to the modellers. The model development was informed by the decisions of the core model development group (led by me), and incorporated the input of the wider stakeholder engagement process with the modelling consortium that I also facilitated. I summarised the outcomes of the participatory process activities for input into the model by the technical modellers. Over the course of the projects, two of the postgraduate students were outposted from CEPHIL to The Australian Prevention Partnership Centre to work on the model and another student worked on the model while based at CEPHIL. This collaboration enabled the development of a sophisticated multi-method model which leveraged the knowledge gained from previous diabetes modelling projects undertaken at CEPHIL [4-7], while being developed to meet the decision requirements of local stakeholders within ACT Health.

Dynamic simulation models require significant data and evidence, and the compilation and synthesis of this evidence was an important additional analytical role I undertook in the model development process. I searched for and reviewed evidence from published meta analyses, systematic reviews, individual studies, population surveys, census and administrative health service data. All of the statistical analysis of survey, census and administrative data to inform and/or validate the model was also carried out by me. More information about the data analysis and evidence synthesis processes involved in informing DSMs is provided in Chapter 6. The data sources used in the DIP model are described in detail in the model documentation in Chapter 7.

3.3.4 Model development for the two additional case studies

The two additional modelling case study projects were undertaken by The Australian Prevention Partnership Centre, in collaboration with the Centre for Population Health, NSW Ministry of Health. These projects were undertaken to inform policy and strategy dialogues in NSW for the prevention of alcohol-related harm and for the reduction and prevention of childhood overweight and obesity. The technical programming for the additional case
studies was undertaken by members of the Decision Analytics team and was led by Associate Professor Jo-An Atkinson, Dr Geoff McDonnell and Mr Mark Heffernan. Further information about these projects is available here: https://preventioncentre.org.au/resources/dynamic_simulation_modelling/.

3.3.5 Qualitative data collection and analysis

A qualitative approach was chosen for this research as it provides flexible and useful research methods, which combine effectively with a participatory action research framework [2, 3, 8]. As outlined in Chapter 2, the core principles of participatory modelling include planning stakeholder engagement; being aware of social dynamics, power, and special interests within the participatory group; flexibility in the process; openness and transparency; and encouraging learning through the process. Qualitative analysis can provide rich and detailed, yet complex, meaning from data collected using a variety of methods including interviews, recordings, observations and document analysis [9, 10]. The participatory process involved interactive stakeholder workshops, small group meetings and written communications (mostly by email). The observations and recordings of workshops and meetings, together with email communications and written documents were important data sources arising from the participatory research process that provided insights into the core principles outlined above. Further data were collected via semi-structured interviews to provide individual perspectives from participants, both about their expectations prior to participation and reflecting on their experience of the process and the core principles post-participation. The methods used to collect and analyse data for this thesis are described below.

Participant observations, recordings and analysis of participatory model development process

The participatory model development workshops for the three case study projects were held during 2015 to 2017 (details reported in Chapters 4 to 6). Further model development meetings for the primary case study (DIP model) were held during 2018. For the primary DIP case study, the participatory workshops, web-based meetings with participants and some core model development group meetings were recorded with participants’ consent to facilitate the in-depth analysis of the model development process (Chapter 5).
For the two supplementary case studies, I also documented participatory field notes based on observations of the workshops, and subsequent debriefing discussions between myself, my supervisors and the project officers working on those case studies (Eloise O’Donnell, Nick Roberts, Jacqueline Davison and Christine Whittall - see acknowledgements). Debriefing discussions occurred either immediately following or within one week of the participatory workshops, and the field notes were compiled at this time. I also prepared further follow up summaries of all our discussions. The primary role for the above-named project officers from The Australian Prevention Partnership Centre was to provide administrative and logistic support for the NSW participatory modelling workshops. One project officer (NR) also played an active role in facilitating the workshops for the obesity project. Those project officers with particular areas of content expertise also joined as participants some of the small group model development activities.

In the debriefing sessions I led the discussions to focus on reviewing the participatory activities, and identifying what had worked well, and what hadn’t worked well. The possible reasons were explored based on observations of group dynamics, level of engagement from participants, and conversations with participants during and after the workshops. Strategies to address any issues or concerns about participation, engagement or representation in the workshops were discussed and actioned where appropriate. For example, observers identified that some participants had not been contributing to a discussion when another expert was perceived to have greater authority. This observation was used to modify the facilitation of subsequent workshops to ensure that all participants were provided with a range of opportunities to contribute e.g. in small and large group activities, and through individual discussions.

All of the workshop and meeting recordings and field notes were reviewed, coded and analysed by me. The data coding and analysis for the workshops and meetings used thematic analysis that was guided by the “theoretical” approach to thematic analysis described by Braun and Clarke [9]. The focus research questions (Table 3) for this thematic analysis (reported in Chapter 5) were: What were the key elements and features of the participatory approach that were required to successfully develop a policy relevant DSM from a qualitative systems map? What types of questions were asked by the stakeholders, what concerns and issues were raised, and what was the feedback from participants during
the process? What challenges and tensions arose in the process and how were they managed?

After I had listened to and coded each recording, I reviewed the coding notes and used coloured highlighting to identify themes. An analytic memo was written for each coded recording to highlight important themes and concepts identified from the coding process. I used worksheets in Microsoft Excel to compare data collected from each workshop or meeting and to collate the data into important themes and categories. The progressive analysis involved an iterative process of coding and analytical memos to develop themes and conceptual categories and explore their inter-relationships. The analysis was iteratively reviewed and refined as new data became available and themes and insights identified were triangulated across the different data types and sources. The analyses were iteratively discussed with and reviewed by my supervisors, Jo-An Atkinson and Lucie Rychetnik, and my analytic memos were also shared with them to facilitate the analysis review process.

*Interviews with participant stakeholders pre- and post-participatory process*

I conducted pre-process interviews with participants in the DIP case-study in April and May 2016 and post-process interviews with participants across all three case studies in September and October 2017. Two pre-process interviews were unable to be conducted by me, and Ms Eloise O’Donnell (project officer within the Australian Prevention Partnership Centre) conducted these two interviews using my interview schedule. All other interviews and all of the data analysis were conducted by me. The interviews took place in the participant’s workplace, or if that was not possible, via telephone or web-conferencing. Each interview lasted between 30 and 60 minutes. Face-to-face and telephone interviews were of comparable quality and length and telephone interviews were particularly useful in enabling me to speak with experts in distant locations throughout Australia and overseas.

I used a semi-structured interview format, with questions and prompts designed to elicit the interviewee’s views (indicative questions are shown in Box 1 in the published research protocol, included above in this Chapter). I began each interview with the consent process (either written or verbal), and an introduction broadly outlining the topics for the interview questions. A common occurrence in the pre-process interviews was interviewees expressing a concern that they had little or no experience with DSM, and thus they were
uncertain as to what they could contribute to the project. Therefore, I provided those participants with a preliminary explanation of what participatory DSM involved, and explained the rationale for their role in the model development process as expert participant stakeholders.

For the post-process interviews with end-users I explained that I was interested in hearing about their experience of participating in a modelling project; and that I was collecting information from end-user participants on the value and impact of this type of modelling from three different settings and at different stages of model maturity. I also emphasised that I was interested in hearing their honest perceptions of the pros and cons of the participatory modelling methods. Although the broad topic areas were the same across all interviews, I tailored some of the questions to the local project-specific experience of the interviewees. Indicative questions are shown in the supplementary material for the paper presented in Chapter 6. As my data collection and analysis progressed, I adapted my question prompts to elicit further information that I had identified from previous interviews as being interesting or important. I continued recruiting end-user participants until I found that no new concepts or ideas were being raised during the interviews.

All interviews were recorded and professionally transcribed as soon as practicable. After each interview I wrote a short memo which included some brief information about the participant, their role in the modelling projects, my initial impressions from our discussion and any new information and ideas that had emerged from the interview. Once each interview transcript was available, I checked and corrected the transcription while listening to the recording. I then deleted any identifying information.

The interview data analysis process was guided by methods of grounded theory [10, 11]. Using Microsoft Word, I formatted the transcripts into three columns with the first indicating the speaker (i.e. interviewer or interviewee), the second column contained the transcription and my analysis codes were entered in the third column. After each transcription was checked for accuracy, I read them again, highlighting phrases and concepts that seemed important and entering codes in the third column. Initially I used line-by-line coding to become familiar with the data and to ensure that I did not miss any important concepts. I made use of gerunds to focus my analysis on actions and processes and to make explicit the connections between the data, concepts and themes [11]. As
common themes and core concepts emerged from the data, I used colour coded highlighting to easily identify these within my codes. I also applied the colour coding to highlight sections of text from the transcripts that were enlightening for a particular theme or category, and potentially useful for direct quote examples. After each transcript had been coded, I reviewed the interview memos and added additional information based on my analysis. After all the interviews had been analysed, I returned to the first transcripts to review the coding and memos for alignment with my later analysis and added further insights to my analytical memos.

Following the detailed coding process, I transitioned to focused coding to categorise the data into the common and important conceptual groupings that had emerged from the analysis [10, 11]. This process involved reviewing the line-by-line coding, reviewing the transcript text and comparing across interviews to identify the dominant and most important thematic and conceptual categories in the data. I used worksheets in Microsoft Excel to collate the focused codes and to analyse the data across interviews. Where I had highlighted transcripts as particularly important or insightful, I transferred these direct quotes into the worksheets. For Chapter 6, the findings from the interview data were then triangulated with further analysis of other data collected from the three case-studies including: analysis of group process, email exchanges, participant observations I had recorded, notes from workshop debriefing meetings, field notes and memos based on meetings and de-identified discussions with participants and the modelling team. Analytical memos for each key theme were further developed and integrated across the sources of data.

3.4 Ethics approvals

I obtained ethics approval for my research from the University of Notre Dame, Australia Human Research Ethics Committee (015119S) and the ACT Health Human Research Ethics Committee (ETHLR.15.150). The committees specifically approved my participant information sheet and consent form. The documentation is included in Appendices 2 and 3.
An amendment was submitted to and approved by both committees in July 2017 to interview participants from additional modelling projects to explore their experience and perceived value of participatory DSM.

All participants gave individual consent. Those who were interviewed in person were given the consent form to read, and all signed it. Those who were interviewed over the telephone were sent the consent form and returned it prior to the interview being conducted. Participants were informed that they were free to withdraw from the study at any stage, but none have withdrawn. All the participants were assured confidentiality, and because of the relatively small pool of participants, steps were taken to preserve anonymity in the findings. For example, when providing information on the professional roles of quoted experts in my published papers I did not provide sub-specialty information, preferring to use more general descriptors such as “clinician” or “public health professional”.
Appendices for Chapter 3


2. Ethics approval letters from:
   - ACT Health Human Research Ethics Committee; and
   - University of Notre Dame Australia Human Research Ethics Committee.

3. Participant Information Sheets and Consent Forms

4. Participatory workshop one report – Diabetes in Pregnancy in the ACT


6. Participatory workshop two report – Diabetes in Pregnancy in the ACT

References


Chapter 4: Results part 1: Knowledge mobilisation for policy development: implementing systems approaches through participatory dynamic simulation modelling

The paper presented in this chapter describes the implementation of participatory dynamic simulation modelling as a knowledge mobilisation tool in Australian health policy settings.

This paper reviews best practice knowledge mobilisation strategies and describes how participatory dynamic simulation modelling builds on these elements. The participatory activities and stakeholder engagement strategies utilised in the case studies are described. The strategies used to actively engage participants and to address the technical and socio-political issues that arose during the participatory processes are explained. The paper compiles the experiential lessons derived from workshop observations and field notes across the three case-studies.

Paper 2:

Knowledge mobilisation for policy development: implementing systems approaches through participatory dynamic simulation modelling

Louise Freebairn1,2,3*, Lucie Rychetnik2,3, Jo-An Atkinson2,4, Paul Kelly1,2,5, Geoff McDonnell2,6, Nick Roberts2, Christine Whittall7 and Sally Redman2

Abstract

Background: Evidence-based decision-making is an important foundation for health policy and service planning decisions, yet there remain challenges in ensuring that the many forms of available evidence are considered when decisions are being made. Mobilising knowledge for policy and practice is an emergent process, and one that is highly relational, often messy and profoundly context dependent. Systems approaches, such as dynamic simulation modelling can be used to examine both complex health issues and the context in which they are embedded, and to develop decision support tools.

Objective: This paper reports on the novel use of participatory simulation modelling as a knowledge mobilisation tool in Australian real-world policy settings. We describe how this approach combined systems science methodology and some of the core elements of knowledge mobilisation best practice. We describe the strategies adopted in three case studies to address both technical and socio-political issues, and compile the experiential lessons derived. Finally, we consider the implications of these knowledge mobilisation case studies and provide evidence for the feasibility of this approach in policy development settings.

Conclusion: Participatory dynamic simulation modelling builds on contemporary knowledge mobilisation approaches for health stakeholders to collaborate and explore policy and health service scenarios for priority public health topics. The participatory methods place the decision-maker at the centre of the process and embed deliberative methods and co-production of knowledge. The simulation models function as health policy and programme dynamic decision support tools that integrate diverse forms of evidence, including research evidence, expert knowledge and localised contextual information. Further research is underway to determine the impact of these methods on health service decision-making.

Keywords: Participatory dynamic simulation modelling, Decision support, Knowledge mobilisation, Childhood obesity, Alcohol, Diabetes in pregnancy

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Key messages

- Participatory dynamic simulation modelling is being implemented as a knowledge mobilisation strategy in Australian health policy settings.
- Key elements of this knowledge mobilisation approach have included:
  - Moving beyond evidence synthesis to providing dynamic decision support tool to compare policy options.
  - Embedding deliberative methods to build shared understanding of complex issues and intervention outcomes.
  - Emphasising stakeholder participation in the co-production of knowledge.
- Operationalising participatory simulation modelling relied on:
  - Effective and equal partnerships.
  - Active participation of all stakeholders in the modelling process.
  - Transparency and trust in model outputs to facilitate consensus for action.

Background

The utilisation of evidence has come a long way since the advent of evidence-based medicine – a term coined in the early 1990’s [1–3] when the leading proponents were described as radicals [4]. Evidence-based healthcare captured the zeitgeist and coalesced into a mainstream movement built on decades of population-based research, clinical epidemiology, critical appraisal and systematic review methods [5]. Interventions aimed at supporting the use of evidence in policy and practice have spawned new theories and frameworks, translation research, and an evolving lexicon [6]. A recent scoping review identified 51 different taxonomies to categorise research translation interventions [7].

Yet, despite great progress and mainstream acceptance of evidence-informed decision-making there remain many operational challenges. Researchers who understand the scientific evidence are often not engaged, or unheard, when important policy decisions are made [8, 9]. Similarly, practitioners familiar with the local context and those who are considered the ‘end users’ of the research are often not engaged in the research process [10]. A common dilemma is the apparent mismatch between the information priorities of policy decision-makers and programme or service funders, and the research priorities of investigators and research funders [11]. To be policy relevant, research must reflect an understanding of decision-making environments, be responsive to end-user needs, and be supported with stakeholder engagement and strategic communication [11, 12]. Contemporary thinking also suggests locally co-created knowledge, derived from researcher and end-user partnerships, preferably on the location where it is to be applied, is particularly useful for addressing policy and practice questions [13, 14]. This is akin to Senge’s description of the art and practice of collective learning [15].

The conceptual and empirical developments of contemporary strategies to support evidence-informed action are reflected in the evolving terminology. While knowledge translation focuses on the transfer of investigator-driven research to policy and practice settings [6, 11, 16], knowledge exchange has emphasised the relational two-way communication required for research uptake to be effective and useful [17, 18]. The most recent adoption of knowledge mobilisation further highlights organisational structures and system design requirements, and more explicitly values the ‘co-creation’ of knowledge [19, 20]. It is also the broadest term to encompass all activities that involve generating, sharing and using research [19]. Best et al. [21, 22] described these developments as the three generations of translation, namely linear, relational and systems-based approaches. Whichever terminology one may prefer, however, it is widely acknowledged that mobilising knowledge for policy and practice is an emergent process, and one that is highly relational, often messy and profoundly context dependent [23–27].

Systems thinking and systems science have growing influence on many aspects of public health discourse and research [28, 29]. Important elements of systems thinking include more conscious attention to how new forms of knowledge are ‘gained, managed, exchanged, interpreted, integrated and disseminated’, and an emphasis on “transdisciplinary, translational and network-centric” science [28]. There are natural synergies between knowledge mobilisation methods and systems science methods. Knowledge mobilisation refers to a range of active approaches deployed to encourage the creation and sharing of research-informed knowledge [30]. Systems science methods encompass a family of approaches that can be used to elucidate the behaviour of complex systems, inform efforts to address one or more system problems [31], and have the capacity to examine both complex health problems and the context in which they are embedded [29, 32, 33]. Key elements of a systems science approach include synthesising diverse knowledge and evidence, exploring the potential for non-linear relationships between contributing factors and unanticipated emergent behaviour of the complex systems (including policy resistance) [31, 34, 35]. The value of systems thinking for conducting reviews of evidence and integrating other forms of knowledge are well described [26, 36]. However, applying systems thinking to knowledge mobilisation is conceptually challenging and
difficult to operationalise [37]. A recent multi-method review of knowledge mobilisation across health and other sectors concludes that the most fruitful lessons about the future role of systems thinking will come from natural experiments and case studies [19].

In this paper, we describe our experience of implementing a systems-based approach of participatory dynamic simulation modelling as a knowledge mobilisation strategy in Australian real-world policy settings. We describe how this approach combined both systems science methodology and some of the core elements of knowledge mobilisation best practice using three case studies (two published [38, 39] and one as yet unpublished). We describe the strategies adopted to address both technical issues (e.g. synthesising diverse evidence into a quantifiable model) and socio-political issues (e.g. user engagement and trust), and compile the experiential lessons derived. Finally, we consider the implications of these knowledge mobilisation case-studies and provide evidence for the feasibility of this approach in policy development settings.

**Participatory dynamic simulation modelling draws on many elements of knowledge mobilisation best practice**

Dynamic simulation modelling is a systems science method that recreates complex systems and human behaviours in a virtual world. These models can answer ‘what if’ questions about the likely impacts over time of different policy and intervention options and combinations so that they can then be deliberated and considered more broadly before implementation in the real world [40, 41]. Dynamic simulation modelling has been used to map health system components and their interactions, synthesise evidence, examine and compare the potential outcomes of interventions, and guide more efficient investment and conscientious disinvestment of resources [41]. This is important for preventive health policy and practice, where decision support tools must have the capacity to steer a course through the complexity of interactions that give rise to real-world public health problems such as the global epidemic of chronic disease [40–42].

The concept of ‘evidence-informed decisions’ is challenging in population health policy and practice interventions that require engagement and partnership with sectors outside of health. Many factors, including types of information, opinion and experience, timing, the political cycle, local norms, the influence of external players, and the availability of funds, all influence decision-making [9, 43]. Many of the current ‘big questions’ in public health are complex and not easy to address. These problems have multiple interacting causal factors with competing possible courses of action for decision-makers to choose between, each course of action potentially resulting in complex and unintended consequences [40, 44].

However, to date, the potential of participatory simulation modelling as a knowledge mobilisation tool in the health sector has not been adequately explored. In particular, stakeholder engagement and involvement of end-users in health-related simulation model development has been lacking [41]. This has limited the use of simulation modelling across the range of potential applications, hindered the implementation of model findings [45, 46] and led to a reluctance among ‘non-researchers’ to use models as decision support tools [46, 47]. A systematic review of the use of simulation modelling to inform surgical patient flow processes found that only half of publications stated that the goal of the model was to inform policymakers and health service managers, and only 26% actually included these end-users in the simulation modelling process [10].

Below, we discuss how participatory simulation modelling can build on contemporary knowledge mobilisation approaches to offer a tool for timely and dynamic policy decision support, both by embedding deliberative methods and emphasising the co-production of knowledge in the modelling process. We then reflect on the experience and learnings drawn from three Australian case studies of participatory dynamic simulation modelling conducted in collaboration with jurisdictional health departments [38, 39].

**Moving from evidence synthesis to timely and dynamic decision support**

Evidence-informed policy and practice has traditionally relied on systematic reviews, evidence summaries and policy briefs to provide decision-makers with rigorous, timely and concise information [48–50]. While their inherent value is acknowledged, there are limitations in their use and utility for health policy decision-making [12].

Systematic reviews and meta-analyses synthesise the available evidence to answer the question ‘what do we know about this issue?’ They focus on clear and specific questions and usually have a narrow scope of investigation with limited potential to examine complex questions [51, 52]. These methods produce static reports that rely on decision-makers to navigate the complexity and uncertainty of translating the evidence for their local context and weigh up the options for responding to their problem [53]. Many systematic reviews fail to address the policy implications of their findings [12] in a timely way to inform decision-making [54].

More recently, there has been a shift towards rapid reviews investigating policy questions. Here, the focus is on providing immediate value to addressing the problem
at hand. For example, rapid reviews like Evidence Check from the Sax Institute [55, 56] commence with a collaborative process where policymakers and a knowledge broker develop a structured review proposal that describes the policy issue or decision for which the evidence review is required, and articulate the review questions and scope. The process aims to ensure the review will provide policymakers with information specific to their decision and context in a timely way. This collaborative approach has been shown to be well suited for assisting in planned policymaking processes and choosing between specific policy options [55, 57]. The use of knowledge brokers is integral to organising the interactive process between researchers and policymakers so that they can co-produce feasible and research-informed policy options [56].

Policy briefs begin with a policy issue and present evidence to answer the question ‘What should we do?’ A policy brief provides a rationale for choosing a policy alternative or course of action based on the synthesised research findings. They are more practical, flexible and timely in supporting evidence-informed decision-making [49] and can also consider how the evidence fits with prevailing values, beliefs and political context [49]. However, the final product is still a static assessment that is unable to adequately account for changes over time or test the prevailing real-world hypotheses and assumptions [53, 58].

However, participatory dynamic simulation modelling processes go further, providing a platform for explicit synthesis of empirical evidence, local data, expert- and practice-based knowledge, conceptual models and theory to construct, quantify and test a detailed representation of causal factors and the mechanisms of intervention effects [40, 41, 58, 59]. The resulting dynamic model becomes a decision support tool that can step beyond comprehensive approaches, for example, in the prevention of chronic disease, to be used as a ‘what if’ tool to simulate various policy and practice scenarios, and systematically explore the trade-offs of a range of intervention options [41, 58].

Processes such as deliberative dialogues involve group interactions that integrate and interpret multiple forms of evidence to inform policy development [61]. Key elements of a deliberative dialogue process include a meeting environment that is conducive to open deliberation about a policy issue, bringing together a mix of participants that ensures fair representation of all relevant interests, and fostering a more equal knowledge base among participants through the presentation of research evidence [60].

Deliberative approaches tend to emphasise the rigour and fairness of the process and try not to anticipate or pre-determine the outcomes of the deliberation. They rely on skilled and neutral facilitation and, while consensus building may be achieved, it is not the primary aim [62]. This requires flexibility and acceptance that the boundaries and scope may be changed as people reflect and discuss the problem, and sometimes modify the questions they want to address.

Thus, translation of research has progressed from managed and controlled dissemination initiatives with pre-defined targets [63]. For knowledge mobilisation, the social, relational and contested nature of true deliberative dialogue or ‘exchange’ relies on negotiated meanings and less predictable outcomes [62, 64, 65].

Participatory dynamic simulation modelling incorporates a deliberative process where stakeholders articulate and develop their understanding of how multiple variables, factors and interventions interact [66, 67], and provides a neutral platform for engaging stakeholders with conflicting views [59]. The participatory model development necessitates in depth deliberation to map a shared mental model of the causal pathways for the focus issue, and the mechanisms by which interventions have an effect on outcomes [68]. The map is then quantified, drawing on research evidence and other data sources through an iterative process of theory testing and building in collaboration with participants. Model outputs are compared with real-world historic data patterns across a range of indicators to establish the validity of the model as an accurate representation of the real-world system. The resulting model becomes a decision support tool that can be used to consider and compare alternative policy options [66, 67]. The model can be refined, updated and customised through ongoing dialogue. Both the process of model development and the results produced by the model enhance stakeholder knowledge and understanding of the system and its dynamics in varying conditions. The process identifies and clarifies complex and contested real world problems [47] and the impact of solutions, and facilitates the implementation of actions based on the available evidence [68, 69].

Embedding deliberative methods
An important strategy in knowledge mobilisation theory and practice is the incorporation of deliberative methods. The value of the deliberative process is that it increases understanding of the evidence, and of the competing issues and values, through the engagement and contribution of participants with different perspectives [60]. By deliberating on a problem and its potential solutions, participants strengthen their capacity to address a policy issue and gain confidence in influencing the policy agenda [60].
Emphasising co-production of knowledge

Co-creation and co-production are two terms used to refer to the process of individuals from different sectors working together to produce an output or outcome such as goods, services or research [70]. Co-production of evidence aims to overcome the often described disconnect between researchers and research end-users, such as health policymakers and programme planners [14]. This concept has been applied to social service design and delivery [71] and increasingly to health research [72–74].

Research translation is embedded in the co-production and partnership approach as the end users are active participants in, and in some cases the drivers for, all phases of the research project [14]. The key elements of co-creation include involving participants as active and equal partners from beginning to end, encouraging reciprocity and sharing of resources and knowledge, and aiming for a ‘transformative’ outcome, i.e. where the research builds capacity and/or has a practical impact on decision-making [14, 71]. The establishment of effective co-production partnerships is an iterative journey, where structures, boundaries and even the purpose of the project are re-negotiated throughout the project dialogue [75].

Relationships and collaborations are routinely identified as key factors in systems approaches [76]. Participatory dynamic modelling provides a structure to facilitate multidisciplinary partnerships, co-learning and co-production. The participatory approach adopts co-production as its driving principle and places the end-user decision-makers at the centre of the process. The decision-makers define the model scope and purpose, and engage multidisciplinary expert stakeholders in the model design and parameterisation (and contribute the identification of data to be used in the model).

Participatory dynamic simulation modelling involves engaging multidisciplinary stakeholders in a deliberative group model-building process where participants discuss evidence and share knowledge about the causal mechanism of the issue being modelled and where and how interventions have their effect within the articulated mechanism. Participatory modelling approaches aim to combine diverse perspectives to tackle the social complexity of problems and recognise that different types of knowledge contribute alternative and valuable perspectives to the problem discourse [47, 59]. The involvement of decision-makers as participants in the model development and validation increases their sense of ownership and confidence that the model is valid for their local context; they are therefore more likely to draw on the model’s outputs to inform decisions about priority interventions and policies [68, 77, 78].

Reflections on process and early learning from participatory dynamic simulation modelling as a knowledge mobilisation approach

The Australian Prevention Partnership Centre (http://preventioncentre.org.au/), in collaboration with jurisdictional governments, has pioneered the co-production of sophisticated, multiscale dynamic simulation models to support policy and practice. In developing these models, researchers partnered with health departments, clinicians and regional planners in collaboration with a multidisciplinary group of stakeholders using a participatory process [38, 39]. The case studies are described in Box 1.

Box 1. Case study descriptions

Case Study 1. Model behaviour: A systems approach to reducing alcohol-related harm

This project was implemented as a collaboration between The Australian Prevention Partnership Centre, the New South Wales Ministry of Health (NSW Health), and local and national alcohol researchers, clinicians and programme planners to inform strategies for reducing alcohol-related harms in NSW.

Alcohol misuse is a complex, systemic problem. Globally, alcohol has been estimated to cause 3.3 million deaths each year, and the costs of alcohol-related harms amount to more than 1% of gross national product in high-income countries. In Australia, alcohol accounts for approximately 3.2% of the total burden of disease and injury, and is estimated to cost AU$15.3 billion each year [79, 80].

The design of effective responses to this problem has been challenged by a lack of clarity on the mechanisms driving alcohol misuse and its associated harms, differing views of stakeholders regarding the most appropriate and effective intervention approaches, a lack of evidence supporting commonly implemented and acceptable intervention approaches, and strong evidence for less acceptable interventions. As a consequence, political considerations, community advocacy and industry lobbying contribute to a hotly contested debate on what is the most appropriate course of action.

The developed model uniquely captures the heterogeneity of drinking behaviours across the NSW population, the dynamics of those drinking behaviours across the life course, the acute and chronic harms that arise from those behaviours, and the differential effects of interventions across subgroups in the population. Testing of the model demonstrated its ability to reproduce a range of real world data patterns, which provides confidence that the model can produce robust forecasts of the comparative impacts of interventions into the future. The model is currently being used to engage with broader policy stakeholders to demonstrate the value of such models in informing effective and acceptable strategies for reducing alcohol-related harms [38].

Case Study 2. Premier’s Priority Project – reducing childhood overweight and obesity by 5%

In September 2015, the NSW Premier unveiled 30 State priorities to grow the economy, deliver infrastructure, protect the vulnerable and improve health, education and public services across NSW. Included in these areas of focus were the 12 Premier’s Priorities, including an ambitious target to reduce childhood overweight and obesity in children by 5% over 10 years.

Based on population projections and the anticipated impact of enhancing the existing suite of interventions delivered by NSW Health, it was estimated that additional strategies, or combinations of strategies, would be required to achieve the Premier’s target. However, the complexity of the problem and uncertainty about where best to target resources and efforts presented a challenge to decision-makers. To address this, the Australian Prevention Partnership Centre in partnership with NSW Health undertook to co-develop a system dynamics model of childhood overweight and obesity.
The participatory simulation modelling processes and activities utilised in these case studies have been described in detail elsewhere [38, 39]. However, a brief overview of the process and examples of activities are provided in Box 2 to give context for the discussion below.

Box 2. Overview of the process and examples of activities

**Project planning and engagement** (Fig. 1)

Early engagement with stakeholders for each case study was undertaken to identify a priority problem, and determine and define policy priorities requiring decision support methods. A domain expert, preferably from the primary partner organisation (partner), was identified to be a lead collaborator in the project (lead domain expert). This role included supporting the engagement of stakeholders and co-facilitating workshops.

**Case Study 3. Simulation modelling for Diabetes in Pregnancy (DIP) in the Australian Capital Territory (ACT)**

This project was implemented as a collaboration between The Australian Prevention Partnership Centre, ACT Health Directorate (ACT Health), local and national researchers, clinicians and policymakers. DIP is increasing both in the ACT and Australia, and diabetes services are having difficulty meeting demand with existing resources. The increase in DIP is associated with increasing prevalence of risk factors such as overweight and obesity, older maternal age and increasing numbers of women from high-risk ethnic groups. Changes to diagnostic screening has resulted in women being diagnosed with DIP earlier in their pregnancy and therefore requiring services for a longer period of time. Women are also more frequently presenting with a number of risk factors resulting in more complex care needs.

A dynamic simulation model focusing on DIP from an ACT perspective was developed. The national context was considered in the model development, with the model being considered a proof of concept with the potential to expand more broadly.

The model considers the short, intermediate and long-term implications of the increasing prevalence of risk factors for DIP. Prevention of risk factors was prioritised in the model as small delays in the development of diabetes services will have large implications for the longer term burden of disease and costs to the health system.

Alternative models of care for DIP were considered in the model. The rising prevalence of DIP is having a significant impact on health service demand and resources, and the need to ‘do things differently’ was identified by participants. The model informs the investments for intervention in DIP, including both clinical and population health interventions. Workload and resource use has been incorporated into the model to enable it to act as a resource allocation decision support tool. At the time of publication, this model was being finalised.

The model development process engaged a broad range of multidisciplinary stakeholders working in the area of childhood obesity spanning the fields of academia, service delivery, policy, planning and infrastructure. Through a series of participatory workshops the problem was collaboratively mapped and interventions to be included in the model prioritised. The map was conceptualised as a computational model, quantified, tested and validated against historic data, and iteratively refined through feedback sought during and between workshops.

The model is being used by NSW Health and their stakeholders to test the likely impacts of a range of policies and programmes, and to inform the combination of interventions that might achieve the Premier’s target.

**Model building and validation**

Through a series of participatory workshops, the model building group, informed by collated evidence and data, collaboratively identified and mapped the key risk factors and likely causal pathways leading to outcomes of interest for the focus topic of the model.

The proposed model architecture was presented at the first workshop, and subsequent versions of the model were developed to reflect participant language, input and feedback as well as providing increased detail and maturity.

Participants were familiarised with the model infrastructure using paper-based physical representations. For example, during one activity, participants built a physical representation of the model, with model components represented in card and tape. Participants worked collaboratively to document factors that contribute to the problem being modelled and mapped these directly onto the card and tape representation (Fig. 2).

Similar activities were conducted to involve participants in mapping the mechanisms through which interventions would impact the model (Fig. 3).

The interim conceptual map or model was tested and validated in collaboration with the model building group during each workshop.

The workshop structure was flexible to account for differences in group size and incorporated a range of activities with the whole group or smaller sub-groups as appropriate to allow participants to raise issues, negotiate perspectives and build consensus. For activities where the group was split, the modelling team allocated participants to ensure each sub-group included a range of perspectives and areas of expertise, and to encourage productive group dynamics.

**Consensus building for policy actions**

Final half-day workshops and follow-up webinars were conducted where the model was presented back to the model building group for verification, discussion, consensus, feedback of results and further input on preferred visualisation of model outputs.

Outputs from modelled scenarios were presented to participants to facilitate the development of new insights and knowledge about the likely impact of interventions and discussion about potential policy actions.

Examples of the user interface and model outputs are presented in Figs. 4 and 5. These figures illustrate how model users create scenarios to test and compare the outcomes for different combinations of selected interventions. Figure 4 includes the user interfaces from the Alcohol-related harm (top image) and the Premier’s Priority (bottom image) case studies.

The model outputs take the form of dynamic visualisations and graphs that represent model outcomes for created scenarios, e.g. for variations of intervention effectiveness and reach. These can be compared against benchmark or ‘business as usual’ model outputs. Figure 5 presents example outputs from the Alcohol-related harm case study.

(Continued)

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(Continued)

Project planning meetings were held to clearly define the aspects of the problem to be modelled and its scope and boundaries, as well as to identify key outputs of interest and intervention options to be included and tested by the model.

Experts and key participants with an important ‘stake’ in the topic were identified and invited to participate in the model development group (participants). Group composition was purposefully considered to ensure inclusion of a diverse range of views and identification of participants who were considered reliable and reputable representatives of broader stakeholder groups (stakeholders). Background reading material regarding simulation modelling and the topic of interest was sent to participants prior to the workshop to provide a platform of common understanding.

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Key aspects of operationalising participatory dynamic simulation modelling

In the remainder of this paper we draw on our experience of operationalising participatory dynamic simulation modelling to support chronic disease prevention policy and practice in Australia. We consider three key aspects of the process, (1) establishing partnerships with stakeholders, (2) engaging participants actively in the modelling process and (3) using co-production methods to build trust in the model and its outputs. We then discuss some of the lessons and implications for adopting these approaches in contemporary knowledge mobilisation practice.

Establishing effective partnerships with stakeholders

In each of the case studies, the focus of the model was proposed by Australian Capital Territory Health or New South Wales Health as a priority area with current local concern, complex causal risk factors and as issues where previous policy responses had limited impact. The health jurisdictions were therefore coming to the process with a view that they needed to do things differently and were motivated to work on innovative solutions.

Engagement with these primary partner organisations (partners) continued throughout the modelling process, from identifying relevant subject matter experts to be involved (participants), to soliciting input on relevant data and literature sources, negotiating the model purpose, scope and structure, and encouraging involvement in the facilitation of modelling workshops.

Identifying and including a lead domain expert for each case study, e.g. a public health practitioner or clinician, who was well respected and associated with the partner, increased engagement, solidified the

Fig. 1 Participatory simulation modelling phases used in the case studies, from Atkinson et al., 2017 [40]

Fig. 2 Causal factor mapping activity – Alcohol-related harm case study workshop

Fig. 3 Intervention mapping to model architecture activity – Diabetes in Pregnancy case study workshop
partnerships and built trust in the modelling process. These lead domain experts acted as co-facilitators for model development workshops, along with the project leader from the modelling team. The combination of domain and modelling expertise allowed workshop co-facilitators to navigate interdisciplinary participation through a process of developing a common language and understanding to facilitate model development.

Engaging participants actively in the modelling process
Facilitated workshop activities were designed to involve participants actively in the modelling process (examples in Box 2). These methods supported participant engagement and investment in the model as they deliberated and negotiated with each other to prioritise causal factors, their interactions, and interventions and outcomes to be captured in the model. Significant learning occurred through these deliberative dialogues, with participants reporting that their ‘interaction was key’ to the modelling process. The mapping activities provided an interactive opportunity for participants to synthesise their collective knowledge and expertise with quantitative evidence.

The practical hands-on mapping activities used during workshops (Box 2) also familiarised participants with the model architecture. The model architecture (the diagrammatic representation of the computer model) physically represented how the identified causal factors, interventions and resulting outputs were incorporated into the model. This allowed for two-way learning as increased familiarity and confidence in understanding the model architecture enabled participants to critique and provide feedback to modellers to ensure the model

Fig. 4 User interfaces from Alcohol-related harm (top image) and Premier’s Priority Project (bottom image) case studies demonstrating the facility for participants to choose intervention combinations and vary parameters to generate unique scenarios.
accurately represented their shared understanding. Taking an iterative approach facilitated collective learning, and the demonstration of the evolving model at the second and subsequent workshops further validated and improved model design.

At times, the priorities of policy partners (in terms of interventions and outputs to be included in the model) differed from those of subject matter experts. The participatory process of negotiation helped to build consensus on what to prioritise in the model and enhanced each participant group’s understanding of the others’ knowledge and research or policy. Expert facilitation skills were necessary to draw out diverse contributions, maintain engagement in the process and negotiate compromises where necessary. Explicit processes, including voting, were used to democratically resolve disagreements and to clarify priorities in model development.

Co-production built trust in model outputs and facilitated consensus for action
The strong partnerships and active engagement of partners and participants throughout the iterative model development were critical for building trust in model outputs and providing the best opportunity for impact on policy and programme decisions.

The use of co-production methods as described above increased transparency in the model building process. Demonstrating the model conceptualisation to participants at each workshop and highlighting their contributions increased participants’ understanding of the model. This transparency reinforced the value of their participation and their ownership of the model, and provided an opportunity to establish the face validity of models against expert and local knowledge.

Another important aspect to building trust in model outputs was to encourage discussion about the limitations and assumptions in the model design and available data sources. Documentation of data sources and assumptions built into the models was shared with participants to critically evaluate and provide feedback.

Building participants’ trust in the model was necessary for its acceptance by stakeholders/experts who were not involved in its development (stakeholders). Involvement of key opinion leaders in the model development groups brought credibility to the models as participants acted as ambassadors for the model within their broader stakeholder groups. Diversity of expertise within the participant group was also important so different stakeholder groups felt their perspective had been represented.

When some model outputs did not confirm long held beliefs about likely effects of interventions and their combinations, there was robust debate about the implications and caution in using such results to inform decision-making. In these situations, it was particularly
useful to invite stakeholders to interact with the model, challenge their assumptions, provide alternative data and test their expectations against model outputs. Iterative, open and non-defensive communication was critical to facilitating these interactions, advancing understanding of the complex problem and building trust in the decision support tool.

Model validation is an essential stage of all model development, including models developed using participatory approaches [77]. Demonstrating to partners, participants and stakeholders that the models reproduced historic data patterns across a range of indicators confirmed their validity, and built confidence that the models would produce robust forecasts into the future.

Collaborative processes were also used to maximise the potential usability of the model. Participant engagement with the model was encouraged to test and refine the user interface. This user testing ensured that the interface was intuitive and accessible for a diverse range of users.

**Conclusion**

The participatory dynamic simulation modelling processes utilised in these case studies built on knowledge mobilisation best practice and produced dynamic decision support tools that integrated diverse forms of evidence, including research evidence, expert knowledge and localised contextual information. The participatory approach placed end-users at the centre of the process and embedded deliberative methods and co-production of knowledge. Policymakers, researchers, scientists, clinicians, consumers and modellers collaborated and explored policy and health service scenarios for priority public health topics.

An important element of co-production in these case studies was equal partnering with key stakeholders to negotiate the priority issue to be modelled. These were ‘hot topics’ that were current, locally relevant, had complex causal mechanisms, and for which decision-makers needed to decide between competing courses of action. It was in these circumstances that participatory dynamic modelling provided an opportunity for policy and programme options and combinations to be tested within a safe, simulated environment before being implemented in the real world. The case studies revealed valuable lessons for the participatory dynamic simulation modelling process in health policy settings. The case study topics were complex and multi-faceted, and the diverse representation of stakeholders in the modelling groups was essential as no one individual could be an expert on all aspects of the issue. An aspect of the process was thus to emphasise the need for knowledge sharing among stakeholders and to develop a common understanding of the issue, and of the potential interventions to address it. Differential participation did occur in some of the workshops, e.g. participants sometimes deferred to those they perceived to have greater authority or expertise for particular aspects of the content. However, the workshop facilitators promoted the value of diverse perspectives in building a robust model and regularly sought to draw out those who were less vocal.

Consistent with other knowledge mobilisation approaches, the participatory process was time consuming and required ongoing efforts to maintain and coordinate diverse engagements. However, the challenges were outweighed by the positive outcomes of effective collaborative networks, co-production of knowledge, and capacity to integrate diverse evidence and expert opinion. In our case study settings, many participants had limited or no prior experience with dynamic simulation models or the modelling process. An important dimension of the knowledge mobilisation process was the translation that occurred between disciplines, e.g. clinicians, computer scientists and population health professionals, to ensure that everyone understood each other’s perspectives and were working toward a common goal.

The processes of data gathering and synthesis commonly highlighted gaps in local programme outcome data, as well as in the published literature. For example, locally available evaluation data was frequently limited to process and participation measures, rather than programme outcomes and effectiveness. Often, the local contextually relevant data was utilised and triangulated with other potentially more reliable but less locally relevant sources to inform the models. Whilst evidence gaps are an ongoing challenge in all settings, the process of uncovering these gaps through the participatory process, and prioritising data needs through sensitivity testing in the model, provided important information for prioritising future research and guiding refinement of local programme evaluations and routine data collection.

An important challenge of knowledge mobilisation using this participatory modelling approach was the building of trust in the model outputs. This was less of an issue when the model outputs confirmed existing preconceptions of underlying causal mechanisms, but significantly more challenging when model outputs were contrary to participants’ long held beliefs. This could be particularly challenging for subject matter experts who were required to reassess their prior expectations. However, the dynamic, interactive nature of the models as decision support tools facilitated ongoing dialogue and negotiation with stakeholders and developed understanding and trust.

Our analysis of participatory model building methods is ongoing. Further activities in this programme of
research involve evaluating the perceived value of the participatory process; the commitment and confidence of partners and participants to implement policy and programme decisions identified through the modelling process; and the impact of the process, i.e. how model outputs will be used to inform policy and programme decisions in the local public health settings.

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Authors’ contributions
LF, LR and JA conceptualised the manuscript and LF wrote the first draft. All authors made important intellectual contributions to multiple draft revisions. All authors read and approved the final manuscript.

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Case Study 3 was reviewed and approved as low risk by the ACT Health Human Research Ethics Committee (ACTHLR.15.150) and the University of Notre Dame Human Research Ethics Committee (0151195).

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Chapter 5: Results part 2: Turning conceptual systems maps into dynamic simulation models: revealing the analytical deliberations and decisions of participatory dynamic simulation modelling - an Australian health sector case study

The paper presented in this chapter is based on a qualitative, empirical analysis examining the activities, processes and decisions involved in converting a qualitative system map into a rigorously quantified, dynamic simulation model for diabetes in pregnancy. The analysis uncovered the analytical work underlying the model development process and provides unique insights to facilitate better understanding of participatory modelling and inform future modelling projects.

Analyses of workshop and meeting recordings were triangulated with field notes and other documentation to uncover the deliberative methods and decisions involved the participatory model development process.

Paper 3:

Turning conceptual systems maps into dynamic simulation models: An Australian case study for diabetes in pregnancy

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Abstract

Background
System science approaches are increasingly used to explore complex public health problems. Quantitative methods, such as participatory dynamic simulation modelling, can mobilise knowledge to inform health policy decisions. However, the analytic and practical steps required to turn collaboratively developed, qualitative system maps into rigorous and policy-relevant quantified dynamic simulation models are not well described. This paper reports on the processes, interactions and decisions that occurred at the interface between modellers and end-user participants in an applied health sector case study focusing on diabetes in pregnancy.

Methods
An analysis was conducted using qualitative data from a participatory dynamic simulation modelling case study in an Australian health policy setting. Recordings of participatory model development workshops and subsequent meetings were analysed and triangulated with field notes and other written records of discussions and decisions. Case study vignettes were collated to illustrate the deliberations and decisions made throughout the model development process.

Results
The key analytic objectives and decision-making processes included: defining the model scope; analysing and refining the model structure to maximise local relevance and utility; reviewing and incorporating evidence to inform model parameters and assumptions; focusing the model on priority policy questions; communicating results and applying the models to policy processes. These stages did not occur sequentially; the model development was cyclical and iterative with decisions being re-visited and refined throughout the process.
Storytelling was an effective strategy to both communicate and resolve concerns about the model logic and structure, and to communicate the outputs of the model to a broader audience.

Conclusion

The in-depth analysis reported here examined the application of participatory modelling methods to move beyond qualitative conceptual mapping to the development of a rigorously quantified and policy relevant, complex dynamic simulation model. The analytic objectives and decision-making themes identified provide guidance for interpreting, understanding and reporting future participatory modelling projects and methods.

Introduction

This paper contributes to the current knowledge gap about the development from qualitative to quantitative modelling [1]. It examines the detailed implementation of the analytic processes and practical strategies used to convert the qualitative systems maps into a rigorous and policy relevant dynamic simulation model. Dynamic simulation models are quantified, computer-based representations of complex systems that draw on best available evidence and provide a decision support tool to conduct policy experiments and forecast potential impacts. The models enable working hypotheses of causal pathways to be explicitly and quantitatively operationalised to evaluate the effectiveness of potential interventions, or combinations of interventions, via computer simulation before they are implemented in the real world [2–6].

This paper provides a qualitative analysis of the stakeholder deliberations and decisions that occurred within an Australian health sector participatory modelling case-study. This case study applied the participatory approach to the development of a multi-method (or hybrid; these terms are explained below) dynamic simulation model focusing on diabetes in pregnancy. We present the findings together with real-world examples of some of the core questions and decisions made, to inform health service researchers, policy makers and modellers who may be considering undertaking participatory modelling projects. The findings detail important aspects of project implementation, and the types of input from end-user participants. This includes the feedback, critiques, issues raised, and questions asked by stakeholders as part of their engagement in the participatory modelling process; their analytical and material contributions to model development and peer-to-peer learning; and their role in the process of identifying and selecting different forms and sources of evidence. We also report on the intellectual and practical challenges experienced by the core model building team—and strategies used to overcome them, as well as the overall challenges and significant opportunities arising from the participatory process itself.

Background

Knowledge created through application of the scientific method requires effort to translate into action [7]. Knowledge mobilisation is defined as a dynamic and iterative process that includes synthesis, dissemination, exchange and application of knowledge to improve health, provide more effective health services and products and strengthen the health care system [8]. It is widely acknowledged that using research evidence for policy and practice is an emergent and context dependent process, that relies on relationships, and can be time consuming and
lack clear policy direction particularly in the face of complexity that characterises many of our persistent health and social problems [9–13].

The many synergies of combining evidence-informed policy principles with systems science methods are increasingly recognised [14]. Systems science encompasses a range of approaches that can be used to explore and understand public health problems as complex systems; in order to intervene more effectively and adapt to each particular context [15–19]. Key elements of a systems science approach include synthesising diverse knowledge and evidence, exploring the potential for non-linear relationships between contributing factors, and identification of unanticipated emergent behaviour of the complex systems (including policy resistance) [15, 19–22].

The collaborative exploration of a complex issue or problem using systems thinking can generate a conceptual system map which reflects the qualitative, group understanding of the complex issue [23, 24]. These qualitative maps and models can engender a high degree of ownership and consensus about the nature of the problem, as they are based on the collective expertise of the participants involved [25]. However, the practical application of these maps in exploring and testing hypotheses about the impact of policy intervention options is limited [25, 26]. Such hypothesis testing and comparison of the impacts of alternative scenarios relies on subsequent rigorous quantification of the components, connections and relationships that comprise the system using methods such as dynamic simulation modelling [25–27]. Simulation modelling allows experiments to be conducted to see how a system behaves under different conditions and scenarios [22, 28]. The postulated theory of causation is refined and shaped through the participatory process of model building [6]. The process can enable health policy and practice decision makers to sharpen their understanding of the key components and behaviour of a health-related issue as a complex system [6, 21, 22]. Once commissioned, these models allow decision makers to draw on and learn from this joint understanding to better inform their policy and practice decisions [6, 9, 15, 21, 22, 28–30] and further model development and modification, post-commissioning, facilitates ongoing learning [6].

Participatory modelling approaches are an important feature of system dynamics modelling and have been widely adopted in environmental modelling projects [1, 26, 27, 30–39]. Many guidelines and principles for participatory modelling have been developed with varying degrees of prescriptive detail [30, 32, 36, 40, 41]. The guidelines commonly emphasise the principles of: careful planning for stakeholder engagement; awareness and management of social and group dynamics; flexibility and responsiveness to stakeholder input; iterating and refining, being open and transparent; accepting uncertainty; and encouraging learning through theory building and hypothesis testing [30, 32, 36–43]. The implementation of these principles of participatory modelling processes are often not well described, or only reported in narrowly defined discipline-specific forums (e.g. system dynamics projects reported in system dynamics journals), thus limiting opportunities for interdisciplinary learning for public health policy and practice [25, 44, 45].

Many participatory modelling projects have focussed efforts on qualitative mapping or semi-quantitative modelling of systems using methods including fuzzy cognitive mapping, rich picture diagrams, causal loop diagrams and systems structure diagrams [1, 23–26]. Understanding the process of transforming these representations into quantitative models is important, particularly for complex, quantitative models developed with an inter-disciplinary participant group, such as the one described in this case study [1, 36, 41]. More detailed understanding is needed about the participatory modelling process and the impact of facilitators and constraints [25]. Recent multi-method and systematic reviews of knowledge mobilisation and participatory dynamic simulation modelling across health and other sectors also conclude that more knowledge is needed about which approaches work best, in what settings, and how and
why they are effective [42, 46, 47]. Effective learning about the future role of systems approaches will come from natural experiments and case-studies, and the field of knowledge mobilisation will benefit from empirical studies of participatory modelling in applied ‘real-world’ settings [46, 48, 49].

Three case studies, focusing on alcohol related harms, childhood overweight and diabetes in pregnancy, utilising participatory dynamic simulation modelling methods have been implemented in Australian health policy settings [50–55]. Key aspects and activities of the novel participatory modelling methods used to collaboratively develop qualitative representations of the complex systems being modelled; participant experiences of the modelling process; and the model outputs and their application as decision support tools have been described elsewhere [50, 51, 53, 56, 57]. This paper focuses on the diabetes in pregnancy case study. It reports the findings of a qualitative analysis undertaken to examine the stakeholder deliberations, analytic processes, and decisions involved in using a participatory process to transform qualitative conceptual maps of diabetes in pregnancy into a quantified dynamic simulation model.

Case study context
Diabetes in pregnancy (DIP) is a complication of pregnancy that is defined as carbohydrate intolerance resulting in hyperglycaemia (abnormally high blood sugar). It includes women for whom the first recognition or onset of the condition occurs during pregnancy, as well as women with pre-existing type 1 and type 2 diabetes mellitus [58]. The prevalence of DIP is increasing both in Australia and internationally [59], and increasing the burden on the health care system. Approximately 16% of women who gave birth in the Australian Capital Territory (the case study focus region) in 2016 were diagnosed with diabetes in pregnancy, increasing from 6% in 2008 [60]. There are short- and long-term health risks for both mother and baby, including increased risk of birth injury in the short term and development of diabetes later in life [61–64]. The available evidence does not definitively guide health services on how best to prevent and manage DIP. For example, questions regarding the timing and methods of prevention and screening, criteria for diagnosis, targets for treatment and differential effects of treatment are all current challenges for DIP policy and treatment planning [65–68]. These issues cross the spectrum from specialised clinical management to population health interventions and such policy and service decisions are likely to benefit from sophisticated analytical tools, such as dynamic simulation modelling.

Methods
The qualitative study involved analysis of data methodically collected during the participatory process for the development of a dynamic simulation model for diabetes in pregnancy (the case study). The case study (Box 1) and the participatory modelling process (Box 2) are described below to provide background contextual information. The data sources and qualitative analysis methods for this study are described below.

Data sources
Data sources for preparing this paper included recordings of participatory workshops (n = 3), web-based meetings with participants (n = 3) and model development meetings (n = 3) with the core modelling team. The face to face meetings were audio recorded and photographed and the web-based meetings were audio-visually recorded. The core modelling group comprised of 11 people including computer scientists, computer science students, public health practitioners and medical specialists. LF, JA, GM, NO and PK were members of the core modelling group. Key meetings with members of the core model development group were
Box 1: Case study description

Researchers partnered with an Australian jurisdictional health department, and a multi-disciplinary group of stakeholders including clinicians, health economists, public health practitioners, simulation modelling experts and health policy decision makers, to co-produce a sophisticated, multiscale dynamic simulation model to support health policy and practice decisions for diabetes in pregnancy. The case study, participants, key project roles and participatory processes have been described in detail elsewhere [51, 54, 57].

The hybrid model was developed between 2016 and 2018 and integrates multiple modelling methods (agent-based, system dynamics and discrete event simulation modelling—see the following references for more information about these modelling methods [32, 69–72]). The purpose of the model was to explore short- and long-term implications of rising rates of diabetes in pregnancy and associated risk factors. The model simulates alternative policy, program, and clinical intervention scenarios to inform prevention and management decisions [51, 54].

Data coding and analysis

The analysis presented in this paper builds on previous work focusing on the experiences and perceptions of decision makers who engaged in the participatory modelling processes [57]. The previous analysis was conducted using grounded theory, whereas this data coding and analysis used thematic analysis focusing on the research questions outlined below. It was guided by the “theoretical” approach to thematic analysis described by Braun and Clarke [73] with the focus being guided by the researcher’s analytic interest, and therefore more explicitly researcher driven than inductive coding and analysis [73]. The thematic analysis focused on the problem solving and decision-making processes underlying the explicit activities in which stakeholders participated during the model development described in Fig 1. The analysis was guided by the following research questions: What were the key elements and features of the participatory approach that were required to successfully develop a policy relevant dynamic simulation model from a qualitative systems map? What types of questions were asked by the stakeholders, what concerns and issues were raised, and what was the feedback from participants during the process? What challenges and tensions arose in the process and how were they managed?

The audio-visual recordings were viewed, coded and analysed by the lead investigator (LF). Field notes, observations, records of reflexive discussions, email exchanges and recordings of meetings / workshops were analysed progressively by LF and discussed regularly with JA, and LR throughout the process. An iterative process of descriptive coding and analytical memos
Box 2: Participatory modelling process

An overview of the approach used to build the dynamic simulation models using participatory methods has been described previously [51]. Broadly, this involves an iterative process of convening expert stakeholders, conceptual problem mapping, synthesising evidence, quantifying the key dynamic relationships within the system, presenting model versions to participants and end users, refining the model, and applying the model to support evidence-informed dialogues about policy options.

The end-user participants were central to the model development process. Contact was initiated early and engagement was negotiated to ensure that the scope of the model reflected key policy and planning questions, the interaction of key risk factors, and context specific intervention priorities [51]. The participatory process involved workshops, web-based and face-to-face meetings and ongoing communication via email or telephone. Participants had differing levels of intensity and duration of involvement in the project, ranging from those who contributed to group activities primarily as workshop participants, to others who also contributed as workshop facilitators, attended the regular project team meetings, and facilitated subsequent communications about the application of the model.

An overview of the activities involved in the participatory process is presented in Fig 1. Workshops were conducted where participants interacted and engaged in group activities to develop conceptual maps of the factors contributing to diabetes in pregnancy and its potential outcomes. During the workshops, they also discussed the quality and availability of evidence to inform the model development, prioritised interventions and outcomes to be explored in the model, and provided feedback to refine the model. The model development process was iterative at every stage, with the core model building team gathering information from participants, integrating it with other evidence and data sources to inform the model development process and receiving feedback from participants before proceeding to the next step (Fig 1). Interaction with participants also occurred between workshops, and continued for some months after the final workshop. In the later stages of model development, the iterative feedback process centred around the presentation and discussion of the model results.

was used to develop themes and conceptual categories and explore their inter-relationships. Themes and insights were triangulated across the different data types and sources. The progressive analysis was further revised as new data was incorporated. Analytic memos written by LF were shared with JA and LR to facilitate the analysis review process. Vignettes based on data from the case study were written to demonstrate practical examples of important decision points and the processes used to develop model components.

Ethics and consent to participate

This study was reviewed and approved as low risk by the ACT Health Human Research Ethics Committee (ACTHLR.15.150) and the University of Notre Dame Human Research Ethics Committee (0151195).

All participants gave individual written consent, were assured of confidentiality, and were free to withdraw from the study at any stage.
Results

The qualitative analysis uncovered the iterative cycles of engagement, analysis, negotiation and refinement involved in the process of developing a dynamic simulation model as a quantified decision support tool for diabetes in pregnancy. The core analytical objectives and decision-making themes involved in the participatory model development process are described below and represented in Fig 2. In summary, the process of engaging with participants to develop a quantitative model involved five distinct phases including: (i) defining and negotiating the model scope; (ii) finding, critiquing and using evidence; (iii) analysing and refining the model; (iv) ensuring that the model remained focused on priority policy questions; and (v) engaging with, evaluating and communicating model outputs. Each of these phases are explained in detail below. The schematic diagram in Fig 2 illustrates how each of these conceptually and practically distinguishable aspects of model development involved interaction and engagement with participants at the centre of the process. However, it is important to note that these phases did not occur in any linear or chronological order. Instead interactions and discussions that occurred later in the model development process, as the model was analysed and refined, resulted in earlier phases being re-visited and refined or revised. The results section concludes with a description of the overarching challenges that arose from the participatory process itself, and the strategies used to overcome them, as well as the model application opportunities that resulted from the participatory process. A glossary explaining modelling terms is provided in the supplementary file: S1 Glossary.

Defining model scope

A primary aim of the first participant workshop was for the core model building team and workshop participants to jointly conceptualise and qualitatively map the ‘system’ of Diabetes in Pregnancy in the form of a ‘draft model structure’. In this instance, it was represented in the form of ‘state charts’ as used in agent-based modelling methods [51, 54]. State chart elements...
relating to diabetes in pregnancy were derived from discussions with participants prior to the first workshop and were pre-printed and presented as a draft model structure to facilitate the activity. Participants were invited to add to and modify the draft model structure and encouraged to highlight and explain the interconnections between the components of the system, any
changes over time, feedback loops, and sources of inertia and delay. The problem conceptualisation for diabetes in pregnancy as it appeared at the end of Workshop 1 is shown in Fig 3.

The participants’ initial problem conceptualisation was a detailed, qualitative representation of the interacting factors contributing to the development of diabetes in pregnancy, jointly developed to incorporate the multiple perspectives of the expert participants. However, the initial map developed in workshop 1 (Fig 3) required further synthesis and refinement of its
conceptual representation before it could be operationalised as a computational model. To achieve this, the core model development team, in subsequent consultation with the expert stakeholders, used the map and voice recordings of the mapping exercise to identify important themes, events and interconnections to be captured in the model. This involved systematically reviewing the diagram to determine the priority factors that influenced the postulated causal pathways, and the most important events and agents to be quantified in the model. These factors are presented in Table 1. For example, factors were prioritised for inclusion in the model if they were identified in multiple places in the concept map, or emphasised by stakeholders as influencing causal relationships between, and transitions within, the developed state charts.

The modelling methods used in the case study included system dynamics, agent-based and discrete event modelling—a decision that was primarily made by the technical expert modelers, in consultation with the others in core modelling group. The current understanding of the aetiology of diabetes in pregnancy (as described in Vignette 1 below) facilitated decision making about the modelling methods. Advances in computer simulation tools have meant that the multiple modelling methods mentioned above can be used in a single model, allowing focused selection of the most appropriate method to articulate different components of the model. This flexibility leveraged the advantages of each method without needing to constrain the representation with the limitations of a single method. Aggregate model components, such as with system dynamics, don’t allow for exploration into individual differences in predisposing factors, adherence to diet or medication, or other circumstances such as social determinants of an individual’s health. Therefore, agent-based modelling methods were chosen to enable the exploration of individual differences in predisposition and risk exposures. Agent-based modelling methods were also used to capture individual trajectories through risk exposures, inherited risk due to maternal history and ethnicity and consequent development of disease. A system dynamics stock and flow ageing chain structure was initially chosen to initialise and represent the population. Population members who met the definition for ‘high risk’, i.e. according to the Australian Diabetes in Pregnancy (ADIPS) definition, ‘budded’ from the aggregate stock and flow structure and became agents within the model. Agent-based modelling state charts were implemented to represent pregnancy transitions, weight transitions and the development of diabetes. Discrete events simulation components were implemented to represent agent use of health services.

Table 1. Factors influencing the development of diabetes in pregnancy prioritised from problem conceptualisation.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family history / genetic factors</td>
<td>Family history of obesity or diabetes</td>
</tr>
<tr>
<td>Food environment / diet</td>
<td>Unhealthy diet, access to healthy foods, food security</td>
</tr>
<tr>
<td>Physical Activity</td>
<td>Level of physical activity or sedentary behaviour, physical environment</td>
</tr>
<tr>
<td>Health state</td>
<td>Diabetes in previous pregnancy, other obstetric risk factors, personal history high birthweight</td>
</tr>
<tr>
<td>Health care system</td>
<td>Universal or selective screening, access to health care, government policy</td>
</tr>
<tr>
<td>Metabolic functioning</td>
<td>Glycemic regulation, insulin sensitivity, weight status, gestational weight gain</td>
</tr>
<tr>
<td>Non-modifiable factors</td>
<td>Maternal age, high risk ethnicity, migration</td>
</tr>
<tr>
<td>Psychosocial factors</td>
<td>Social network, education level, cultural norms, psychological factors</td>
</tr>
<tr>
<td>Events</td>
<td>Examples</td>
</tr>
<tr>
<td>Medical interventions</td>
<td>Screening, specialist services, diabetogenic medications, bariatric surgery</td>
</tr>
<tr>
<td>Model components</td>
<td>Examples</td>
</tr>
<tr>
<td>Agent types</td>
<td>Mothers, babies, health care workers</td>
</tr>
</tbody>
</table>

https://doi.org/10.1371/journal.pone.0218875.t001
Analysing and refining the model to maximise relevance and utility

Versions of the model were presented back to participants at the second and third workshops and other web-based meetings to demonstrate how the core modelling group had operationalised the qualitative conceptual map of diabetes in pregnancy. The participants’ analysis and critique of the evolving model were an important contribution to improving the structure, and refining the causal pathways, and their underlying logic and assumptions.

We include here an illustrative example of how the evolving draft model was presented to participants in the second workshop using a simplified representation of the model elements in Insightmaker™ (Fig 4). The examples of agent “life stories”, presented as clinical case histories, were used to talk participants through the model structure and logic.

For the expert participants, particularly those from clinical backgrounds, the presentation of individual case histories, as “stories” from the model, was a familiar and well-understood method of communication. It provided an opportunity for participants to become familiar with a strategic view of the model, without becoming swamped by the detailed structures used in modelling software. Participants asked questions of the core modelling team, clarified the use of terminology, and helped to refine the model logic. They also provided feedback based on their clinical and policy expertise that identified important gaps in the model; for example,
the need to incorporate a representation of the complex heterogeneity of diabetes aetiology as discussed in Vignette 1.

Vignette 1. Improving the representation of the development of diabetes in pregnancy

An issue raised frequently during workshops and meetings was the complex heterogeneity in the development of diabetes in pregnancy. Participants emphasised that the causal mechanisms for development of the condition were complex, multifaceted and an area requiring further knowledge development. For example, a baby may be born with diminished beta cell mass and function due to genetic predisposition. The intrauterine environment also impacts on risk; being exposed to dysglycemia (high blood sugars) in-utero can lead to short- and long-term effects on the baby including macrosomia, risk of high weight status in childhood and adult life and increased risk of early development of diabetes. The causal mechanism for diabetes development in some individuals was through increased insulin resistance, however for others, declining beta cell mass and function was the driving factor. A third group experience a combination of both. These causal mechanisms were also influenced by non-modifiable factors, such as ageing, and modifiable factors, including weight status, diet, and physical activity levels.

The definitions used in the model were aligned wherever possible with those used in accepted clinical guidelines, and the collaborative process of deciding on the terms and definitions helped to facilitate shared understanding of these within the group. Participants also proposed credible assumptions to be used in the model e.g. all women from ethnic groups defined by ADIPS as high risk should be defined as “high risk” in the model. Versions of the simplified model were printed and used in small group activities in workshop 2 to map directly to the model architecture the prioritised interventions, as identified by the group (Fig 5). This decision making process was aided by technological advancements in the user interface of the selected modelling software, so that ‘state charts’, ‘action charts’, ‘stocks and flows’, and process modelling components can be used to replace thousands of lines of code to clearly visualise and communicate model logic and thereby facilitated transparency and enabled stakeholders to meaningfully critique the model.

The repeated opportunities for stakeholder participants to actively interact with and discuss the model allowed them to test the evolving model structure against their “real-life” professional experience of working in diabetes in pregnancy research, policy and practice. It also allowed the modellers to test their own understanding of the issue (and how this knowledge had guided their technical model development) against the knowledge of content experts working in the field. The multi-disciplinary group of health sector participants brought to modelling discussions a breadth and depth of knowledge and rich experience regarding the issue that would be impossible to gain from reviewing the data / literature alone. Participants were able to contextualise the logic and structure of the model, identify additional questions and data to be investigated, and additional factors to consider for inclusion.

Finding and using the best available evidence

Over the duration of the model development process many published studies and other evidence sources were synthesised and used to inform assumptions and parameter values in the model. Participants were motivated to understand and review the data and evidence utilised and demonstrated their strong commitment to this process by continuing to engage and respond to requests for evidence. The potential sources of data and evidence that could be used to inform the model were, therefore, an important focus for discussion at workshops, meetings and out of session communication. Participants drew on their extensive knowledge
of the literature, identified and explained the most relevant studies and their main findings, and offered advice to the modelling team about local population characteristics, exposures, and service variations that contextualised published study results. Importantly, participants also identified limitations of the available evidence and data, such as quality concerns about identification of diabetes in health service administrative datasets.

Agent-based models are valuable to explore individual differences in disease aetiology; however, they can have substantial data needs, and complex models like the diabetes in pregnancy model require quantification of many parameters and relationships between model components. Requests for evidence were circulated to the participant group for discussion as they arose during the model development. There were many requests for evidence that were identified by the core modelling team and discussed with participants during the model development process. Some examples include:

Fig 5. Intervention mapping to model architecture from workshop 2.
https://doi.org/10.1371/journal.pone.0218875.g005
1. What is the probability of adverse perinatal outcomes for women according to their level of glycemic control during pregnancy (normal through to high levels of dysglycemia)?

2. Relating to the mechanism by which exercise affects insulin sensitivity—is it direct or moderated through weight status? Can physical activity have a positive impact on metabolic function but no impact on weight status?

3. What is the effect of insulin during pregnancy and does it differ from pre- or post-pregnancy?

These questions were framed with a brief contextual explanation of the model pathways and structures that required the additional information. Where possible, participants answered these questions by referring the core modelling group to quality published studies, including randomised control trials and prospective longitudinal outcomes studies where available; providing health service administrative data; or providing expert advice based on their extensive experience. The core modelling group also independently searched the literature for evidence and conferred with the expert participants about the robustness and appropriateness of the evidence identified before and while it was used to inform model development.

The expert participants were also able to critique and identify limitations in the published literature and health service data as well as knowledge gaps. For example, the health service routinely collects perinatal statistics with respect to perinatal outcomes, such as birth weight and admission to neonatal intensive care, however, only diagnosis of DIP is recorded and not level of glycemic control during pregnancy. These data were therefore unable to directly inform relationships between glycemic control and perinatal outcomes to answer question 1 above; and more detailed studies in the published literature were utilised instead. Where the published evidence was relevant but not specific enough to apply to the local context, it was often used to assist with calibration or validation rather than used as input parameters i.e. it was used to evaluate the model behaviour rather than as evidence incorporated into the model equations.

A common question that arose during the model development process was what to do when there was insufficient local data or other published evidence to inform the model structure or parameterisation. Strategies such as calibration of key parameters using historic trends for diabetes in pregnancy incidence and sensitivity analysis were utilised. These strategies are established in modelling literature and practice as robust methods to address these common modelling challenges but were unfamiliar to many participants. However, the mutual respect that had developed between participants and the core modelling team and the recognised value of dynamic modelling as a learning tool were helpful sources of confidence. The overall framing of the process was that dynamic simulation modelling is a tool that allows contributors to articulate a hypothesis of complex causal pathways in the emergence and progression of disease (including possible latent factors) by bringing together best available evidence and data, and then testing and refining that hypothesis through computation, simulation and validation against real-world historic data patterns.

Sensitivity analysis was used to determine which uncertain parameter estimates were most important to the outcomes of interest, which informed priorities for future research. This identification of future research priorities was another function of the modelling process that was highly valued by the participants.

Finally, the DIP model also utilised, as sources of evidence, the existing diabetes modelling literature. For example, existing, peer-reviewed mathematical models of diabetes progression were presented and explained to the clinical and policy expert participants for consideration as evidence to help quantify parameter estimates and equations, such as those representing...
variations in the development of diabetes. These mathematical models enabled the modellers to quantify and operationalise the latent variables and causal mechanisms underlying the heterogeneous development of diabetes, an identified gap in clinical diabetes research. Grounding the model in this established, and peer-reviewed, mathematical literature also enhanced the rigour and reliability of the model outputs.

Focusing the model on priority policy and program questions

The model was primarily developed as a planning tool for exploring the resource implications and service costs of alternative policy and program options. Participant feedback guided decisions about which components of the larger system model of DIP would be prioritised for these health service decisions. They selected alternative health service options and service pathways as a priority for inclusion in the model.

The expertise of the participant group grounded the model in the real-world experience of intervention effectiveness. For example, studies of interventions delivered during pregnancy to prevent the development of diabetes have yielded disappointing results, and it was deemed important for the model to be able to compare early intervention options. Pre-pregnancy and inter-pregnancy interventions were prioritised for inclusion in the model; both at the population level, and those targeting high risk women. The mechanisms for impact were mapped to the printed model structure during the workshops and subsequent discussions. Participants indicated the transitions, states, parameters and other structures that were likely to be impacted by each intervention. For example, for interventions targeting weight loss, the impact on the weight status state chart were discussed by the group, and then mapped to indicate how this could flow through to impact on other model structures. These discussions with participants guided the core modelling group where to focus their efforts to ensure that the necessary components were operationalised to allow the most important policy and program questions to be explored (Vignette 2). Based on the detailed understanding of the expert participants, the structure of the model captured the impact of duration and level of exposure to dysglycemia on beta cell function for individual agents, and thus enabled the testing of both clinical and lifestyle intervention strategies targeted at different stages of the life course.

Vignette 2. Accurately capturing impact of prolonged exposure to dysglycemia on intervention effectiveness

Participant input emphasised that the model needed to account for the length of exposure to dysglycemia as this has a significant impact on intervention effectiveness. When a person is exposed to dysglycemia for an extended period of time, they lose effective beta cell function, and therefore, the ability to recover glycemic control even after engaging in an intervention. In contrast, an individual who has just been newly diagnosed with impaired glucose regulation or diabetes in pregnancy can recover glycemic control if they engage in physical activity or dietary modifications that lower their blood sugar levels and reduce damage to their beta cell function. Early interventions, for example, for a woman who experiences gestational diabetes in her first pregnancy, may therefore have more effectiveness than interventions for people with prolonged exposure to poor glycemic regulation.

These important policy and planning questions focused on the underlying physiological mechanisms impacting on intervention effectiveness. They motivated the development of more detailed model mechanisms to capture the impact of actualised glycemic control on both maternal and perinatal outcomes. A detailed articulation of glycemic control, rather than simply considering the diagnostic status of an individual agent in broad terms, was required for the model to robustly explore clinical intervention scenarios of interest to participants.
Engaging with and communicating results and applying the model

Being open to and welcoming critique from diabetes experts was key to genuine co-design of the model. It was also important to ‘socialise’ the results of the model; that is, to test them against the knowledge and experience of the participant group. Viewing and discussing model results / outputs was a critical phase of the model development process and was essential to more fully elicit the expert knowledge of participants. Two types of knowledge were elicited through discussion of model outputs, namely: tacit expert knowledge, i.e. the knowledge that people generally won’t mention unless prompted; and explicitly considered expert knowledge that couldn’t be applied to the model directly, i.e. knowledge that wasn’t reducible to any one parameter or assumption and instead reflected the emergent behaviour of the system. In both cases, the elicited knowledge served as key sources of evidence to challenge the working dynamic hypothesis captured in the model. Simulation experiments enabled examination of the logical implications of the hypothesis, represented in the model structure, logic and assumptions, by exposing the performance of the model for outcomes of interest. For example, increases or decreases in insulin sensitivity occurred for individual agents in association with other physiological changes, such as pregnancy or weight gain or loss. This was consistent with the elicited knowledge from participants and the empirical evidence.

Viewing and discussing the model results also ensured that the model had fidelity i.e. that it produced results that were consistent with retrospective data and considered plausible by experts working in the field. These discussions emphasised that the model was not a “crystal ball” that would discern the future with pinpoint accuracy but could be used to make robust forecasts and enhance understanding about the relative value of alternative policy and planning choices. Full transparency about how the model scope was defined, and the limitations of the underlying data, also ensured that the participants were informed about its strengths and limitations, and thus more confident to make decisions about its application and value.

Storytelling was an important communication tool used in the model building process, and in discussing model outputs. The “life stories” of agents in the model were used throughout the participatory process to communicate the model structure and its capacity to demonstrate health outcomes at an individual level. Agents in the model were born with a risk profile based on both their mother’s history and her glycemic control during pregnancy. The agents aged during the model run time (80 years), gained and/or lost weight, underwent lifestyle and medical interventions, and experienced their own pregnancies. The model captured information (outputs) for individual agent health outcomes that both influenced feedback loops within the model and could also be used to report statistics from the model. This functionality offered great power to support telling rich and compelling stories that illustrated the textured evolution of agents over time. The presentations of individual trajectories were an effective communication tool to improve participant understanding of the model structure and logic. The communication of agent stories as “case histories” facilitated the ability of participants to relate the model logic and assumptions to their real-world experience providing services to women with diabetes in pregnancy. The process prompted questions and comments and facilitated participants’ engagement in analysing, refining and informing the model.

Storytelling for individual agents was also viewed by the expert participants as a valuable tool to communicate model results to a broader, less technical, audience. During discussions about the model outputs, participants identified that presentation of the knowledge gained from the model development process, as well as the results it produced, would be a critical determinant of knowledge mobilisation and communication with a broader audience. But they also reported that despite the improved transparency of the new software interfaces, the sophisticated and highly technical nature of the model would be a barrier to developing clear
and easy to understand policy messages. Thus, supplementing model outputs with storytelling about individual patient journeys was viewed as a powerful tool to ensure that the results were relatable and easily understood. A plain language fact sheet was developed for the model incorporating both real-world and individual agent stories and is available at: https://preventioncentre.org.au/wp-content/uploads/2018/08/080818_Diabetes_FactSheet.pdf and a podcast was also made to communicate the project to a broader audience, available here: https://preventioncentre.org.au/resources/tackling-the-pandemic-of-diabetes-in-pregnancy/.

Feedback and iteration
An important overarching theme derived from these findings was that of continual feedback and iteration, in which decisions about model logic and structure were regularly re-visited as new information became available. This is also represented in the configuration of Fig 2 in which the processes of model development fit together as non-linear phases. For example, as noted above, the process of participants viewing and discussing individual agent stories, and engaging with results from the model, elicited additional information and developed new forms of shared knowledge. This additional information and knowledge were then considered for incorporation into the representation of causal pathways and other model components. This led to further refinement of the model, and identified the need for additional evidence to inform that refinement. The highly iterative nature of the participatory process resulted in both challenges and opportunities that are discussed below.

Overcoming the challenges that arise from the participatory process

1. Tensions between model complexity and model simplicity
   Desire for complexity and detailed representation—The expert participants had highly evolved and detailed knowledge about many aspects of diabetes in pregnancy; including disease aetiology, the technicalities of treatment and testing regimens, and complex health service delivery. It was common for the conversations to go deeply into complex details, for example, about service pathways, issues with diagnostic testing methods, and participation rates for screening. However, while such topics are important for real-world service delivery, they were often too detailed to be captured in the model. Thus, an important challenge for the participatory model development process was to distinguish which aspects of DIP were important to represent in detail, and which aspects could be left out or represented in a more stylised, or simplified, way. It was important to address the opportunity cost of including details and for the participants to prioritise only those aspects that were essential for more detailed inclusion. These discussions considered the extent to which the details would be needed to adequately represent intervention mechanisms, and their outcomes, and the likely pathways of impact for the prioritised policy and practice questions. A road map analogy was an effective communication tool to facilitate these discussions, i.e. like a road map, the model needed to include essential landmarks to make it fit-for-purpose and did not need to include every tree or driveway along the route. When particular details were considered important by some individuals but could not be prioritised in the agreed scope of the model, they were recorded as opportunities for future model expansion in subsequent projects.
   Desire for speed and simplicity—a contrasting challenge was the tension between developing a sophisticated and highly articulated model that could reliably and plausibly evaluate the interventions of interest to participants and their co-existing desire for a simpler, faster model both in terms of development and running time. In these circumstances, the
onus was on the core modelling group to balance this tension between complexity and simplicity and determine the "minimal viable model". The minimum viable model is the simplest solution that has the requisite robustness, completeness and reliability to rigorously address the participant needs. These negotiations and decisions relied on the extensive knowledge and experience of the lead modeller to ensure that the model developed was robust and rigorous considering these pressures.

2. Ensuring the model design and structure are appropriate

Decisions about how to represent prioritised factors in the model were challenging. An early version of the model incorporated a simplified, statistical representation of the interaction between risk factors. For example, an individual’s probability of developing diabetes in pregnancy was programmed as increasing according to a linear correlation with their count of risk factors. However, this representation was not dynamic, did not allow for other important elements, such as the length of exposure to dysglycemia, lacked the ability to robustly capture the effects of counter-factual interventions, and limited the use of the model to explore the combination and interaction of intervention options in the development of DIP. Later versions of the model used endogenous or latent variables to represent the causal physiological mechanisms, thus allowing exploration of complex interactions between risk factors, and the exploration of counterfactuals.

The use of endogenous or latent variables created challenges in the interpretation of model outputs. For example, it was challenging on occasions when the model outputs didn’t produce familiar or expected results, e.g. when the emergent outcomes were counterintuitive. This was managed by identifying model outputs that could readily be checked against historic trends and empirical evidence, which reassured the participants when the model reliably replicated existing data. Unexpected results from the model also provided an opportunity to explore the logic and assumptions of the model and make improvements. For example, model results showed DIP incidence plateauing in contrast to the increasing rates observed in administrative data, and this led to an investigation of possible explanations. The investigation explored whether the plateau effect was due to the length of the ‘burn-in’ period used in the model and different burn-in lengths were tested to assess their impact. The impact of the representation of weight dynamics was also examined, leading to further changes as detailed in Vignette 3 below. Participant discussions regarding unexpected results also helped to identify quality issues and anomalies affecting the administrative data used to determine historic trends. For example, variations in the implementation of changes to the blood glucose standard used for diagnosing diabetes in pregnancy and changes to diagnostic testing assays impacted historic incidence rates leading to rapid increases. These artefactual increases resulted from process changes rather than changes to the underlying population rate of diabetes in pregnancy and it was important to consider this when assessing the model results against trends in administrative data.

Vignette 3: Challenges in representing weight dynamics

High weight status is an important and modifiable risk factor for the development of diabetes in pregnancy. Weight status was identified in the initial problem conceptualisation and included in model versions from the inception. The representation of weight status evolved significantly through the participatory model development process. Initially weight status was represented as BMI categories in a state chart specifically characterising an individual as present in one of healthy weight, overweight and obese states. Each agent was assigned an initial state based on an age and ethnicity specific distribution and transitions between states occurred according to hazard rates. As the model evolved and interventions were prioritised,
defined and quantified, it became evident that a more detailed representation of weight status would be required. The representation needed to capture:

- Intervention effects that resulted in weight loss for an agent but were insufficient to move that agent from one BMI category to another i.e. a weight loss of five kilograms may reduce an agent’s BMI by one or two units but may not move them from an obese to an overweight state.

- Dynamics in weight status across the life course

- Population changes in weight distributions over time

- Impact of weight status on physiology underlying the development of diabetes in pregnancy, particularly on insulin resistance, and distinct effects during and outside of pregnancy.

The representation of weight status was evolved to capture agent weight as a continuous variable that changed dynamically with age and pregnancy events based on published evidence. An agent’s weight status (BMI) impacts on their insulin sensitivity with increasing weight leading to decreasing insulin sensitivity.

3. Deciding when the model is ready

   Dynamic simulation models can always be further refined and improved. Another important challenge arising from the participatory process was achieving consensus on when the results were “good enough” to inform decision making. This decision was primarily informed by the following considerations:

1. Reliability—How reliably the model results matched historic data trends across a range of indicators, including diabetes in pregnancy incidence overall and for important sub-groups; population weight status categories over time; and general demographics such as age structure.

2. Completeness—How satisfied the core modelling team were that they had captured the most salient aspects of the issue in enough detail to robustly explore policy questions.

3. Experimentation—did the model produce plausible results during scenario testing of interventions, i.e. did the simulated intervention scenarios producing results that had face validity among participants who had extensive professional expertise in diabetes in pregnancy and sound knowledge of relevant research?

4. Timing—having the model results ready in time to be used in policy dialogues.

5. Acceptability—Was there sufficient acceptance of the fidelity and plausibility of results produced by the model among the expert participants? Were significant concerns raised and adequately addressed?

4. Being transparent about uncertainty

   It was also important to be transparent with participants about model uncertainty, for example, differentiating parameters based on quality, comprehensive evidence and those where the evidence was less certain. Sensitivity analyses determined how influential the parameters were on the model results. This information was shared with participants and discussions focused on either identifying new studies that could be utilised or confirming that the evidence gaps still existed and were therefore a priority for future research.
Opportunities arising from the participatory process

The participants in this case study were nationally and internationally acknowledged experts and included health professionals who were embedded in local service provision and policy decision making. The participatory model development process included drawing on the participants’ networks to socialise the model to other decision makers, who had not been involved in the process. The participants also identified opportunities for the model to be presented and applied as a decision support tool for policy and programs. Through their professional networks, the participant group facilitated new relationships and useful leads for additional expertise and evidence to improve the model. Participants continued their engagement with the model after the formal activities of the process were finalised and advocated for the model to be used in policy decision making.

In summary, the participatory process resulted in a robust, highly transparent model with an agile, responsive design. The multiple modes of engagement and interaction with participants provided a built-in peer review-like process to ensure that the model was valid and fit for purpose. The network of participants involved in the project also facilitated the identification of new priorities and opportunities for research and further model development.

Discussion

The primary goal of participatory dynamic simulation modelling is to provide decision support and facilitation in planning and policy contexts. The initial exploration of diabetes in pregnancy conducted at the commencement of the model development process resulted in a qualitative conceptual map that was complex, not yet well-defined, and of limited value for guiding policy. Through a deliberative participatory process that included synthesis and exchange of data and information, and iterative cycles of negotiation and refinement, a quantified decision support tool was developed. To fully understand and evaluate the rationale and logic of the participatory modelling process, both the interaction among the model building group, and the relationship between the participatory process and the decision context needs to be described [25].

The key elements of an interdisciplinary, participatory approach to develop a dynamic simulation model for diabetes in pregnancy included: determining the focus topic; defining the model scope; iteratively refining the model structure and logic; reviewing and using evidence; ensuring that the model was focused on priority policy questions; communicating results; and applying the model to inform health policy decisions. The decisions required were highly interactive; with participants engaged via multiple forums e.g. workshops, web meetings, emails, and small group meetings. Participants identified important sources of evidence to inform model parameters and assumptions. The professional networks available through the participant groups ensured that the model was focused on current, priority policy questions and initiated opportunities for it to be applied in practice. Storytelling was an effective strategy for facilitating participant understanding of the structure and logic of this complex model and to communicate model results to a wider policy audience.

A new framework for reporting participatory modelling projects has been proposed within the environmental modelling field as a tool to facilitate sharing of knowledge about the participatory process and stimulate innovation [25]. The 4Ps framework has highlighted the need to describe “how” participants are involved in model development: firstly, to contribute to the interpretation of models developed using participatory methods; and secondly, to facilitate learning about participatory modelling tools and strategies [1, 25]. The 4Ps framework identifies purpose, process, partnerships and products as key dimensions of participatory modelling projects and practices: (1) the Purpose for selecting a PM approach (the why); (2) the Process by which the participants were involved in model building (the how); (3) the Partnerships that
formed around different parts of the process (the who); and (4) the Products resulting from these efforts (the what) [25]. Our analysis from the DIP case study falls within the Process component of the 4 Ps framework in that it explored how the participants were involved in the model building process. Three questions are raised in this component: What were the characteristics of the interaction between the participants and the model? What was the level of participation? What was the relationship between the participatory modelling and decision-making processes? [25]. We consider these questions below in relation to the DIP case study and other modelling literature.

**Contribution of expertise to develop and refine the model**

Participant interactions contributed significant expertise and local context knowledge to the development and refinement of the model. Advances in modelling software are improving the visual representation of model components, making them easier to use, and more transparent to stakeholders not trained in modelling [6, 42]. This facilitates a participatory process by which the significant combined knowledge of expert groups can be applied to model development [6]. By repeatedly exposing and explaining the underlying model components in workshops and meetings, the participants in this case study were able to understand, analyse and refine the overall logic and structure of the model. They were able to identify areas where more detail was required or where assumptions could be improved. However, their involvement in decision making about the type of modelling methods used was limited e.g. which factors to represent using system dynamics vs agent-based modelling components. As health stakeholders become more experienced with dynamic simulation modelling, the potential will increase for them to contribute to technical decision-making regarding modelling methods. The experience and knowledge developed by participants in this case study may enable them to even more confidently and effectively contribute to future modelling projects.

Incorporating participatory processes in simulation modelling also facilitates learning by building shared understanding of the problem and potential solutions, and which is refined with data and evidence through group interactions [36, 41, 74]. Through the exchange of information, knowledge is shared, and new knowledge is created, leading to changes in understanding [25, 36]. The interdisciplinary dialogue facilitates the sharing of different types of knowledge on critical issues from a range of perspectives [36, 44, 52].

The model developed in this case study utilised and integrated diverse evidence sources to quantitatively operationalise a theory of the causal mechanisms of intergenerational, social, cultural, economic and environmental factors that influenced behaviour and development of diabetes in pregnancy based on the qualitative map developed interactively with participants. Model assumptions and parameter values were derived through a process of evaluating and critiquing the many sources of evidence, including those considered both at the top e.g. systematic reviews and meta-analyses, and the bottom, e.g. case reports, of traditional evidence hierarchies [52, 75]. Integration and triangulation of evidence from systematic reviews, local analytic studies, conceptual models, and expert and local knowledge was required to map and quantify a broad range of complex public health issues [19, 52]. The model simulations allowed robust examination of the logical and quantified consequences of the postulated dynamic causal hypotheses and to test the impact of policy and planning decisions and counterfactuals using experimentation.

**Participants were highly engaged in the co-production process**

Stakeholder input and acceptance are important factors in increasing the usefulness and application of models [25, 36, 42]. The degree of success of a participatory process can be discerned
from stakeholders’ trust in modelers’ expertise and the amount and quality of information they give, as well as whether they intend to use the model and will participate in future collaborations [36]. Most participants in the case study reported here remained highly engaged throughout the project. They continued to contribute to discussions, attended meetings and were responsive to email communications. The level of interest in the model and associated communication products was high. Participants contributed advice on how to ensure the model could be applied to high priority policy questions and identified opportunities to facilitate its use in this context.

Models cannot comprehensively reflect the real world as details need to be omitted and boundaries defined around what is to be modelled [42, 71]. Highly-detailed models often require more data than is available; take longer to develop; can be difficult to calibrate and validate; and most importantly, they can be hard to understand [1, 42]. Both stakeholders and modellers can struggle with determining the level of detail to include and get drawn into trying to model reality instead of the decision essentials [42]. This challenge was evident throughout this case study. The model scope and level of abstraction was frequently re-visited and needed careful negotiation throughout the participatory process.

### Participatory modelling facilitated the use of the model for decision making

Finding effective strategies to communicate about both the model and the model results were an important challenge in this project. Modelling to inform policy relies on clearly explaining results, and their limitations, building confidence in the modelling process and outputs, and ensuring that the outputs are appropriately used [42, 57]. Active collaboration builds confidence in the model and enlists local champions for its application [42, 57]. The participatory process facilitated the identification of opportunities for making the model accessible to policy audiences, and strategies to address likely communication challenges. Opportunities to use the model to identify the policy options that were likely to have the greatest impact in local service planning were proposed. Participants were also interested in using the model to test whether highly advocated, but contested, interventions would be effective and or scalable to the population level.

Additional opportunities and potential applications of the model beyond the primary purpose of policy analysis were identified through the participatory interactions. For example, participants proposed that the model could be used to inform health education messaging by primary practitioners, such as demonstrating the risk of developing diabetes based on weight status, and the positive impact of engaging in lifestyle modification. This messaging was viewed as potentially leveraging women’s motivations to protect the health of their baby to encourage them to reduce their own risk profile pre-pregnancy and maintain good glucose control during pregnancy.

### Conclusion

The model developed in this case study moved beyond qualitative system mapping to a sophisticated, rigorously quantified, multi-method dynamic simulation model which represents the complex interrelationships underlying the development of diabetes in pregnancy. The challenges of the participatory process were outweighed by the benefits. The process allowed for the contribution of participants’ extensive and rich understanding of the issues, which was combined with the expertise of the modelling team to inform, analyse and refine the model logic and structure. The core analytical objectives and decision-making themes reported in this paper provide valuable insights for understanding and elucidating the process components
Turning conceptual systems maps into dynamic simulation models using participatory methods

of the 4Ps framework. Our analysis makes explicit the deep analytical work that occurs within the workshops, interactions and meetings of the participatory process. Like the workings underlying a clock face, the underpinning analytic processes are fundamental to participatory model development, but not readily observed without ‘lifting the lid’ through systematic data collection and analysis. In detailing the core analytical objectives and negotiations underpinning the participatory process, our findings provide unique insights for the planning and reporting of future participatory modelling projects.

Supporting information

S1 Glossary.

(DOCX)

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References


Chapter 6: Results part 3: Decision makers’ experience of participatory dynamic simulation modelling methods for public health policy

The published manuscript presented in this chapter reports on the experiences of end-user decision makers who engaged in the participatory DSM processes and their perceptions of the feasibility and value of this approach.

The paper focuses on the experience of participating in the interactive model building activities, the perceived benefits and challenges of the approach and how the DSMs were being used to inform policy and program decisions from the perspective of these decision makers. Participants from the DIP case study were interviewed before and after the participatory modelling process, and the participants from the two additional case studies were interviewed after their participatory process to gain their perspectives on the efficacy and value of the approach to inform decision making.

Paper 4:


The interview schedule was published as supplementary material for this manuscript and is included in Appendix 8 of this thesis.
Decision makers’ experience of participatory dynamic simulation modelling: methods for public health policy

Louise Freebairn1,2,3*, Jo-An Atkinson2,4,5, Paul M. Kelly1,2,6, Geoff McDonnell8 and Lucie Rychetnik2,3

Abstract

Background: Systems science methods such as dynamic simulation modelling are well suited to address questions about public health policy as they consider the complexity, context and dynamic nature of system-wide behaviours. Advances in technology have led to increased accessibility and interest in systems methods to address complex health policy issues. However, the involvement of policy decision makers in health-related simulation model development has been lacking. Where end-users have been included, there has been limited examination of their experience of the participatory modelling process and their views about the utility of the findings. This paper reports the experience of end-user decision makers, including senior public health policy makers and health service providers, who participated in three participatory simulation modelling for health policy case studies (alcohol related harm, childhood obesity prevention, diabetes in pregnancy), and their perceptions of the value and efficacy of this method in an applied health sector context.

Methods: Semi-structured interviews were conducted with end-user participants from three participatory simulation modelling case studies in Australian real-world policy settings. Interviewees were employees of government agencies with jurisdiction over policy and program decisions and were purposively selected to include perspectives at different stages of model development.

Results: The 'co-production' aspect of the participatory approach was highly valued. It was reported as an essential component of building understanding of the modelling process, and thus trust in the model and its outputs as a decision-support tool. The unique benefits of simulation modelling included its capacity to explore interactions of risk factors and combined interventions, and the impact of scaling up interventions. Participants also valued simulating new interventions prior to implementation in the real world, and the comprehensive mapping of evidence and its gaps to prioritise future research. The participatory aspect of simulation modelling was time and resource intensive and therefore most suited to high priority complex topics with contested options for intervening.

Conclusion: These findings highlight the value of a participatory approach to dynamic simulation modelling to support its utility in applied health policy settings.

Keywords: Dynamic simulation modelling, Participatory modelling, Public health, Prevention policy, Diabetes in pregnancy, Gestational diabetes, Alcohol, Childhood obesity, Decision support, Multimethod modelling, Hybrid modelling, Knowledge mobilisation

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Background

Evidence informed decisions are essential to ensure that health policies provide cost effective and high-quality programs and services. However, barriers to the use of evidence to inform decision making remain [1]. Policy and program decision making processes are frequently non-linear and iterative. They are influenced by a range of factors, that compete with research evidence, such as the political environment, budget and resource constraints, and public perceptions of the value of policy options being considered, [1–6]. Evidence provided to policy makers needs to be in a form that is useful and relevant in this context [4, 7, 8]. Policy makers require synthesised and contextualised evidence that establishes the need for a policy response, compares and prioritises the evidence, answer hypothetical questions about the potential outcomes of policy and intervention options, and demonstrates cost-effectiveness of interventions [4, 9].

Research evidence for the prevention of chronic disease often points to a large range of contributing risk factors, including broader social determinants of health [10, 11]. Without tools to make sense of this complex array of evidence it is difficult to understand the dynamic interactions of risk factors and interventions [12], potentially leading to the adoption of approaches that may seem intuitive but fail to deliver reductions in disease burden at the population level or lead to unintended consequences [12, 13].

Systems science methods are well suited to public health and disease prevention questions because the approach takes into account the complexity, context, dynamic nature, and system-wide behaviour associated with public health issues [14]. Dynamic simulation models recreate complex systems and human behaviours as computer simulations. They can be used to synthesise evidence, answer hypothetical questions about the potential outcomes of policy and intervention options, and inform decision making [13, 15].

Incorporating a participatory process into the development of dynamic simulation models can facilitate the exploration of how multiple environmental factors, individual risk profiles and interventions interact [16, 17]. It can be used to enhance knowledge about the focus issue from the perspective of different disciplines, explore conflicting views, test potential solutions to complex issues and even to develop a shared language about the issue which can support ongoing communication [18–21]. The participatory model development process involves an in-depth, interdisciplinary deliberation and co-production process to initially map the causal pathways for the focus issue, and the mechanisms by which interventions have an effect on outcomes [19]. A range of evidence is synthesised, including empirical evidence, expert and practice based knowledge, and theory, to develop, quantify and test a simulation model of the issue [13, 18, 19, 22, 23]. The resulting dynamic simulation model can be used as a decision support tool to explore complex problems such as the prevention of chronic disease and simulate proposed policy and practice scenarios [13, 23].

Advances in technology have led to increased adoption of tools and methods aimed at integrating diverse evidence sources to inform decision making [13, 17]. However, rigorous assessment of the value and utility of these methods and tools is required if their adoption to support evidence informed policy and planning in the health sector is to be achieved. The uptake of dynamic simulation modelling in health has lagged behind other sectors, such as the environmental sciences and business industry [24], and it has been argued that this has, at least in part, been due to limited engagement with stakeholders and involvement of end-users in health-related simulation model development [13, 21, 24, 25]. This has also impacted on the implementation of model findings [24, 26] and led to a reluctance among “non-researchers” to use models as decision support tools [21, 24]. Where policy makers have been included in the simulation modelling process there has been limited examination of their experience; e.g. perspectives on the utility of the model, learning relating to the development and use of the model, or commitment to implement the model findings [13, 27, 28].

This paper reports on the experience of end-user decision makers, including senior policy makers and health service providers, who participated in three participatory simulation modelling case studies in Australian health policy settings. We report on their perceptions of the value and efficacy of this method as a tool for evidence synthesis and decision support in applied health sector policy and service planning contexts.

Methods

Context

The Australian Prevention Partnership Centre (http://preventioncentre.org.au/), in collaboration with jurisdictional governments have pioneered the co-production of sophisticated, multiscale dynamic simulation models to support health policy and practice decisions [29–33]. In developing these models, researchers partnered with health departments, clinicians and regional planners in collaboration with a multidisciplinary group of stakeholders using a participatory process [32, 33]. This research is based on three of these case studies described briefly below (Table 1). The case studies and participatory processes are described more fully elsewhere [34].

Procedure

The evaluation of the participatory modelling process was informed by the Challenge and Reconstruct Learning
The CHaRL framework involves assessing formalised and facilitated learning among decision makers and decision influencers at varied policy levels in deliberative processes. The key component of the CHaRL framework is the change in perception or belief about assumed causality within the system. The change in perceptions or beliefs can be measured using individual value and attitude/belief orientations recorded by participants before and after the modelling process [35].

The three modelling case studies were chosen to allow for data to be collected at all stages of the participatory process. The model development process had been finalised in two of the case studies, and data were also collected on the use of models to inform decision making. Data collections are described below.

For data triangulation, key informant interviews and participant observation during workshops (field notes kept by lead author LF) were used to collect information across the three case studies as outlined below.

1. Pre-workshop interviews (Diabetes in Pregnancy project \( n = 5 \))
2. Post workshop interviews (all case studies \( n = 7 \))
3. Workshop observations (all case studies, total workshops \( n = 9 \))

Qualitative analysis was conducted for the transcripts from the semi-structured interviews, and the observation field notes. The data collection and analysis methods are described in detail below.

**Participants and sampling**

Purposeful sampling was used for each case study to recruit participants with a range of expertise, including providing or planning health services, undertaking research or developing policy for the issue in focus. Pre-process interviews in the DIP case study occurred with six participants that included senior clinical and public health policy decision makers.

Sampling for the post workshop interviews \( (n = 7) \) ensured representation across the three case studies to include perspectives from case studies with models at different stages of development and project roles, (e.g. facilitator or participant), or policy making roles, (e.g. clinical, policy, or public health executive). Some interviewees had participated in more than one case study. Focus for selection in the post-process interviews was on the setting where policy change decisions would occur i.e. interviews were with participants who were employed within government agencies with jurisdiction over the relevant policy decisions. Recruitment of interviewees continued until saturation was reached for the main themes and categories.

**Data collection**

Participant experiences and perspectives across all three case studies were collected in semi-structured interviews with key informants focusing on their personal response to the participatory modelling process and perceptions of the:

- Value of simulation modelling as policy decision support tool

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**Table 1** Description of dynamic simulation modelling case studies and context

<table>
<thead>
<tr>
<th>Topic area</th>
<th>Type of model</th>
<th>Model development period</th>
<th>Context</th>
<th>Application to decision making</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reduction of alcohol-related harms (Alcohol)</td>
<td>Agent based model</td>
<td>2015–2016</td>
<td>Alcohol misuse is an important public health issue for which there are complex causal mechanisms and contested intervention options. This model was developed to inform jurisdictional government strategies for reducing alcohol-related harms.</td>
<td>The model represents the heterogeneity of alcohol use across the population, how the dynamics of drinking behaviours vary across the life course, the harms, both short and long term, that arise from alcohol use, and the differential effects of interventions across subgroups in the population.</td>
</tr>
<tr>
<td>Reduction of childhood overweight and obesity (Obesity)</td>
<td>System dynamics model</td>
<td>2016</td>
<td>In 2015, an Australian State Premier set an ambitious target to reduce childhood overweight and obesity in children by 5% over 10 years. It was predicted that additional strategies, or combinations of strategies, would be required to achieve the Premier’s target. Decision makers were presented with the challenge of determining where best to focus resources and efforts.</td>
<td>The model explores the complex issue of child overweight and obesity, incorporates existing programs and tests the likely impacts of a range of policies and programs. It forecasts the combination of interventions required to achieve the Premier’s target.</td>
</tr>
<tr>
<td>Prevention and management of Diabetes in Pregnancy (DIP)</td>
<td>Hybrid model (system dynamics, agent based modelling and discrete event simulation)</td>
<td>2016–2017</td>
<td>Diabetes in pregnancy is increasing in Australia and internationally and exploration of new strategies to prevent and manage the condition is needed. The model considers the short, and long-term implications of the increasing prevalence of both DIP and associated risk factors.</td>
<td>The model focuses on the development of Diabetes in Pregnancy (DIP) from the perspective of the individual. Prevention interventions were prioritised in the model as delays in the development of diabetes will potentially result in reduction in the longer-term burden of disease and costs to the health system. However, the model can also explore clinical interventions. Health service utilisation has been captured in the model enabling it to explore the resource impact of model of care scenarios.</td>
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strengths and limitations of the method and intention to use simulation modelling in the future
○ perceived enablers and barriers to the use of simulation modelling

Interviews were conducted face to face where possible \( (n = 5) \), however telephone and web conferencing interviews \( (n = 8) \) were also used to allow interviews with participants in distant locations. Interviews across formats were of comparable length (ranging from 30 to 60 min) and depth of exploration of the issues discussed. Interviews were conducted by the lead author and a research officer (EO - two pre-workshop interviews, see acknowledgements). Indicative questions for pre- and post- interviews are presented in Additional file 1. Field notes were based on observations of the participatory workshops and debriefing discussions between the authors and research officers (EO, NR and CW, see acknowledgements).

Data coding and analysis
Interviews were audio recorded and transcribed using a professional transcription company, checked for quality and de-identified. The transcriptions were coded and analysed by LF. The analysis was guided by grounded theory principles [36, 37]. An iterative process of descriptive coding and analytical memos was used to develop themes and conceptual categories, explore their inter-relationships, and to triangulate insights from the interview and field note data. The progressive analysis was iteratively reviewed by JA and LR and further revised as new data was incorporated. Analytic memos written by LF were also shared with JA and LR to facilitate the analysis review process.

Results
Table 2 provides an indication of the data analysed for each results section.

Pre-modelling perceptions of evidence use in decision making
Prior to the commencement of the participatory modelling process, respondents consistently emphasised the importance of evidence-informed decision making however, they identified challenges relating to the availability, applicability, persuasiveness, timeliness and accessibility of evidence to inform decision making.

Lack of evidence was described as the “biggest challenge” in circumstances where no policy relevant evidence existed, or the available evidence was not sufficiently robust to inform health policy or service decisions. In situations where rigorous studies like randomised controlled trials were not likely to be conducted due to ethical, practical, or funding constraints, there was a clear view that an ongoing lack of evidence was unlikely to be resolved using traditional methods of research. Further, when evidence was available, it was not necessarily applicable to local health service or population context, making it difficult to use for local policy decisions.

Evidence was reported to be only one of many competing factors involved in decision making and respondents described other factors as more powerful decision influencers. Evidence needed to be convincing to compete with these other influences, including the input of advocacy groups, incentives and restrictions built into funding models and internal (organisational) and external (political and community) competition for resources.

It was also reported that the use of evidence in policy decision making continued to be limited by poor accessibility. Thus, research needed to be communicated in more accessible ways to policy makers who vary in their level of expertise in interpreting and applying research findings. Policy makers and program planners often prioritised government reports and statistics, and non-government organisation reports to inform decisions as they used more accessible language and were free to access. Some policy makers were unable to access journal articles behind a “pay wall”. It was widely reported that there was little time in policy settings to explore evidence in detail or to conduct research. In this context, respondents consistently identified that there was significant room for improvement in the way evidence was translated and used to inform policy and practice decisions. As a result, respondents were
motivated to explore new methods, such as participatory dynamic simulation modelling, to see how they could improve and increase the use of evidence in their applied settings.

**Experiences of the participatory simulation modelling process**

As identified in Table 2, this section is based on post-modelling interviews across the Diabetes in Pregnancy, Alcohol and Childhood overweight and obesity case studies.

**Motivations for participating**

Due to the significant time investment involved in participatory dynamic simulation model development, the opportunity costs and likely outcomes from the modelling projects were significant factors in policy makers’ decision to participate in the process. Targeted and tailored engagement, facilitated by a trusted domain expert, with key participants in the planning phase of the project was important to justify the benefits of participating and ensure that from the policy makers’ perspective, the topic was high priority, of professional interest, complex and had contested options for intervening. Across the modelling case studies, many interviewees reported that they explicitly considered the opportunity cost of participating in the dynamic simulation modelling project before deciding to become involved. They went through a process of weighing up whether the likely outcomes from the modelling projects would be worthwhile given the significant time commitment required.

Commonly reported reasons for agreeing to participate included: the person’s professional involvement and expertise in the topic being modelled, the trusted relationship with either the modelling team or the lead domain expert involved in the project, curiosity about dynamic simulation modelling and participatory methods, and aspirations to improve the use of evidence in decision making. These are explored further below. A few participants were directed to participate by their organisation.

The choice of focus topic to be modelled was a key criterion for agreeing to join the participatory dynamic simulation modelling project. The topic needed to be an important local priority of current professional and or organisational concern with complex causal risk factors and need for policy or programme response. In order to justify the commitment to participate the topic needed to be complex with different perspectives of which causal factors and exposures were important, different intervention options to decide between, contested views about what works and what doesn’t, and where the combined impact of interventions was unknown.

Trust in and familiarity with the project team were commonly identified as important factors influencing the decision to participate. Most interviewees embarked on the project with little or no experience of dynamic simulation modelling, however they had trust in the modelling team or domain expert who initially approached them, and this facilitated their decision to participate.

“It’s having known [facilitator] for a long time through the [work area], and our work with the [topic X]. [Facilitator] knowing that part of my research was based about [topic X] disease, and various other things I’ve been looking at.” (Senior clinician)

An interest in learning new methods to facilitate evidence informed decisions in public health was commonly identified as a reason to participate in the case studies.

“I was interested in processes for better being able to inform and educate the policy making process” (Public health executive)

“It’s an incredibly useful policy tool if it’s done appropriately with the right people asking the right questions. It’s a very powerful tool.” (Public health executive)

Goals for participating in the case studies included learning about the process of developing a simulation model and how it can be used to inform decision making. The participatory approach was highly valued by most interviewees as it provided an opportunity to combine their expertise with the expertise of the modelling team to produce an innovative decision support tool.

**Engaging in the participatory activities**

Workshop participants engaged in a range of large and small group activities to collaboratively develop a conceptual map of the problem, prioritise and map the impact of interventions to model architecture and identify data and evidence to incorporate into (or parameterise) the models. These activities have been described in detail elsewhere [34].

**Collaboration and co-production**

Collaboration and co-production were identified by participants in these case studies as the unique and highly valued aspect of the participatory dynamic simulation model development. The participatory approach facilitated the contribution and synthesis of a significant knowledge base and was critical to eliciting and negotiating priority causal factors, exposures and interventions to be represented in the model. The process of contributing expertise and then explicitly seeing how it was
used in the model were important factors in facilitating engagement and a sense of ownership in the model.

“The session with lots of string and sticky notes and things on the board, it looked a mess and going away thinking, “How are they going to use all that?” But I actually was surprised, pleasantly surprised, at how that was actually used to inform the development of the model, and it really was.” (Senior clinician)

The contribution of considerable knowledge and diverse expertise of participants was consistently identified as important. Many respondents commented that they were surprised at the willingness of participants to contribute their experience, ideas and knowledge to educate the modelling team about the issue and guide the model development.

“I think the participatory approach, you're having people in the room that have accumulated knowledge, expertise in the area over quite a number of years, actually brings a lot of knowledge into that room, and it's not possible for one or three or five people to do the literature searches and understand all the information” (Senior clinician)

Respondents also noted that people “put their egos aside” during the workshops as the interdisciplinary and co-production approach meant that participants were learning from each other. The content expert participants learned about dynamic simulation modelling and the modellers learned about the priority public health issue being modelled.

While being time consuming and personally challenging for some respondents to engage in; the interactive activities and group discussions were viewed as critical to eliciting and negotiating priority causal factors, exposures and interventions to be represented in the model. Many respondents noted that the same outcome could not be achieved through one on one discussions as the inclusion of a diverse range of participant perspectives was important to guide the model development.

“By having everybody in the same room, you got to really be able to relate to everybody’s little piece of the puzzle. I think if you had just done that with individuals, you wouldn’t have got the model that you’ve developed.” (Senior clinician)

The lack of consumer involvement in the modelling case studies described in this paper was identified as a gap in representation. However, respondents also noted that finding consumer representatives and strategies to realise the benefits of consumer input can be challenging in some circumstances e.g. when the discussion is focused on highly specialised biological causal mechanisms of disease development and progression.

Some respondents reported that they initially perceived the workshop activities to support active participation as less rigorous or evidence-based than they had expected. For example, that some participants were relying on their opinion rather than evidence, were advocating for causes or had a priori preferences for particular actions and thus a potentially biased view of the evidence. A couple of participants noted that they observed differential engagement by other participants with the activities and “people not taking it as seriously as perhaps they should have”. However, most of these respondents also noted that as the model development process progressed they were reassured by the use of good data and evidence to inform the model and to test hypotheses that came from expert opinion.

“I was a bit sceptical of that process, and in terms of input given that it’s meant to be evidence-based inputs through that conceptual mapping of the bits of paper and string, and plaster, ... I expected it to be more rigorous, but I learned by doing it, that really it was more about informing the modelling team in terms of logic, structure and models, and then they went away and found the evidence, if you like, to support the link of this, and of course all pathways, and the association pathways.” (Public health executive)

Contributing expertise and then explicitly seeing how it was used in the model were important workshop activities. The process of unfurling the model by describing the logic and architecture and relating it to discussions at previous workshops was highly regarded by participants. The model was viewed as “the fruits of their labour” and a sense of innovation and excitement was expressed by many respondents.

Two key roles were identified as facilitating engagement in these case studies. The first was having a trusted domain expert for each project who was a well-respected authority on the focus issue and played a lead role in the project planning and workshop facilitation. The domain expert facilitated the approaches to key stakeholders, increasing the likelihood of their agreement to participate, and was a known colleague to promote engagement in the participatory process. The second “translator” role was identified by respondents who were more closely involved in facilitating workshops and working with participants. This role involved both explaining the policy context, e.g. current policy priorities and interventions, and contextualising the data, e.g. explaining data collection methods, representativeness and limitations, for
the modelling team and conversely translating the model requirements and development process to the workshop participants.

Having an embedded policy officer, who along with the lead domain expert, played the role of translator working within the modelling team ensured that the model was policy relevant, well understood and used. A key aspect of this was being able to run model scenarios independently of the modelling team to provide timely responses to policy questions (e.g. switching interventions on and off and/or modifying parameters such as reach and effectiveness and producing results).

**Participant learning through group model building**

Respondents reported that the participatory process worked well in facilitating interactions and contributing expertise. The process also provided an opportunity for the expert participants to be exposed to multiple perspectives and frameworks for viewing the problem but was not identified as resulting in individual learning about the focus issue. A commonly cited reason for this was the selection of participants who were experts in the focus issue, many of whom had dedicated their career to working on it. They came to the process with a good understanding of the different perspectives and complex causal relationships e.g. costs, drivers, and evidence-based strategies.

“I think it gave people a broad picture and they recognised where everybody’s different areas fit. But whether it actually changed how they link things together, I don’t know.” (Senior clinician)

However, all respondents reported that they learned about the potential of dynamic simulation modelling to support decision making and the process of developing simulation models through the participatory process.

“What we learned is the potential value of developing a simulation model. Talking to the others, everyone was quite impressed by where it’s got to, so the exchange and knowledge between the different discipline areas, I guess, was the most positive. ... I don’t think you’ve changed our views very much on [topic X]. ” (Senior clinician)

Interviewees identified that the participatory modelling process and model outputs allowed participants to develop insights into the interrelationships between causal factors and emergent behaviour of the system i.e. “If you change your practice how does that impact on other parts of the system”; explore the combined impact and interaction between interventions; and explore new and untested interventions in the model prior to them being implemented in the real world. These important learning outcomes and how they can be used to facilitate policy conversations are discussed in more detail below.

“That’s I think what the benefit of the model will be, is that it can show to people if you change one thing here, what’s it going to change for everything else.” (Senior clinician)

**How dynamic simulation models facilitate the use of evidence to inform decision making**

The following analysis is primarily based on responses regarding the two simulation models that were finalised at the time of writing (Alcohol and Childhood obesity). The exception to this is the discussion regarding the identification of evidence gaps which includes responses from all case studies.

**Participatory approach and trust in the model as a decision support tool**

The participatory approach used in the model development engaged respondents actively in the process and increased their familiarity and trust in the model outputs. Respondents reported an increased sense of ownership and interest with these models compared with other modelling projects that had not used a participatory approach.

“...there were times where I’m thinking, “Really? We know all this stuff, and do we have to spend all this time?” But you realise that that’s the nature of it, that if we didn’t go through those processes there wouldn’t be the same trustworthiness, or people wouldn’t trust it as much, they’d be questioning it.” (Public health executive)

Respondents valued that the model was transparent about “what’s under the hood”. They noted that they understood the logic of the model and the evidence used to inform it and this increased their trust and willingness to use the model to facilitate policy and program planning conversations.

Model outputs were described as involving a bit of “science and magic” or “computer magic” that was engaging and useful, however concern was expressed that model outputs could be interpreted by people not involved in the participatory process as reality rather than as a decision support tool to compare alternative strategies. Respondents emphasised their awareness of the limitations of the models, the need to ensure that model outputs were interpreted appropriately and for end-users to be aware of the assumptions and limitations of the evidence used in the models.
Many respondents discussed the importance of ensuring that the participant group included representatives for the policy and intervention options being considered in the models. For example, if regulatory interventions were being considered then stakeholders who have regulatory oversight for the issue should be included in the participatory process to increase trust and reduce the risk of resistance from these stakeholders to using the model to support decision making.

**Using the model to synthesise and facilitate use of evidence in policy conversations**

The models were valued as communication tools. They were viewed as giving credibility to the argument for prevention interventions. The ability to manipulate policy levers to switch interventions on and off or to modify the reach and effectiveness of interventions and then observe the impact on outcomes of interest were frequently identified as providing an important evidence base to support policy and planning conversations. For example, model outputs were used to demonstrate the impact of current programs and reinforce with local service providers the importance of maximising reach and effectiveness of their current programs and to inform planning decisions by forecasting the impact of local interventions if scaled up to the population level.

“Well, it’s a neat graphical tool that assists the presentation of data on effectiveness of programmes. It’s quite neat the way you can say, “Well, if we do programme X, this is the result we’re going to achieve on this variable” It’s nice to be able to present a dynamic model like that. In that sense, people engage with it.” (Public health executive)

Dynamic simulation modelling was viewed by most respondents as offering unique benefits, including the ability to investigate the impact of intervention combinations and interactions on outcomes, forecasting delays in intervention effects and therefore informing expectations for performance monitoring of program implementation and providing a tool to test the potential impact of new ‘bold’ innovative interventions before they were rolled out in the real world.

“I think it’s the learning, and the benefits of the modelling, and the things it can do that we can’t do from normal longitudinal studies or trials, qualitative work, it is impossible to do what the model does, but that’s the point of benefit.” (Public health executive)

The ability to dynamically interact with the model to develop insights into which programs needed to be enhanced, which gaps needed to be filled and which target groups to focus on were identified as important benefits derived from dynamic simulation modelling. This dynamic interaction facilitated policy discussions for local health program planning and engagement with other agencies. The model outputs were used to explore which interventions with which target groups would yield bigger benefits in the long term.

Many respondents noted that the interaction with and communication of model insights were areas requiring further development. The development of communication tools, such as interactive user interface tools and presentations that could be easily adapted to different audiences, were viewed as critical to facilitate the use of the models in policy and program discussions to inform decision making.

Due to delays in model development, the intended presentation of one of the models to a broader range of stakeholders was unable to occur within the anticipated project timeline. A small number of respondents identified this as an important missed opportunity from a co-production and participatory research perspective that undermined the application of the model findings to policy decisions.

**Model maturing process**

The dynamic simulation models were commonly viewed as tools that would mature over time. The maturing process was described in terms of continuously refining the inputs, assumptions and parameters used in the model as new knowledge and evidence became available; building on the model when new policy questions arose and maturing the methods used to communicate model outputs such as user interfaces and presentation of results. The allocation of sufficient time to familiarise participants with the use of the model, train “super users” and socialise the models with broader stakeholder groups were identified as important elements to support the communication of model outputs and increase their use in decision making.

Identifying and prioritising gaps in the existing evidence base was an important component of the model maturation process. The interactive discussions regarding the causal factors and impact of interventions for each focus topic facilitated the identification, clarification and prioritisation of gaps in current knowledge and evidence and could be used to guide future research.

**Discussion**

The aim of this research was to explore the experience of end-user decision makers who participated in participatory simulation modelling projects and the perceived value and efficacy of this method as an evidence synthesis and decision support method in an applied health sector context from their perspective. Overall, the participatory approach used to develop the dynamic
simulation models was valued by these participants, including both senior clinical experts and public health executives, and was an essential process for building trust in the model as a decision support tool. The collaborative, co-production principles used to develop the simulation models facilitated participant understanding of the logic and evidence used in the models and increased their sense of ownership and willingness to use the models for decision making. The models were broadly viewed as useful and convincing communication tools to facilitate policy discussions. The unique benefits of the models included the ability to explore the interaction of risk factors and causal mechanisms; the interaction and combination of public health interventions; the impact of scaling up the reach and effectiveness of existing programs and the impact of new and untested interventions in simulation before they were implemented in the real world. The participatory process was time consuming, changeable and resource intensive. Therefore, complex issues with contested options for intervening were more likely to be viewed as worthwhile for the significant time investment required for participatory model development.

Motivations for participating
Participating in research activities, including participatory modelling, requires significant time investment for stakeholders and it is important to consider the factors that motivate their participation when planning research [38]. Studies focusing on stakeholder inclusion in health research, have often been from the perspective of the researchers. Factors such as the difficulty of finding stakeholders with the right skills and knowledge who are interested and available to participate or the difficulty of dedicating time to stakeholder engagement in a context where it isn’t measured and may not be valued [39, 40], have been the focus rather than the perspective of the stakeholders and their motivations for becoming involved. The case studies reported here provide insight into the motivations from the stakeholder perspective. Targeted recruitment of stakeholders with a professional involvement and expertise in the topic being modelled, facilitated by a trusted relationship with either the modelling team or a lead domain expert involved in the project were found in these case studies to be important and successful strategies to motivate policy makers to invest their time.

Motivations for community groups to engage in participatory modelling have been found to be highest when the problem needs to be solved with some urgency and existing approaches have already been tried and failed or known to be unsuitable for the problem at hand [16]. In the complex and contested context of the priority focus issues for the case studies reported here, policy makers and health service providers were motivated to engage in dynamic simulation modelling as a new method for evidence synthesis and exploring “what if” scenarios for policy analysis, particularly with a familiar and trusted team.

Collaboration and co-production were key elements valued in the participatory approach
Relationships and collaborations are frequently identified as critical factors in systems approaches [41, 42]. Participatory dynamic modelling provides a structured process to facilitate inter-disciplinary dialogues and co-production methods involving a range of participants, including end-user decision makers. Participatory modelling approaches aim to combine diverse perspectives to tackle the social complexity of problems and recognize that different types of knowledge contribute alternative and valuable perspectives to the problem discourse [18, 21, 23, 43]. Participants in the case studies reported in this paper viewed the participatory process as a valuable co-production approach to understand the focus issue from a system perspective, for example, enabling the consideration of how decisions made in one part of the health service, or indeed by other government departments, could impact on programs and services in another. The ability to combine the significant knowledge from multiple experts to guide the model development as a decision support tool was viewed as a unique benefit of the participatory process.

Participatory model development and validation has been shown to increase confidence that the model results were both valid and useful for the participants’ local context [19, 27, 44, 45]. Decision maker involvement in model development resulted in them being more likely to draw on the model’s outputs to inform decisions about priority interventions and policies [27, 43, 46]. The involvement of key stakeholders and decision makers in these case studies was identified as critical to developing trust in the use of the model to support decision making. Participants also noted the importance of ensuring that representatives of important stakeholder groups, such as consumers and relevant policy agencies, were included in model development process.

The domain expert and translator roles were identified in these case studies as important to facilitate engagement in the participatory process and use of the model to inform decision making. Similar roles have been identified in community based environmental modelling contexts [16, 45] as playing an important role liaising between the modelling team and stakeholders. The key elements for the translator role include being a member of the stakeholder community who can both identify with the needs and articulate them within a group model building session and has credibility in translating and conveying insights from the modelling process [16]. In
the health setting case studies reported here, it was important that the “translator” was embedded within the stakeholder organisation and facilitated the acceptance and use of the model to support policy discussions. Thompson et al. (2010) described the beneficial relationship between the translator and the modellers as the translators driving the modellers to integrate the participants’ requests and insights into the model, and the modellers driving the translators to introduce complex science and dynamic interrelationships to the stakeholders [45].

**Participant learning**

Simulation modelling aims to enhance knowledge of participants from the perspective of different disciplines and more thorough exploration of focus problems using systems science [21, 38]. The evaluation framework used to guide the design of this research focused on changes in perceptions about the assumed causality pathways in the system to assess participant learning [35]. Interviewees reported that the participatory process provided opportunity to be exposed to multiple perspectives, interact and contribute expertise, however they did not identify that they had learned about the causal pathways for the focus issue. Participants in the case studies reported here were long term experts in the focus issue, many of whom had dedicated their career to working on the issue, therefore they came to the process with a good understanding of the different perspectives and complex causal relationships and therefore may not have gained new knowledge through the participatory process. However, this finding is consistent with Rouwette et al. who found that participants in group model development processes experienced difficulty identifying their learning from these processes without specific prompting [19].

Participatory modelling processes can be characterised as social learning exercises [27], and the shifts in perceptions and learning that result can play out differently at the individual and group levels [47]. Participatory modelling involves the sharing of knowledge through group discussion, interactive activities and interactions with the model [27, 47]. Recent participatory modelling research in the environmental sciences has found measures of individual cognitive change to be informative, but unable to reflect how the group evolves in their capacity to make decisions informed by the model [47].

All respondents in these case studies reported that they learned about the potential of dynamic simulation modelling to explore complex interrelationships for the focus issue and emergent behaviour of the system to support decision making and the process of developing simulation models through the participatory process. This was identified as an important learning outcome and is consistent with the key benefit of participatory modelling that people learn how to model better, and with better modelling comes better insights to improving the system [16]. To increase the sophistication and effectiveness of participatory modelling facilitation methods, better understanding about how different stakeholder groups evolve the knowledge and skills to work with decision support tools like simulation models to plan policy and programs will be an important area of future research.

**Intentions to use dynamic simulation modelling to inform decision making**

Stakeholders are more likely to trust a model if they have been involved in informing and grounding the understanding captured in the model, they understand it and they feel ownership [18, 48, 49]. The participatory approach used in these case studies engaged policy decision makers actively in the model development process which fostered their interest and trust in the model outputs. Making the model understandable and accessible to stakeholders has been identified as an important principle of participatory modelling [49] and was a key benefit commonly identified across these case studies. Participants understood the logic of the model and the evidence used to inform it and this transparency increased their trust and willingness to use the model to facilitate policy and program planning conversations.

Ensuring stakeholder representation for the policy and intervention options being considered in the models was identified as a key consideration for project planning to realise the benefits of the participatory process. Participatory modelling has been shown to successfully facilitate productive problem solving across agency boundaries by providing a neutral platform for discussion and scenario testing to explore a broad range of options and solutions [16, 18, 48, 50]. The participatory process can bring key stakeholders from different agencies responsible for implementing policy and programs together to explore and test “what if” policy scenarios and explore which interventions represent the most effective leverage points in the local context and therefore align and mobilise prevention efforts of community stakeholders [51].

The finalised models in the case studies reported on here are being used as credible, communication tools to synthesise and facilitate use of evidence in policy conversations regarding prevention interventions. The models capture the complexity of real-world policy questions and provide a dynamic analytic tool that can overcome the limitations of traditional analysis methods [52, 53]. The ability to manipulate policy levers to determine impact of interventions on health outcomes (including the ability to test alternative reach, adoption, and effect scenarios) provided an important evidence base to support
health policy and planning conversations and develop realistic insights into the impact of enhancing or expanding existing interventions and identify priority gaps and areas of need.

The unique benefits offered by participatory dynamic simulation modelling have previously been identified from the perspective of modelling teams. For example, helping stakeholders understand how multiple variables, factors, and interventions interact, being able to test the potential impact of programs and policies in the “safety” of a virtual environment before they are implemented, saving time, effort, costs and resources, guiding and prioritising data collection and facilitating discussions among stakeholders [49]. The importance of these benefits to end-user decision makers was confirmed by these case studies with participants identifying that the ability to dynamically investigate the impact of intervention combinations and interactions on outcomes, forecast delays in intervention effects and test the potential impact of new innovative interventions before they were rolled out in the real world were valued and utilised in policy and program decision making discussions. The benefits of participatory dynamic simulation modelling methods identified by the policy makers are summarised below. These are benefits that dynamic modelling provides over other forms of knowledge mobilisation [34, 23] from the perspective of end-users of these models as decision support tools.

**Summary - unique benefits of participatory dynamic simulation modelling identified by policy makers**

- Increasing familiarity and trust in the model by use of participatory, co-production methods.
- Synthesising diverse evidence in an interactive and dynamic decision support tool that facilitates the exploration of “what if” scenarios and policy options.
- Exploring the combination and interaction of interventions to develop insights into which interventions to enhance, which gaps to fill and which target groups to focus on.
- Exploring the impact of new and untested interventions prior to implementation in real world.
- Forecasting delays in intervention effects to guide implementation monitoring.
- Identifying and prioritising evidence gaps.

**Implementation challenges and future work**

The co-production and participatory approaches to model development were time consuming, unpredictable and messy, making them more suitable for longer term planning in the first instance. However, once the models were developed they could be used for short-turnaround policy advice. For these case studies, the intended presentation of one of the finished models to a broader range of stakeholders did not occur due to timing and resource constraints. This was as an important missed opportunity from a co-production and participatory research perspective that undermined the application of the model findings to policy decisions.

The refinement of communication tools, such as interactive user interface tools and presentations that could be easily adapted to different audiences, will be critical to facilitate the use of the models in policy and program discussions to inform decision making.

Supporting good understanding of the model development process, for example, how decisions are made regarding the methods used to represent causal mechanisms dynamically, where to add complexity, where to simplify the model and how to deal with and communicate uncertainty in the models are important ongoing challenges. These are the subject of future work in this program of research on participatory modelling.

The dynamic simulation models are tools that mature over time with the inputs, assumptions and parameters being continuously refined and updated as new knowledge and evidence become available. The identification and prioritisation of gaps in the existing evidence base was facilitated by the interactive discussions regarding the causal factors and impact of interventions for each focus topic and used to guide future research priorities.

Key implementation strategies are summarised below. The strategies cover practical aspects of the workshop facilitation and important aspects of communication and engagement with participants before, during and after the model development workshops. It is important to acknowledge that these strategies are not intended to be prescriptive. Each modelling has project has unique requirements, stakeholders and policy context, and therefore being flexible and responsive to project needs and stakeholder feedback is critical.

**Summary of implementation strategies for project phases**

**Key project roles**

*Domain expert* – well-respected authority on the focus issue who can play a lead role in the project planning and workshop facilitation.

*Translator* – person who can contextualise the policy environment and data for the modelling team and translate the model requirements and development process to the participants.

*Expert participants* – people with a range of expertise, including providing or planning health services, undertaking research or developing policy for the issue in focus.
**Dynamic simulation modeller** – person with computer programming and data analysis expertise in developing dynamic simulation models.

**Super-user** – person who learns to use the model interface and apply it to explore policy scenarios “in-house”. They are usually employed by the jurisdictional health department in analytic roles.

**Planning phase**

1. Use a domain expert to facilitate engagement and trust.
2. Engage a broad range of participants to provide diverse and representative perspectives. Important to include “domain expert”, “translator”, “clinical experts”, “modeler”, “policymakers”, “super users”
3. Provide background briefing material about the participatory process prior to the workshops to enable participants to prepare and do “pre-thinking”
4. Increase motivation to participate by engaging with key stakeholders from lead agencies in the planning phase to ensure the focus topic is high priority and of professional interest. Complex issues with contested options for intervening are more likely to be viewed as worthwhile for the significant time investment required for participatory model development.
5. Wherever possible, book workshops and meetings well in advance to provide the best opportunity for a broad range of stakeholders to be able to attend.

**Participatory model development phase**

1. Use “translators” to facilitate the communication of technical concepts between the content experts and the modelling team.
2. Use intuitive and engaging activities and ensure that these are sufficiently prepared in advance. The activities used in these modelling case studies are described elsewhere [34].
3. Prioritise opportunities for participants to actively engage and interact with each other and hands-on model development activities over less interactive update sessions. Provide opportunities to have fulsome discussions about priority issues.
4. Have a clear agenda and keep to time, as much as possible, while maintaining flexibility to allow important discussions to continue or to move on from activities that are completed.
5. Use small group work where possible to increase active participation.
6. Choose venues with sufficient physical space and technical capacity.

**Communication outside workshops**

1. Maintain frequent communication with participants providing progress reports, answering questions, requesting advice and evidence.
2. Provide opportunities for direct interaction between key participants and the modelling team to refine the model scope and direction.
3. Identify where key issues remain for participants and work together to try and resolve them e.g. refining the definitions of categories or parameters used in the model.

**Using the model to inform decision making**

1. Be transparent about the logic, assumptions and parameters used in the model.
2. Use “translators” to facilitate ongoing interaction with the model and communication of model outputs to stakeholders.
3. Ensure that time is provided to socialise the model with a broader stakeholder group who were not involved in the participatory process.
4. Develop simple, clear and concise key messages about insights from the model
5. Develop associated tools to facilitate communication e.g. an intuitive and interactive user interface and adaptable presentations to suit a variety of audiences.

**Limitations**

Two of the three models developed in these case studies were finalised at the time of the interviews. The participant perspectives of the utility of participatory dynamic simulation to inform decision making was thus limited to these two case studies. The perspectives included in this analysis were limited to participants employed by government agencies with jurisdiction over many of the policy and program decisions relevant to the focus topics being modelled in these case studies. Their perspectives may vary from those of other participants in the case studies, for example academic researchers or representatives from non-government agencies. Decision maker’s views of different methods of dynamic simulation modelling, e.g. system dynamics vs agent based modelling, will be an important issue to explore in future research as decision makers develop and broaden their experience of different forms of modelling.

The lack of consumer representation in these case studies is a limitation. The development of strategies to realise the benefits of consumer involvement in participatory dynamic simulation modelling to inform health policy decisions is an important area for future focus.
Conclusion
The case studies reported here have provided new insights into the experience of engaging in participatory dynamic simulation modelling from the perspectives of the end-user policy makers and senior clinicians with decision making roles in Australian jurisdictional health departments. The participatory, co-production process was viewed as an essential approach to ensure the dynamic simulation models incorporated the best available knowledge and evidence for the focus issue and that the models were well understood or “transparent” to build trust in the model as a decision support tool for policy discussions. The unique benefits of the dynamic simulation models included being able to synthesise diverse evidence; explore the combination and interaction of risk factors and interventions; explore the impact of new and untested interventions in silico; and identify evidence gaps to prioritise for future research. Given the commitment of time and resources to the participatory model development process, it was important to ensure that the topic justified the investment i.e. It was a high local priority, complex and had contested options for intervening. Engaging domain experts and people to work as “translators” from within the stakeholder organisation were important to facilitate engagement in the process and use of the models as policy decision support tools. Participatory modelling processes are more suitable for longer term planning in the first instance (prior to the model being developed), however are responsive to short-turnaround policy advice once developed as a decision support tool. The ongoing refinement of model development workshop activities and communication tools to support the application of model findings to policy decisions will be important foci for future research on these methods.

Additional file

Additional file 1: Indicative questions for pre-modelling workshop interviews. Indicative questions for post-modelling semi structured interviews. Interview scripts and questions. (DOCX 16 kb)

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- CRN top-up scholarship for supervision travel expenses

Availability of data and materials
The datasets generated and analysed during the current study are not publicly available as they contain information that may identify individual interviewees.

Authors’ contributions
LF, LR, JA, GM and PK were involved in the planning for this study. Interview analyses were conducted by LF, LR and JA. LF, LR and JA conceptualised the manuscript and LF wrote the first draft. All authors have made important intellectual contributions to multiple draft revisions. All authors read and approved the final manuscript.

Ethics approval and consent to participate
This study was reviewed and approved as low risk by the ACT Health Human Research Ethics Committee (ACTHLR.15.150) and the University of Notre Dame Human Research Ethics Committee (0151195).

All participants gave individual written consent, were assured of confidentiality, and were free to withdraw from the study at any stage.

Consent for publication
Not applicable.

Competing interests
All authors were involved in conceptualising, planning and implementation of at least one case study described in this manuscript. PK and part LF salary was provided by ACT Health, who also part-funded the ACT model development. No other conflicts of interest to declare.

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Chapter 7: Results Part 4: ‘Turning the tide’ on diabetes in pregnancy: Insights from advanced dynamic simulation modelling

This chapter presents the model developed for the primary case study focusing on diabetes in pregnancy (DIP) and reports on the model findings. These results are presented using three methods of communication: an academic manuscript for publication as a journal article, communication products that I developed and used to disseminate insights arising from the model to decision makers within the ACT Health service, and some technical supplementary information about the model itself.

Section 7.1 includes the journal manuscript describing the model development, structure and logic, and reporting on the insights from scenario testing (model findings) to inform decision making. The manuscript included in this chapter is currently undergoing external clinical review prior to journal submission. The communication products aimed at disseminating knowledge about both the project and the policy insights to a non-technical, policy audience are included in Section 7.2 and Appendix 9. These communication products included a plain language fact sheet about the project, an interactive dashboard and a podcast interview. The detailed documentation of the model structure and associated parameters, functions and data sources are included in Appendix 10. Some of this material was included in a technical paper on which I am a contributing co-author (as listed in the front of this thesis) that was led by the computer science members of the modelling team. The model documentation will also be published as supplementary material to the manuscript included in Section 7.1.
7.1. ‘Turning the tide’ on diabetes in pregnancy: Insights from advanced dynamic simulation modelling

**Authors** (order to be confirmed)

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Abstract

Introduction: Diabetes in pregnancy is rapidly increasing, with both short- and long-term risks to the health of women and their babies. Strategies to manage and prevent this condition are contested. Dynamic simulation models (DSM), developed using participatory methods, can be used to explore and test policy and program scenarios before they are implemented in the real world. This paper reports on the development and use of an advanced DSM to explore the impact of interventions on maternal weight status and incidence of diabetes in pregnancy (DIP, including gestational diabetes and pre-existing type 1 and type 2 diabetes).

Method: A consortium of experts worked collaboratively to develop a hybrid dynamic simulation model of diabetes in pregnancy comprising of integrated system dynamics, agent-based and discrete event model components. The structure and parameterisation of the model drew on a range of data sources. A series of scenarios comparing the impact of population-level and individually targeted prevention interventions were investigated to identify the combination of interventions that would deliver the greatest impacts.

Results: Population interventions promoting weight loss in early adulthood were found to be more effective (17.6% reduction in incidence by 2030) than targeted pre-pregnancy (5.2% reduction) and post-pregnancy (4.2% reduction) interventions in reducing the population incidence of DIP. Combining targeted interventions for high risk groups with population interventions promoting healthy weight in early adulthood was most effective for reducing DIP incidence (28.8% reduction by 2030). Scenarios exploring the impact of scaling up or scaling back interventions promoting healthy weight in childhood demonstrated significant changes in the selected outcome measure for glycemic regulation, insulin sensitivity, in the short term and diabetes in pregnancy in the long term.

Discussion: Population-level weight reduction interventions will be necessary to “turn the tide” on DIP. Weight reduction interventions targeting individuals identified as high risk, while beneficial for those individuals, did not significantly impact forecasted diabetes in pregnancy incidence rates. The importance of maintaining interventions promoting healthy weight in childhood was also demonstrated.
Keywords

Dynamic simulation modelling, evidence synthesis, public health policy, prevention policy, diabetes in pregnancy, gestational diabetes, multimethod modelling, hybrid modelling

Research in context

Evidence before this study: The rising prevalence of diabetes in pregnancy (DIP) is having a significant impact on health service demand and resources, yet the strategies for screening, diagnosing, preventing and managing DIP remain contested. Exploration of effective decision support tools is needed to guide evidence-informed policy and programs for this complex problem. We searched PubMed and Medline (OVID) databases from inception up to August 24, 2018 using the search terms: “dynamic simulation” “agent-based model” “system dynamics” with a combination of “diabetes” and “pregnancy” and “gestational diabetes”, without language restrictions. We identified only one Canadian study, by members of this modelling consortium, reporting on a dynamic simulation model exploring the intergenerational effects of DIP on the development of type 2 diabetes in an Indigenous population.

Added value of this study: This study brought together local, national and international researchers, clinicians and policy makers to collaboratively develop a multi-scale DSM for DIP capable of exploring the likely impact of policy and health service scenarios to prevent and manage DIP before they are implemented in the real world. The DSM incorporated the complex and interrelated causal factors that contribute to the development of DIP and explored intervention options and combinations, spanning the spectrum from clinical to population health interventions. For the first time, this study brings together the best available evidence and data with integrated DSM approaches to deliver insights for the challenging problem of DIP. Additionally, the unique tripartite structure of the model incorporates multiple integrated dynamic modelling methods. This represents unparalleled sophistication and allows representation of the problem of DIP at multiple integrated levels of abstraction (biological dynamics, individual-level behavioural dynamics and service dynamics) which accommodates a complex systems perspective, while also optimising model performance.
Implications of all the available evidence: The scenario testing capacity enabled by this multi-scale DSM advanced the findings from previous studies and provided guidance for decision making for the prevention of DIP. The scenarios reported in this paper confirmed the importance of public health interventions to maintain healthy weight status in childhood and support women to achieve healthy weight prior to pregnancy. These interventions were shown to improve insulin sensitivity and reduce the incidence of DIP in the modelled population.
Introduction

Diabetes in pregnancy (DIP), including gestational and pre-existing type 1 and 2 diabetes, is increasing both in Australia and internationally [1-3], challenging the capacity of health care services. The increase in DIP is directly associated with the increasing prevalence of risk factors including overweight, obesity, older maternal age and shifts in population demographics and ethnicities [2-4]. With increasing prevalence of risk factors, service providers report that women are more frequently presenting with more complex diabetes and obstetric care needs [5]. Additionally, diabetes during pregnancy increases risk for later chronic disease for the woman [3] and early onset of type 2 diabetes for her children [2, 6].

The available evidence for DIP policy and treatment planning is not definitive [1] and current challenges include: determining the timing and methods of screening, criteria for diagnosis, targets for treatment, resource allocation, identification and management of pre-existing diabetes during pregnancy, risk stratification, timing and type of prevention activities and individual differential effects of treatment [1, 7-9]. To address the increasing incidence of DIP, there have been increasing calls for upstream prevention activities to focus on lifestyle risk factors pre-conception rather than during or post-pregnancy [10-12]. These contested intervention options cross the spectrum from primary prevention approaches to highly specialised clinical management, which can be implemented independently or in combination and may be phased or implemented simultaneously. Sophisticated analytical tools are required to synthesise diverse evidence types across disciplines and support decision making.

Systems science methods provide decision makers with insights into how multiple causal pathways interact to generate the patterns of disease we see in the real world and how interventions modify those pathways [13, 14]. Dynamic simulation modelling (DSM) is a method that recreates complex systems and human behaviours as a computer, or mathematical, model. The models can answer ‘what if’ questions, via computer simulation, about the likely impacts over time of different policy and intervention options and their combinations [15, 16]. This is important for prevention policy and practice, where decision support tools must steer a course through the complexity of interactions that give rise to real-world public health problems, such as the rapid increase in DIP [15-17]. They are also useful for conditions with slow and variable development, like diabetes mellitus, that
involves underlying dynamics between physiological factors, such as the non-linear interrelationships between weight status, pregnancy, insulin sensitivity, insulin production and glycemic regulation [18-20]. These physiological variables interact and some are difficult to measure empirically, meaning that conditions like diabetes present significant challenges for traditional experimental methods [18, 21]. Analytic methods like dynamic modelling and simulation play an important role in improving understanding of the dynamics of disease progression [18, 22, 23]. The multi-scale, hybrid model reported in this paper builds on current understanding of glycemic regulation dynamics related to weight status and pregnancy [19, 20], leveraging existing peer-reviewed mathematical models of diabetes [18, 22, 23] and explores the dynamics of glycemic regulation, weight status and pregnancy on the development of DIP [24].

Recent advances in modelling software have increased model transparency, making them more accessible to non-modellers. This has facilitated expert stakeholder participation in the model development process, increasing the opportunities for interdisciplinary learning about complex health problems and building trust in the model outputs [25-29]. The aim of this study was to develop a DIP decision support tool for policy and program decision makers, using participatory DSM [30]. The model development process, and discussions of the model outputs enable key stakeholders to explore the likely impacts of both clinical and population level intervention options for DIP, via simulation, before they are implemented in the real world. The process has been reported elsewhere [25, 29-31]. The aim of this paper is to explore the impact of prevention interventions targeting weight status on DIP incidence and insulin sensitivity. Insulin sensitivity, while not being a commonly utilised clinical measure, was selected as an outcome measure of glycemic regulation for these scenarios as it reflects metabolic dynamics both during pregnancy and with changing weight status and is potentially responsive to lifestyle interventions [19, 20]. Intervention scenarios were tested to explore the impact of timing, subgroup targeting, and adherence to lifestyle changes on the incidence of DIP and insulin sensitivity.
Methods

Box 1: Study context

The model explored DIP in Australian Capital Territory (ACT) and was built in partnership with the ACT Government Health Directorate (ACT Health). Approximately 16% of ACT resident women who gave birth in the ACT in 2016 were diagnosed with DIP (increasing from 6% in 2008) [32]. ACT Health services provide government funded health services for the population of the ACT (approximately 410,000) and are the major health referral centre for the Greater Southern Region of New South Wales. The total catchment area population is over 600,000 people. The number of women giving birth in the ACT is over 6,000 per year. Approximately 15% of these women are non-ACT residents who access services in the ACT for high risk pregnancy complications (i.e. those requiring tertiary level care). Models of antenatal maternity care provided in the ACT include hospital based out-patient care, tertiary level care, private midwifery care, and shared care (that is, integrated with primary health care providers). A specialist gestational diabetes service operating from one public hospital with satellite clinics in community health centres works with generalist maternity services to provide education and health services for women with DIP.

Model development

The model development process drew on best practice guidelines for computational modelling and included the grounding of assumptions in theory and evidence, sensitivity testing and calibration [33, 34]. The model was built using a participatory approach that engaged a consortium of academics, clinicians, public health policy makers, program planners, modellers and health economists in the process. This approach has been described in detail elsewhere [25, 30, 31]; and a diagrammatical overview of the process is depicted in Figure 1.
The hybrid model was constructed using AnyLogic simulation software (http://www.anylogic.com/). Detailed information is available in the supplementary resources, including the model documentation and technical paper.

Model inputs and data sources

The structure and parameterisation of the model drew on a range of data sources, including census and population data, systematic reviews, meta-analyses, accepted formulas and conceptual models, survey data, policy/programme effectiveness data, economic data and the expert knowledge of the multidisciplinary stakeholders who participated in model development. Local data was prioritised where this was available. Expert opinion was utilised when other evidence options were exhausted or for

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*Figure 1: Overview of the participatory model development process*
triangulation of multiple data sources when parameters were uncertain. The data included
statistics relating to demographic characteristics and trends, the incidence of DIP and
associated risk factors, and the underlying physiology determining individual glycemic
control including beta cell mass and function based on previous mathematical models of
diabetes progression [18, 22, 23]. Census, population and health system data were sourced
from the Australian Bureau of Statistics and ACT Health administrative data collections.
Model input parameter values, their sources and the data used for model calibration are
provided in the supplementary resource. The model was calibrated to the incidence of DIP
in ACT Health maternal and perinatal statistics from 2008 to 2016.

Model structure

The tripartite model incorporates system dynamics (SD), agent based modelling (ABM) and
discrete event simulation (DES) components with construction and analysis implemented in
AnyLogic® version 7.3.6 Professional (http://www.anylogic.com/). The model structure has
been described elsewhere [24] and is described in detail in the supplementary resource. A
summary is provided here of the following representations:

A. Pregnancy
B. Dysglycemia classification
C. Glycemic regulation including beta cell mass and function
D. Population structure
E. Weight status
F. Clinical service

The overall model structure is depicted in Figure 2 which is intended to depict a high level
overview of model components rather than full details. The model population is initialised
using demographic characteristics e.g., age and country of birth, of the female population of
the Australian Capital Territory (ACT) from the 2011 Australian Census [35]. The model is
initialised in 1948 with time units in years. The model then undergoes a burn-in period of 60
years to 2008. Model outputs from 2008 to 2016 have been calibrated against retrospective
data [24].
Figure 2: Overview of model components and structure
The model incorporates a dynamic representation of the underlying physiological regulation associated with an individual’s glycemic status that is based on previous mathematical models of diabetes progression [18, 22, 23]. The mechanism for glycemic regulation included in the model is referred to as an endogenous dynamic mechanism. This means that the model represents, over time, the evolution of specific, latent factors related to the level of dysglycemia and metabolic load that a woman experiences. Glycemic regulatory capacity is represented as a stock (an accumulation), allowing the level of an individual’s regulatory capacity to increase and decrease over time. Therefore, the factors that influence glycemic regulatory capacity such as increased metabolic load due to pregnancy, changes to diet and physical activity and pharmacological interventions can be modified within the model and the impact measured over time and between generations. Glycemic regulatory capacity is a function of two factors in the model. Firstly, it is a function of biologic regulatory capacity; that is, the changes in insulin sensitivity and insulin production associated with underlying physiology [18, 20, 22, 23]. Secondly, there is a component of external regulation by the individual, that is, their conscious regulation through adherence to blood testing, medication regimens and lifestyle interventions including diet and physical activity. The model mechanism allows for changes in an individual’s adherence to medical and lifestyle interventions over time. The model also incorporates the impact of beta cell decline associated with exposure to dysglycemia based on modelling carried out by De Gaetano et al. [18, 22, 23]. Exposure to dysglycemia results in a decline of beta cell function over time and this eventually limits the individual’s regulatory capacity. Reduced beta cell function decreases the effectiveness of lifestyle interventions on glucose regulation, meaning that, even if an individual with reduced beta cell function makes significant changes to their diet and activity levels, the impact on the blood glucose regulation will be minimal.

Pregnancy occurs according to the ACT age and ethnicity specific fertility rate. The model tracks relevant risk factor information for the occurrence of dysglycemia in the current pregnancy, for example, Body Mass Index (BMI), age, history of diabetes, and family history of diabetes. Insulin sensitivity decreases significantly during pregnancy for both normoglycemic and dysglycemic women, based on findings of studies by Catalano [19, 20]. When a woman gives birth, there is a birth event in which a baby is introduced into the model. The baby inherits characteristics, including the mother’s DIP status and history of diabetes, maternal weight status and ethnicity. Outcomes, including birthweight, type of
birth e.g., caesarean section, neonatal intensive care admission and Apgar scores, are recorded at birth. The model incorporates the glycemic changes occurring during pregnancy [36]; it is notable that such changes can impart physiological impact for mother and child (e.g., on beta cell mass and function) that persists beyond that pregnancy. Responsive to the focus on DIP, the model includes only female agents. Births for male babies occur in the model, however these agents are deleted from the population. Model outputs reflect the impact of interventions on females in the population.

High weight status is an important risk factor for declining insulin sensitivity and the development of diabetes. Weight is represented in the model as a continuous variable that changes dynamically with age [37] and pregnancy [38]. An individual's weight status (BMI) impacts on their insulin sensitivity [18-20], with increasing weight leading to decreasing insulin sensitivity. This paper reports on weight reduction intervention scenarios tested in the model as described below.

Simplifying assumptions about individual behaviour were made to ensure the model is parsimonious, while allowing it to approximate real-world behaviour over time. A summary of the key assumptions is presented below:

1. Age specific fertility rates were calculated using birth rates from 2013. The model assumes that age specific fertility rates will remain stable over the period of the simulation.
2. The model assumes that 60% of pregnancies were intended, providing opportunities for intervention during pregnancy planning [10]. The assumption was applied uniformly across age groups.
3. Adherence to healthy lifestyle behaviours was assumed to increase after exposure to intervention and then decline over the subsequent two years.
4. Individuals, who were eligible, had an equal chance of receiving interventions.

Underlying the model structure and assumptions described above are simple mathematical relationships designed to capture the concept they represent. For instance, the decline in intervention adherence was assumed to follow a curve whose coefficients cause adherence to the weight management intervention to increase immediately following an intervention and decline over the subsequent two-year period.

Health services are captured in the model, with the current service model being represented as a DES component. Future planned work for the model will explore the impact of alternative service models on resources and outcomes.
Scenarios tested in this analysis

The scenarios tested in this analysis focused on the impact of targeted and population-level weight reduction strategies. Many of the risk factors for DIP are not modifiable, however weight status is an important modifiable risk factor for both DIP and type 2 diabetes mellitus. The scenarios prioritised for this analysis are described below.

1. Impact of population vs targeted weight management interventions

These scenarios compared the impact of weight management interventions delivered across the population of females aged 20 to 35 years with targeted interventions delivered to females who were at high risk according to the Australian Diabetes in Pregnancy criteria [1] either before or after their pregnancies. The interventions are described below.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Population intervention</td>
<td>This intervention targets all women aged 20 to 35 years through a public health intervention. The goal of the intervention is to support women to maintain or achieve a healthier weight status.</td>
</tr>
<tr>
<td>2. Targeted pre-pregnancy intervention</td>
<td>This intervention targets women who have one or more risk factor for DIP. It is available to all women who are considering pregnancy (60% of pregnancies [10]). The intervention aims to achieve a healthy weight via adherence to diet and physical activity recommendations and.</td>
</tr>
<tr>
<td>3. Targeted post-pregnancy</td>
<td>This post pregnancy intervention targets women who have had diabetes in a previous pregnancy. The intervention aims to increase adherence to diet and physical activity recommendations and to achieve a healthy weight before the next pregnancy.</td>
</tr>
<tr>
<td>4. Combined</td>
<td>This scenario combines all the above interventions</td>
</tr>
</tbody>
</table>
The effectiveness of each intervention in reducing weight is a model parameter that can be varied. For simplicity, the interventions in these scenario runs were assumed to result in weight reductions that were normally distributed with a mean weight reduction of 1.3 kg/m² (SD = 1.7 kg/m²). The distribution was based on an Australian study of mobile phone based public health intervention aimed at preventing weight gain in young adults [39] and an Australian study of post pregnancy lifestyle change supported by motivational interviewing [40]. Weight loss results for individuals who received the interventions were drawn from this distribution. It was assumed that all eligible individuals received the intervention and that the intervention effectiveness degraded over time, with adherence diminishing over a two-year period.

2. Impact of childhood weight interventions

These interventions explored the impact of childhood weight interventions. As childhood weight dynamics had not yet been fully articulated in the model, these hypothetical scenarios were simulated by modifying the weight distribution of the population on entry to adulthood. Increasing population-wide interventions to reduce childhood overweight and obesity was simulated by shifting the weight distribution of the population to the “left”, so that more individuals entered adulthood within the healthy weight range (normal distribution with mean BMI = 22). Scaling back population-wide interventions addressing childhood overweight and obesity was also simulated. The scaling back intervention shifted the population weight distribution to the “right” so that more individuals entered adulthood either overweight or obese (normal distribution with mean BMI = 30). The interventions were implemented for individuals born from 2018 and the simulations were run for 42 additional years (2060) to allow individuals to age and enter their reproductive years.

Model outputs and data analysis

For the scenario testing, key outcome indicators against which the impacts of scenarios were compared to the baseline were: (1) incidence of DIP (%) and (2) insulin sensitivity (Kxgl). Diabetes in pregnancy incidence was calculated as a percentage based on the proportion of all women giving birth in each year who were diagnosed with DIP. Kxgl was
used as a mathematical index of insulin sensitivity representing insulin dependent glucose tissue reuptake [22].

To estimate latent or poorly measured parameters and to support the projection of status quo future incidence of DIP using model outputs, we calibrated a baseline model without interventions against the following historical data: the incidence of DIP for sub-populations in ACT from 2008-2016 according to ADIPS risk profiles[1]; the prevalence of macrosomia by DIP status in the ACT from 2010-2016 [24].

Outputs from the model were summarised using the R statistical package to obtain means, standard errors and 95% confidence intervals; summary data was tabulated and graphed in Microsoft Excel. Given that runs of the model were computationally expensive, 36 runs were deemed sufficient to account for stochasticity and provide stable predictions of scenario performance and of the variance in performance. The comparison of simulation results between baseline and intervention scenarios was expressed as a percent difference in reported outcomes. 95 % confidence intervals about the means were reported as estimates of the variation between simulation runs and to test statistical significance.

Results

Results for scenario testing simulations are presented below.

Scenario testing results

1. Impact of population vs. targeted weight management interventions

Diabetes in pregnancy incidence for the baseline and scenario simulation are presented as a percentage, based on the proportion of all women giving birth in each year who were diagnosed with DIP, in Table 1 and Figure 3. The baseline incidence of DIP was 15.9% (95%CI 15.5 to 16.3) in 2020; 16.1% (95% CI 15.8 to 16.4) in 2030 and 17.3% (95% CI 16.9 to 17.7) in 2040. The population weight loss intervention in early adulthood resulted in a non-significant 3.0% reduction in DIP incidence by 2020 (15.5%; 95% CI 15.1 to 15.9), however by 2030 the 17.6% reduction in DIP incidence (13.3%; 95% CI 13.0 to 13.6) was statistically significant. In comparison, the impact of targeted pre- and post-pregnancy
interventions on population level DIP incidence ranged from a non-significant reduction of just over 2% in 2020, a small but statistically significant reduction of 4-5% in 2030 and 4-6% in 2040, respectively. Incidence rates with confidence intervals for these scenarios are presented in Table 1. Combining targeted interventions for high risk groups with population weight loss interventions was the most effective scenario for reducing DIP incidence, with a reduction of 14.4% by 2020 to 13.6% (95% CI 13.2 to 14.0), two years after the simulated interventions were implemented, 28.8% by 2030 (11.5%; 95% CI 11.2 to 11.8) and 32.1% by 2040 (11.8%; 95% CI 11.5 to 12.1).

*Figure 3: Comparative impact of scenarios on DIP incidence simulated from 2018 to 2040*
**Table 1: Summary DIP incidence statistics for baseline and scenarios simulated from 2018 to 2040**

<table>
<thead>
<tr>
<th></th>
<th>2020</th>
<th>2030</th>
<th>2040</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>%</td>
<td>95% CI (±)</td>
<td>reduction from baseline</td>
</tr>
<tr>
<td>Baseline</td>
<td>15.9</td>
<td>0.4</td>
<td>-</td>
</tr>
<tr>
<td>1. Population intervention</td>
<td>15.5</td>
<td>0.4</td>
<td>-3.0</td>
</tr>
<tr>
<td>2. Targeted pre-pregnancy</td>
<td>15.5</td>
<td>0.3</td>
<td>-2.8</td>
</tr>
<tr>
<td>3. Targeted post-pregnancy reduction</td>
<td>15.6</td>
<td>0.3</td>
<td>-2.1</td>
</tr>
<tr>
<td>4. Combined - population and targeted pre and post pregnancy</td>
<td>13.6</td>
<td>0.4</td>
<td>-14.4</td>
</tr>
</tbody>
</table>

**Table 2: Summary insulin sensitivity (Kxgl) statistics for baseline and scenario simulations simulated from 2018 to 2040**

<table>
<thead>
<tr>
<th></th>
<th>2020</th>
<th>2030</th>
<th>2040</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Kxgl</td>
<td>95% CI (±)</td>
<td>% increase from baseline</td>
</tr>
<tr>
<td>Baseline</td>
<td>50.3</td>
<td>0.02</td>
<td>48.4</td>
</tr>
<tr>
<td>1. Population intervention</td>
<td>52.2</td>
<td>0.03</td>
<td>3.8</td>
</tr>
<tr>
<td>2. Targeted pre-pregnancy</td>
<td>50.5</td>
<td>0.02</td>
<td>0.3</td>
</tr>
<tr>
<td>3. Targeted post-pregnancy reduction</td>
<td>50.5</td>
<td>0.02</td>
<td>0.4</td>
</tr>
<tr>
<td>4. Combined - population and targeted pre and post pregnancy</td>
<td>55.7</td>
<td>0.02</td>
<td>10.6</td>
</tr>
</tbody>
</table>

*Kxgl* - an index of insulin sensitivity representing insulin dependent glucose tissue reuptake
Insulin sensitivity results for the baseline and intervention simulations are presented in Table 2. Baseline projections of insulin sensitivity (KxgI) were 50.3 (95% CI 50.1 to 50.5) in 2020; 48.4 (95% CI 48.2 to 48.6) in 2030 and 46.4 (95% CI 46.1 to 46.7) in 2040. The population intervention targeting weight loss in early adulthood resulted in a non-significant 3.8% increase in insulin sensitivity by 2020 and a significant 25.2% increase by 2040 (KxgI = 58.0; 95% CI 57.7 to 58.3). Smaller increases in population level insulin sensitivity were found for the targeted pre- and post-pregnancy interventions, with targeted pre-pregnancy weight loss interventions resulting in an increase in insulin sensitivity of 2.3% in 2040 (KxgI = 47.7; 95% CI 47.4 to 50.0). The targeted post-pregnancy interventions had a significantly higher impact by 2040 with an increase in insulin sensitivity of 8.1% (KxgI = 50.1; 95% CI 49.4 to 50.8). Combining targeted weight loss interventions for high risk groups with population-level weight loss interventions was the most effective scenario for increasing insulin sensitivity across the population, with an increase of 10.6% two years after the simulated interventions were implemented (2020) (KxgI = 55.7; 95% CI 55.5 to 55.9) increasing to 52.4% in 2040 (KxgI = 70.7; 95% CI 57.7 to 58.3).

2. Impact of childhood weight status on entry to adulthood

The interventions were implemented for female agents born from 2018 and were simulated to 2060 to allow time for individuals to age into adulthood and their reproductive years. Minimal impact of the interventions was observed on DIP incidence until 2060 (Figure 5), when the scenario with all females entering adulthood at a healthy weight resulted in a 21.2% decrease in the percentage of women diagnosed with DIP from baseline (Table 4) (2060 Baseline 17.0%, 95% CI 16.7 to 17.3; Scenario 13.4%, 95% CI 13.1 to 13.7).
Changes in insulin sensitivity (KxgI) were observed earlier in the simulation, from 2030, for the childhood weight interventions (Figure 5). The scaling up simulation -- with all individuals entering adulthood at a healthy weight -- increased insulin sensitivity, as measured by KxgI, for the population by 8.5% from the baseline simulation by 2030, increasing to 47.3% by 2060 (Table 4). The scaling back simulation shifted the weight distribution for the population further toward overweight and obesity as they entered adulthood. This resulted in a decrease in insulin sensitivity for the population of 31% from baseline by 2060 (Table 4).
Figure 5: Impact of scaling up and scaling back childhood weight interventions on population insulin sensitivity ($K_{xgI}$)

$K_{xgI}$ - an index of insulin sensitivity representing insulin dependent glucose tissue reuptake
Table 3: Summary DIP (percentage) incidence statistics for baseline and child weight status interventions scenarios simulated from 2018 to 2060

<table>
<thead>
<tr>
<th></th>
<th>2020</th>
<th></th>
<th>2030</th>
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<tr>
<td></td>
<td>%</td>
<td>95% CI (±)</td>
<td>%</td>
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<td>95% CI (±)</td>
<td>%</td>
<td>95% CI (±)</td>
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</tr>
<tr>
<td>Baseline</td>
<td>15.6</td>
<td>0.28</td>
<td>15.8</td>
<td>0.31</td>
<td>16.9</td>
<td>0.31</td>
<td>17.2</td>
<td>0.3</td>
<td>17.0</td>
<td>0.3</td>
</tr>
<tr>
<td>All normal weight</td>
<td>15.9</td>
<td>0.26</td>
<td>1.8</td>
<td>15.9</td>
<td>0.31</td>
<td>0.8</td>
<td>17.1</td>
<td>0.31</td>
<td>17.0</td>
<td>0.3</td>
</tr>
<tr>
<td>More overweight or obese</td>
<td>15.7</td>
<td>0.27</td>
<td>0.4</td>
<td>15.9</td>
<td>0.30</td>
<td>-0.6</td>
<td>17.1</td>
<td>0.27</td>
<td>17.3</td>
<td>0.3</td>
</tr>
</tbody>
</table>

KxgI = an index of insulin sensitivity representing insulin dependent glucose tissue reuptake

Table 4: Summary population insulin sensitivity (KxgI) statistics for baseline and scaling up and scaling back scenarios simulated from 2018 to 2060

<table>
<thead>
<tr>
<th></th>
<th>2020</th>
<th></th>
<th>2030</th>
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<tbody>
<tr>
<td></td>
<td>mean</td>
<td>95% CI (±) % change from baseline</td>
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<td>95% CI (±) % change from baseline</td>
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<td>95% CI (±) % change from baseline</td>
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<tr>
<td>Baseline</td>
<td>50.3</td>
<td>0.02</td>
<td>48.4</td>
<td>0.02</td>
<td>46.4</td>
<td>0.03</td>
<td>45.7</td>
<td>0.02</td>
<td>45.6</td>
<td>0.02</td>
</tr>
<tr>
<td>All normal weight</td>
<td>50.9</td>
<td>0.02</td>
<td>1.2</td>
<td>52.5</td>
<td>0.02</td>
<td>8.5</td>
<td>54.2</td>
<td>0.03</td>
<td>16.9</td>
<td>0.03</td>
</tr>
<tr>
<td>More overweight or obese</td>
<td>49.7</td>
<td>0.02</td>
<td>-1.2</td>
<td>44.6</td>
<td>0.02</td>
<td>-7.8</td>
<td>39.3</td>
<td>0.02</td>
<td>-15.4</td>
<td>0.02</td>
</tr>
</tbody>
</table>

KxgI - an index of insulin sensitivity representing insulin dependent glucose tissue reuptake
Discussion

The simulations reported here prioritised scenario testing of several lifestyle prevention interventions promoting healthy weight status. Population-level interventions promoting weight loss in early adulthood were found to be more effective than targeted pre- and post-pregnancy interventions in reducing the population incidence of DIP. Combining targeted interventions for high risk groups with population health promotion supports was shown to be the most effective scenario for reducing DIP incidence, especially in the longer term. Scaling up childhood health weight interventions, resulting in all female children entering adulthood at a healthy weight, achieved a significant improvement in insulin sensitivity in the short term and decreased DIP in the long term. Scenarios testing the impact of scaling back childhood healthy weight interventions, i.e., having more children entering adulthood overweight or obese, resulted in declines in insulin sensitivity across the population and, therefore increasing risk of early development of diabetes mellitus.

The study presented in this paper is unique in that dynamic simulation modelling was used to explore the metabolic dynamics underlying the development of DIP and compare the likely impact of population level interventions with interventions targeting high risk individuals. This simulation study builds on other research assessing the effectiveness of targeted lifestyle prevention programs to prevent DIP incidence [10, 12, 41]. Given the substantial time needed to achieve weight reduction, it has been argued that early intervention at a population level will be necessary to reduce obesity-related outcomes in pregnancy [10], and this was confirmed by the modelling. The scenarios presented in this paper demonstrated that population level interventions will be needed to make an impact on DIP incidence across the population. Targeted interventions, both pre- and post-pregnancy, did not substantially impact on population DIP incidence.

Over half of pregnancies are planned [10], and this was reflected in the model, with only individuals who were planning to become pregnant being eligible to receive the targeted pre-conception intervention. Therefore, the small proportion of the total population receiving the intervention and individual variations in adherence, included in the model to reflect reality, impacted on intervention effectiveness. The targeted interventions resulted in only a modest impact on population incidence rates for DIP. This result should not devalue the role of targeted interventions, as these are important and beneficial for
individuals and their offspring [11]. However, the results emphasise the need for population interventions to support healthy lifestyle behaviours for all individuals, whether they actively plan their pregnancy or not [10].

A recent review of research into antenatal lifestyle programs for high risk women found that they did not successfully prevent DIP [12]. Further examination of the individual and intervention characteristics that facilitated adoption and adherence to interventions has been identified as a priority [12]. The DIP model presented here incorporated representations of the non-linear dynamics and feedback loops that impact intervention effectiveness e.g., the impact of age and pregnancy related weight changes across the life course and the impact of individual adherence to diet and physical activity recommendations on both DIP incidence and insulin sensitivity. The reduction in DIP incidence was only achieved when individuals remained adherent to the lifestyle changes associated with the intervention.

Scenario testing provides an important tool for exploring hypothetical policy options, including “do nothing” alternatives that forecast the impact of ceasing current interventions [14, 33, 42]. In these scenarios, the DIP model hypothetically tested the impact of scaling back interventions promoting healthy weight for children in school settings. This scenario forecasted the impact of more children entering adulthood at a higher weight status on insulin sensitivity, placing them at risk of early development of diabetes mellitus. These results signify the potential importance of the current global focus and efforts to reduce childhood overweight and obesity.

Diverse local perspectives and interests can provide decision makers with conflicting advice regarding the best course of action [16]. Data limitations, insufficient local analytic capacity and inadequate tools to support longer term planning in a context of changing local needs, contribute to the persistence of a trial and error approach to program planning that may delay or prevent the realisation of significant impacts on important public health issues like DIP [15, 42]. The DSM approach described in the present study is one way to address these challenges and can also contribute to prioritising data gaps for future research and data collection, and infrastructure to better support interventions to prevent and manage DIP. The participatory approach facilitated opportunities for interdisciplinary dialogue and combining diverse perspectives in the consideration of policy options. The developed
partnerships and relationships were critical to the model development and to its likely subsequent use to inform health service and policy decisions.

Future applications of the model include further exploration of the: intergenerational impacts resulting from exposure to DIP; factors that influence childhood weight gain e.g. breastfeeding and other aspects of diet, school-based health promotion interventions, and physical activity etc.; impact of model of care alternatives; and impact of prevention interventions on health service utilisation. Health economic considerations will also be added to future iterations of the model.

Limitations

There are limitations to consider when interpreting the findings of this paper. There is potential measurement bias in the range of secondary data used to parameterise the model. Where possible, routinely collected local health service information was obtained to estimate population-based estimates of DIP, birth outcomes, weight status, and fertility rates. There were also some parameters relating to the heterogeneity of aetiology of DIP and the dynamics of glycemic regulation where data were not available, and these are identified as priorities for future research. The model acknowledges these potential sources of measurement bias, and commonly used strategies were employed to address them, including the triangulation of multiple data sources, calibration to refine parameter estimates and the engagement of stakeholders with detailed knowledge of the limitations and likely direction and size of potential measurement biases in key data sources. In addition, sensitivity analysis was undertaken to estimate the impact of uncertainty on primary outcome indicators and guide priorities for new data collection and quality improvement of existing data collection.

Conclusion

Population health interventions will be necessary to “turn the tide” on DIP. Interventions targeting high risk individuals, while beneficial for those individuals, delivered small reductions in DIP incidence rates. The importance of maintaining interventions promoting healthy weight in childhood was demonstrated. Scenarios simulating the impact of scaling back these interventions showed that insulin sensitivity decreased significantly, increasing
the risk for early development of diabetes mellitus. DSMs are learning support tools that can mature over time as new evidence becomes available and methods are advanced to facilitate further development. This decision support tool for DIP was developed as a working model and is being published for transparency and to invite input. A key priority for future research is improved knowledge about the dynamics and heterogeneity in the aetiology of glycemic dysregulation and diabetes mellitus development, and the impact of glycemic control during pregnancy on perinatal outcomes.

Authors’ contributions

LF, JA, GM, NO, CN, AK and PK were involved in the planning for this study. Model and scenario programming were done by NO, WQ, YQ, AS and AM. Model outputs were produced by YQ. Data processing was conducted by LP and AP. LF conceptualised the manuscript and wrote the first and subsequent drafts. All authors have made important intellectual contributions to multiple draft revisions.

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The authors acknowledge the valuable contributions of Professor Lucie Rychetnik to the study design and her comments on this manuscript. The authors also acknowledge the Diabetes in Pregnancy Modelling Consortium (members listed below) for generously contributing their expertise and time to participate in this study.

Members of the Diabetes in Pregnancy Modelling Consortium

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**Role of the funding source**

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- Australian Postgraduate Award scholarship
- CRN top-up scholarship for supervision travel expenses
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7.2 Communication products developed to facilitate model use and knowledge dissemination

Three key products were developed to support communication about this technical modelling project to a non-technical policy audience. The products were a plain language fact sheet, an interactive dashboard and a podcast. The fact sheet and interactive dashboard communication products are described in this section and the podcast transcript is included in Appendix 9.

Project fact sheet

I led the development of plain language fact sheet (below) to facilitate communication about the modelling project. The factsheet was developed with Ms Helen Signy and Ms Ainsley Burgess, communication officers with The Australian Prevention Partnership Centre, and was aimed at Ministerial advisors and a wider health policy audience.

The fact sheet provided background information about diabetes in pregnancy as a priority issue impacting on health services in the ACT, information about the model development process and preliminary results from the model. A local Canberra woman with diabetes in pregnancy was interviewed by Ms Signy and her story was included to illustrate the local impact of diabetes in pregnancy and the importance of prevention interventions.
Preventing diabetes in pregnancy

Diabetes in pregnancy is putting more and more strain on the ACT’s health system. We need to do things differently

Diabetes in pregnancy, including gestational diabetes, is increasing both in the ACT and Australia. This is due to the rise in risk factors such as overweight and obesity, older mothers and more women from high-risk ethnic groups.

Gestational diabetes occurs when high levels of blood glucose are detected during pregnancy that, if untreated, increase the risk of poor pregnancy outcomes. It also predicts a future higher risk of permanent diabetes in mothers and obesity and diabetes in children.

Pregnancy is a time when public health interventions can have a big impact. Women are more motivated to make changes, and these can also positively affect the health of future generations.

Achieving even small delays in the development of diabetes will have significant implications for the longer-term burden of disease and costs to the health system.

**Percentage of women diagnosed with diabetes in pregnancy who gave birth in the ACT,** 2008–2016

*Includes ACT residents only.
Source: ACT Maternal Perinatal Data Collection.

CASE STUDY

Pip is 37, she is about to have her first baby – and has gestational diabetes

Both Pip and her new daughter will be at increased risk of type 2 diabetes in future. Pip is one of about 800 women diagnosed every year in the ACT with gestational diabetes. She joins an ever increasing number of women whose future health and that of her children is at risk.

Before I conceived, no-one ever suggested to me my history of polycystic ovary syndrome, diet, weight or age put me at risk of gestational diabetes. If I had known, I could have made changes before I became pregnant to try and reduce my risk.

Sometimes I feel like I’m doing this alone. Better support before and during my pregnancy would make a big difference, and would mean a better outlook for both me and the baby.
Gestational diabetes increases the subsequent risk of type 2 diabetes in mothers almost ten fold. Babies of mothers who have gestational diabetes are at short-term risk of high birthweight, birth complications and hypoglycaemia. Children of mothers who had gestational diabetes have a 2–4 fold increased risk of being overweight/obese and having long-term impaired glucose tolerance. Both gestational diabetes and type 2 diabetes are associated with modifiable lifestyle risk factors such as diet and physical activity. There are also strong genetic and family related risk factors which are not modifiable.

What did we do?

We brought together diabetes in pregnancy experts including leading academics, policy makers and clinicians from across Australia. Their insights were combined with research and data to develop a dynamic simulation model of diabetes in pregnancy in the ACT.

“With the collaborative modelling approach, the people in the room have accumulated knowledge and expertise in the area over many years. To have that wealth and depth of knowledge involved is incredibly valuable.”

Professor Christopher Nolan, Director of Endocrinology and Diabetes, ACT Health

A dynamic simulation model is a sophisticated computer ‘what if’ tool that can test the likely impact of a range of possible solutions over time. It considers the short, intermediate, and long-term implications of the increasing prevalence of risk factors for diabetes in pregnancy and looks at alternative models of care. Based on real data, the model can be used to test out different solutions to see which will be most effective and cost effective. The expert group identified, clarified and prioritised gaps in current knowledge and evidence which can be used to guide future research and, in turn, further improve the model.

### BUILDING AND USING A DYNAMIC SIMULATION MODEL WITH STAKEHOLDERS

1. **EVIDENCE SOURCE**
   - Research evidence
   - Health service and survey data
   - Expert knowledge
   - Local practice experience

2. **BUILD**
   - Build a conceptual map of the problem collaboratively
   - Convert to a computer model

3. **VALIDATE**
   - Does the model reproduce historic data trends?
   - Refine the model

4. **APPLY**
   - Switch on different intervention combinations. For example:
     - A. Pre-pregnancy intervention to lose weight
     - B. Family–centred programs to reduce weight
   - Run ‘what if’ scenarios through the model
   - Compare predicted impact over time
   - Facilitate discussion to help drive policy action
What did we find?

Early findings from the model reinforce the long-term benefits for women and their children of preventing diabetes in pregnancy:

- Women with obesity experience a sharper decline in insulin sensitivity compared with normal weight women (see image below)
- Interventions delivered between pregnancies or after pregnancy for women who have experienced diabetes in pregnancy could reduce their risk of progressing to Type 2 diabetes
- Pregnancy and pre-conception is a time when interventions can improve health outcomes for whole families
- It is possible to significantly reduce the number of women with diabetes in pregnancy by focusing on risk factors like diet, physical activity and weight
- These lifestyle interventions should target women in early adulthood, before pregnancy, to reduce the incidence of diabetes in pregnancy.

What happens to insulin sensitivity during pregnancy?

- High insulin-sensitivity helps keep blood glucose levels in the normal range
- Low insulin-sensitivity, or insulin resistance, is associated with type 2 diabetes.

Source: Early results from the diabetes in pregnancy dynamic simulation model.
Next steps

This project has demonstrated that participatory dynamic simulation modelling is an effective way of informing program and policy decision-making for diabetes in pregnancy in the ACT. Dynamic simulation models mature over time and can be continuously refined as new knowledge and evidence becomes available.

One of the main benefits of the modelling process was that it brought together a large group of stakeholders, including key decision makers, to discuss the causes of diabetes in pregnancy and impacts of interventions. Building these networks is a crucial step in driving a multi-sector approach that can lead to practical changes on the ground.

What interventions could be modelled in the future?

- Pre-pregnancy population level interventions, for example app-based support for women and couples to make lifestyle changes
- Targeted pre-pregnancy interventions for women with multiple risk factors
- Post-pregnancy interventions to support families to maintain a healthy lifestyle
- Different models of care for women with diabetes in pregnancy.

About this project

This project was implemented as a collaboration between the Prevention Centre and Australian Capital Territory Government Health Directorate (ACT Health).

The model harnesses advances in technology incorporating multiple methods including agent-based modelling, system dynamics and discrete event simulation into a logically consistent decision support tool for health policy and program decision making.

The model incorporates best available evidence, data and expert opinion. We collaboratively developed the model structure with recognised experts in providing care, planning services, undertaking research and developing policy for the diagnosis and management of diabetes. We used an iterative process of model development where we presented the model back to participants at meetings and workshops to continually incorporate their feedback and refine the structure. The model was built by systems modelling experts based in Canada.

Papers published


Interactive dashboard

I led the development of an interactive dashboard designed for use by a policy audience. The dashboard was programmed by Mr Luke Penza and Dr Ante Prodan, computer scientists employed by The Australian Prevention Partnership Centre, in Tableau© using model output data.

The dashboard was designed to be presented to the ACT Minister for Health and Wellbeing; therefore, priority was given to displaying the results in a simplified and clear format. This was intended to facilitate the communication of key messages about the insights derived from the simulated scenarios. To achieve this purpose, it was decided to remove measures of model output variation and uncertainty, such as 95% confidence intervals from the dashboard. These measures of uncertainty were included in papers prepared for publication.

The dashboard allowed policy makers to engage with model outputs dynamically to test “What if” scenarios relating to the impact of population health and targeted interventions. Contextual information about the model and its development were provided on the first tabs viewed by the user. The scenario testing tabs allowed users to select interventions and compare their effect on outcome measures, including insulin sensitivity and diabetes in pregnancy incidence, against the baseline. Being able to forecast the number of women receiving services is important for resource allocation and service planning decisions. Therefore, the dashboard included forecasted estimates of the number of women receiving the selected interventions and the number diagnosed with diabetes in pregnancy for each year. Screen shots from the dashboard are displayed and explained below.
1. **Home tab.** This screen provided an overview of the model development process. It displayed photographs depicting modelling participants engaging in activities to map the causal factors contributing to the development of diabetes in pregnancy. The conceptual maps developed in the activities shown in the photographs were used to inform the model structure and logic.
2. **Model structure tab.** This screen provided a strategic overview of the model structure and showed the relationships between model components. The model structure presented on this tab shows that individual characteristics, weight status and pregnancy status all contribute to an individual’s internal dynamics of glucose regulation e.g. their blood glucose levels and insulin sensitivity. Glucose regulation in turn effects an individual agent’s risk of developing and being diagnosed with diabetes in pregnancy and impacts on their use of health services. The background photograph shows a Canberra woman who was receiving diabetes in pregnancy care. She is depicted in a distinctive local setting to illustrate the local focus for the model.
1. **Scenario testing screen 1.** On this screen, users could choose up to five interventions to compare against the baseline scenario over time. A description of each scenario was displayed when users hovered their cursor over the drop-down arrow. Users selected to display either insulin sensitivity (shown) or diabetes in pregnancy incidence as the outcome presented in the graph at the top left. The percentage difference from baseline for each scenario was displayed in the graphs in the bottom right of the screen. Impact on BMI categories for the agent population for each scenario are displayed in the graphs in the bottom left of the screen.
2. **Scenario testing screen 2.** On this screen users could choose up to four interventions to compare against the baseline scenario in the graph at top left. Users selected to display either insulin sensitivity (shown) or diabetes in pregnancy incidence as the outcome. The percentage difference from baseline for each scenario is displayed in the graphs in the bottom right of the screen. Impact on BMI categories for the agent population for each scenario are displayed in the graphs in the bottom left of the screen.
3. **Model outputs compared with retrospective data.** The ability to replicate historical trends is commonly used to assess model performance. The validation of this model was demonstrated by its ability to closely replicate the percentage of women diagnosed with diabetes in pregnancy from the ACT maternal and perinatal data collection. The retrospective data is shown in black below and the model results are shown in orange.
4. **Forecasted number of women diagnosed with diabetes in pregnancy.** This tab presented the forecasted number of women diagnosed with diabetes in pregnancy for each scenario. The graphs displayed on this tab updated dynamically with the intervention selected on previous tabs or could be manipulated manually by the user on this tab.
5. **Forecasted number of women receiving interventions.** The forecasted number of women receiving interventions was displayed along with more detailed descriptions for each intervention. A grid of graphs was utilised for this presentation to accommodate the significant difference in numbers receiving interventions. For example, the forecasted number of women receiving the population intervention each year settled at around 15,000 after the initial implementation period, whereas the targeted interventions were delivered to significantly smaller numbers of women.
Chapter 8: Discussion and conclusions

This thesis presents an in-depth exploration of the implementation, feasibility and value of a participatory approach to the development of dynamic simulation models (DSMs) that address real-world health policy questions. The participatory process utilised in these projects was novel both in terms of the methods and activities utilised to mobilise knowledge and engage participants actively (Chapters 3 to 5) and in terms of the complexity of the policy questions addressed and the sophistication of the DSMs developed (Chapters 5 to 7). The thesis research examined the participatory model development processes, and analytic objectives and decision-making involved in developing a DSM to inform policy and planning for diabetes in pregnancy in the ACT (Chapters 4, 5 and 7). It also explored the experiences and perceptions of end-user decision makers involved in participatory processes for three DSM case-studies (Chapter 6).

Each manuscript presented in the results of this thesis (Chapters 4-7) includes a discussion of findings and conclusions. Chapter 4 revealed how participatory DSM builds on best practice elements of knowledge mobilisation practice by embedding co-production principles and actively engaging key stakeholders, including end-users, as participants in the model development process. Chapter 5 revealed the iterative cycles of engagement, analysis, negotiation and refinement involved in the process of developing a DSM as a quantified decision support tool for diabetes in pregnancy. The key analytic elements of the interdisciplinary, participatory approach to develop a DSM for diabetes in pregnancy included: negotiating a focus topic that was a current priority for participants; defining the model scope; iteratively refining the model structure and logic; reviewing and synthesising evidence to quantify the main dynamic relationships within the system; ensuring that the model was focused on priority policy questions; engaging with and communicating model results; and applying the model to support evidence-informed dialogues about policy options. Chapter 6 provided new insights about the participatory process from the perspective of end-user decision makers in three case-studies. The participatory aspects were highly valued by both senior clinical and public health decision makers and were viewed as essential for ensuring that the models utilised the best available evidence and focused on priority policy questions that were locally relevant. The participatory process was also critical to building trust in the model as a decision support tool. The diabetes in pregnancy model
(Chapter 7) developed in the primary case study demonstrated a greater need for population level (over targeted) interventions focused on weight loss in order to “turn the tide” on diabetes in pregnancy. These findings from the individual papers will not be discussed again in detail in this Chapter. Instead, the main findings of the thesis are synthesised from across the included papers and discussed below as a body of work. The following sections also present the challenges and limitations of this “real-world” participatory action research study, and recommendations for future research.

**Applying a participatory dynamic simulation modelling approach to public health issues**

As researchers and public health professionals navigate complex health policy environments, there is growing need to engage in interdisciplinary problem solving, including creating and using a wide range of evidence and other information [1-7]. DSM is a rapidly advancing approach to decision support that can move beyond the limitations of traditional static, statistical methods to facilitate greater understanding about challenging public health issues [4, 8-10]. However, adoption of complex DSMs requires a conceptual shift for epidemiology and public health professionals [4, 11, 12]. Dynamic simulation modelling requires a shift in thinking away from statistical association models focused on effect estimates to simulations which can test scenarios under different conditions. It also relies on a synthesis of diverse evidence rather than focus on observed associations within finite and specific datasets [11, 12]. Complex DSMs do still require observational and experimental epidemiological data [11, 12]. However, these data need to be used differently, and in combination with new types of data collected and generated using innovative technologies, such as mobile device technology and machine learning. Prior research demonstrated that data from disparate sources can be synthesised and collated in order to create simulation models that enable the exploration of the key public health questions of interest [4-6, 9, 11, 12].

The technology required for modelling complex domains is readily available and increasingly accessible to use [13]. However, for the full potential of policy-relevant modelling to be achieved, attention needs to be paid to the processes of model development and to the inhibitors and facilitators of model use [4, 13]. In the modelling case studies examined in this thesis, the models were developed in partnership with Australian jurisdictional health departments who were the primary stakeholders with key decision-making responsibilities.
for the complex, public health issues being examined. Participatory modelling processes provided an opportunity for the stakeholders from a range of disciplines, including the end-user decision makers, to work collaboratively on complex and contested problems [5, 9, 13, 14]. The participatory processes adopted in the case studies facilitated the incorporation into the modelling process of participants’ extensive and rich knowledge about the focus issues. Their contributions were used by the modelling teams to inform, analyse and refine the logic and structure for the models. According to the typology of stakeholder involvement proposed by De Gooyert et. al., the role of stakeholders in our research included balancing (identifying alternative decision options and associated trade-offs), structuring (increasing knowledge about the focus issue) and involving (providing multiple viewpoints of the problem issue and potential solutions) [15]. The involvement of these primary stakeholders as partners ensured that the models targeted priority policy and program questions, increased interest and confidence in the use of the models for decision support and increased the likelihood of them being applied in practice (Chapters 4, 5 and 6).

Using co-production to convert qualitative conceptual maps into quantified simulation models

Relationships and co-production of knowledge are key elements of knowledge mobilisation and are critical to ensure that research findings are policy-relevant and can be utilised to inform decision making [16-19]. The participatory approach provided a structured process to facilitate interdisciplinary dialogue and combine diverse perspectives. This research confirmed how the developed partnerships and relationships were critical to the model development and to its likely subsequent use to inform health service and policy decisions. It was important to ensure that partners were engaged early in the project and that they were involved in deciding the priority topic to focus on. The end-user participants actively engaged in modelling decisions; they were interested in ensuring that the model was grounded in rigorous evidence and focused on their priority policy questions. This co-production was a key element for maintaining the partnership relationships throughout the process. Engagement activities and modelling team-participant interactions also occurred both within and outside of formal workshops and meetings to facilitate participants’ contribution of knowledge and their understanding of the model. Interactive activities were designed and implemented to draw out participant knowledge and expertise and to familiarise them with the model. The professional networks available through the participant groups identified and
facilitated future opportunities for the model to be applied in practice. The end-user participants all emphasised the importance of collaboration and valued the opportunity to interact with colleagues to discuss the focus issue from a range of perspectives.

Recent reviews of knowledge mobilisation and participatory DSM across health and other sectors identified the need for more knowledge about the implementation of participatory approaches to model development [13, 20, 21]. Despite acknowledgement of the importance of including end-user stakeholders in model development [13, 22-24] most participatory modelling projects have not explicitly reflected on the participatory process component of the project [23, 25]. Those that have reflected on the participatory process have concentrated on health service and facility design [26, 27] rather than population health policy development. This thesis is the first empirical research specifically focused on understanding and elaborating the participatory method in applied population health policy settings. The in-depth, empirical examination also exposed and reported the joint analytic processes involved in converting the collaborative, conceptual system map developed with participants into a rigorous quantified DSM (Chapter 5). The decision-making processes involved in the model development were highly interactive, as participants identified, reviewed and critiqued important sources of evidence to inform model parameters and assumptions, and deliberated among themselves to ensure that the model was focused on current, priority policy questions. Communication challenges commonly arise during complex modelling projects [13] and were identified in the primary case study in this thesis. For example, finding strategies to communicate a strategic view of the model logic and assumptions without swamping participants in a detailed view of the structures used in the modelling software was important. In my research of the participatory modelling process, storytelling was identified as an effective strategy to overcome these challenges and facilitate participant understanding of the structure and logic of the complex DIP model. Storytelling was also effective to communicate model results to a wider policy audience (Chapters 5 and 7). In the primary case study, the use of “case history” stories derived for individual agents in the model were a familiar method to facilitate communication with participants.
Using participatory modelling to mobilise knowledge and inform health policy decision making

Natural experiments and case-studies have been identified as important methods to facilitate learning about the future role of systems approaches to knowledge mobilisation, particularly, empirical studies of participatory modelling in applied ‘real-world’ settings [20, 28, 29]. The participatory DSM approach implemented in these case studies, and empirically analysed in this thesis, built on elements of knowledge mobilisation best practice by integrating and synthesising diverse forms of evidence into dynamic decision support tools; embedding deliberative methods that placed end-users at the centre of the process and emphasising stakeholder participation to co-produce knowledge. The perspectives of end-users on the unique benefits that participatory DSM provided over other forms of knowledge mobilisation were also identified. These unique benefits are described in Chapters 4 to 6 and included:

- increasing familiarity and trust in the model through the use of participatory, co-production methods;
- the synthesis of diverse evidence into an interactive and dynamic decision support tool;
- the facility to explore “what if” scenarios and policy options;
- exploring combinations and interactions of interventions to consider which interventions to enhance, which gaps to fill and which target groups to focus on;
- exploring the impact of new and untested interventions prior to implementing in the real world;
- and being able to forecast delays in intervention effects to modify expectations, guide implementation monitoring, and identifying and prioritising evidence gaps.

As new technologies enable greater model transparency, increasingly participatory processes can combine the significant knowledge of domain experts with the expertise of modellers to develop complex, dynamic decision support tools [9]. Participants in the case studies examined in this thesis reported that it was especially valuable to learn how decisions in one part of the system impact on other parts i.e. to understand the focus issue from a systems perspective. However, the participatory approach was resource intensive and required a structured and rigorous process to ensure it added value to the modelling process and built
trust in the modelling outputs (Chapters 4 to 6). Being involved in the participatory modelling projects involved a significant time investment for participants. The policy makers who engaged in the projects reported that they had carefully weighed the benefits and costs before agreeing to participate. A significant factor contributing to their decision to participate was that the focus topic was a current, local priority for which effective policy and intervention options were unclear or contested (Chapter 4 and 6). In this context, participants were motivated to explore both the issue in depth and new methods for supporting decision making because the models were developed specifically to address their local priorities and decision needs.

Interrogation of the model logic and model results is important to facilitate refinement of the model and understand the implications for policy [13, 30]. Engaging with and discussing the model findings was a critical phase in the participatory model development process in the primary case study. Participants were encouraged to challenge and question the model and critically review the data used to inform it. Unexpected results generated from the three case study models provided opportunities to explore and challenge both the model assumptions and the assumptions held by the participants in relation to the focus issues (Chapter 5 and 6). Reviewing and discussing model results also provided an important opportunity to elicit further participant knowledge prompted in this context.

Managing Uncertainty

Quantitative modelling methods including scenario analysis, system dynamics, agent based modelling and discrete events simulation are useful to both identify and manage uncertainty [25]. Management of uncertainty is an important element of good practice in model development [31]. The types of uncertainty that are of particular importance for simulation modelling in the health domain include: stochastic uncertainty - the random variability in health outcomes between identical patients; parameter uncertainty - the uncertainty in estimation of the parameter of interest; heterogeneity – the variability between patients that can be attributed to characteristics of those patients; and structural uncertainty - the assumptions inherent in the decision model [32]. The participatory modelling process facilitated transparency of and robust discussion about the uncertainties inherent in the models. The participants comprehensively reviewed and refined the evidence used to inform model parameters and, through this process, identified key parameters that had higher levels
of uncertainty as priorities for future research (Chapters 5 and 6). As described in Vignette 1, Chapter 5, heterogeneity of both disease aetiology and outcomes for different population groups was an important source of uncertainty that was acknowledged and explored at length in the DIP model case study. Through the participatory process, knowledge about individual characteristics that were likely to contribute to differential risk of disease or effectiveness of interventions was elicited and shared between domain experts and the modelling team. These discussions were viewed as providing important information to guide which individual characteristics were represented in the model logic and structure (Chapter 5). Close involvement of participants in the model development process provided opportunity for structural model assumptions to be made transparent and tested against expert domain knowledge to ensure the assumptions were valid and robust. Statistical methods, including drawing parameter values from known probability distributions and calibrating parameters against retrospective data, were used in these case studies for parameter estimation and to reflect stochastic uncertainty about individual differences in health outcomes [9, 32]. Multiple simulations were used to assess variation in model outputs between runs and the variation was measured and reported using 95% confidence intervals for scenarios.

Embedding decision makers in the model development process, and making this process as transparent as possible, facilitated their knowledge about the uncertainty associated with the models. Participants emphasised that this increased their awareness of the limitations of the models, the need to ensure that model outputs were interpreted appropriately, and for non-participant end-users to be aware of the assumptions and limitations of the model (Chapter 6). Issues relating to uncertainty are discussed throughout the thesis, however the term “uncertainty” was not frequently used in the published papers. The audience for published papers included health professionals and policy makers who were less likely to be familiar with this modelling terminology. Therefore, the concepts were mainly discussed using more accessible language such as when describing the tensions inherent in identifying and negotiating quality evidence and prioritising evidence gaps, evaluating outputs and deciding when the model was “fit” for use (Chapters 5 and 6).
Summary of implications for future participatory modelling projects

There were a range of implications and suggested implementation strategies for future modelling projects arising from this thesis: including strategies to facilitate the recruitment and ongoing engagement of policy makers; ensure that the participatory process activities were efficient and engaging and ensure that the models remained policy relevant and focused. These have been outlined in detail in Chapters 4 to 6, however key implementation strategies drawn from across the thesis are summarised in this section. In summary, the engagement of senior clinicians and policy makers in the participatory approach provided many benefits which justified the time and resources required for implementation. The sense of ownership of the models and commitment from policy makers to use what they came to view as ‘their’ model was an important outcome of the participatory process that facilitated the use of the models to inform decision making. It was evident that senior policy makers were selective about their involvement in research activities and would only engage and participate if there was flexibility in the project to set focus questions based on their current priority policy needs, and to revise the questions as needed. Having a known colleague already involved in the project was also a useful strategy to encourage engagement.

The active engagement of stakeholders helped to parameterise and provided face validity checks for the models. The collaboration facilitated the dynamic and continuous integration of significant knowledge and a rigorous evidence base into the models. Through collaboration, the modellers were informed about the complexities of the system they were aiming to represent, and equally, the participants were educated about the capabilities and limitations of the model that they were helping to develop. The participants perceived and valued their role as knowledge contributors to the process and it is important that this is emphasised in the participatory activities. When planning participatory workshops, emphasis should be placed on structuring activities, such as those described in this thesis, that engage participants actively to contribute their expertise. Translation of information between disciplines emerged as an important challenge in these case studies and it is recommended that ‘translator’ roles be implemented, preferably embedded within the policy environment, to facilitate communication between participants, particularly between the primary policy partners and the technical modelling team.
The development of knowledge translation products was also identified as an important phase of participatory modelling research projects. The participants in the primary case study facilitated communication opportunities and identified key messages of interest to a broader policy audience. It is recommended that knowledge dissemination be considered part of the participatory process to elicit and leverage participant expertise. The DSMs developed in these case studies provided an opportunity to explore priority public health issues from a quantified and rigorous, systems perspective. This facilitated the mobilisation of knowledge and generation of policy insights that would not have been possible using more traditional statistical techniques.

Building on the 4 p’s framework for reporting participatory modelling projects in an applied health setting

The detailed examination of the participatory process reported in this thesis has added significant value and new understanding to a recently proposed framework [33] for reporting participatory modelling projects. This framework was developed in the environmental science modelling domain; and provides a useful template to facilitate reporting and communication by structuring the description of participatory modelling projects [33]. The manuscript in Chapter 5 demonstrated how the ‘Process’ component of Gray et al’s framework is relevant to health modelling projects, and can be applied to foster learning across sectors. The Process component explores how participants were involved in the model development, describes the level of participation, and the relationship between the process and decision making.

However the Gray framework also identifies ‘Purpose’, ‘Partnerships’ and ‘Products’ as key components of participatory modelling projects and practices [33]. The Purpose component defines the issue being modelled, describes the justification for building the model and for using a participatory process (the why). The Partnerships component describes the stakeholder partnerships that formed around different parts of the process (the who), defines the owner of the process and the criteria for including participants. The Product component describes the outputs resulting from these efforts (the what) including the policy insights. I have applied these four components to the primary case study, the DIP model, in Table 1 to provide an overview of all of the case-study findings, and to demonstrate how the framework can be used as an interdisciplinary method to report on and facilitate learning.
from participatory modelling projects across sectors. On reviewing this application of the 4P categories to the findings in my thesis, I have proposed that two additional components be added to the 4 P’s framework: i.e. consideration of research ‘imPact’, and ‘Prioritising’ future research. These potential new components have also been added to Table 1 and are explained and discussed below.

Considering imPact

The first additional component arising from this thesis is imPact. There are increasing demands to demonstrate the beneficial impact of research in terms of the social, economic and domain specific outcomes e.g. health outcomes [34-38]. Research impact can be direct or indirect and short or long term [36] and it is acknowledged that it can be difficult to measure and demonstrate, particularly when reporting in short term policy and grant application cycles [35, 36, 38]. However, it is important to consider and report examples of the impact of simulation models beyond the generation of policy insights, where possible, to both provide practical demonstration of their value and promote their ongoing use for policy discourse. Research impact has been defined as the intended positive impact of a research activity or an intervention [38, 39]. A systematic review conducted in 2017 identified 26 research impact frameworks for health care research [37]. The authors synthesised the research impacts that were common across the frameworks into short, mid and long term impact outcomes in five domains including primary research related outcomes (short term), influence on policy making, health service impact (mid term), health and societal and economic impact (long term) [37]. Impact reporting frameworks need to be flexible, not impose onerous reporting requirements and able to be tailored to fit the diverse range of research projects conducted [37]. The following question is proposed to be included in the reporting framework - “What was the imPact of the modelling process?”. Three sub-domains are proposed for this component; process impact, forecast impact and policy impact. These are explained below and are applied to the primary case study in Table 1:

1. Process impact: Describe the outcomes arising from the co-production, participatory process and the model, such as capacity building and knowledge exchange, that increase the likelihood of impact. Provide examples of products used to communicate insights from the model.
2. Forecast impact: Describe how the model outputs can be used to forecast the impact of policy or program interventions. For example, the DIP model outputs forecast the need for population level weight reduction interventions over interventions targeted at high risk groups to impact on the incidence of DIP.

3. Policy impact: Describe how model outputs are being used to inform decision making. For example, the DIP model is being applied to inform the development of a diabetes plan for the ACT.

Prioritising future research

The second additional component is Prioritisation. Identifying and Prioritising gaps in the existing evidence base is an important component of the model development and maturation process (Chapter 6) [4]. Lack of data should not preclude the use of modelling, particularly when the model development applies an iterative, participative approach that allows data needs to be identified and ways of addressing these to be developed [13]. The participatory process in these case studies mapped the causal factors and explored the impact of interventions for each focus topic in these case studies which facilitated the identification, clarification and prioritisation of gaps in current knowledge and evidence which can be used to guide future research. A core factor in policy makers’ motivation for participating in the projects was that the case studies focused on priority topics which had aspects that were not currently well understood and had contested policy alternatives that could be explored using the simulation models. The knowledge gaps identified and prioritised as an important focus for future research in the primary case study included understanding the individual heterogeneity of aetiology of diabetes in pregnancy and the impact of differing levels of glycemic control during pregnancy on maternal and perinatal outcomes (Table 1). The negotiation and prioritisation of evidence gaps was a highly valued benefit of the participatory process for end-user and researcher participants (Chapter 6) and is important to communicate to the broader research community when reporting on participatory modelling projects.
Table 1: Extended 4 P’s framework for reporting participatory modelling projects applied to the primary case study

<table>
<thead>
<tr>
<th>Component</th>
<th>Questions / Dimensions</th>
<th>Application to DIP model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purpose</td>
<td>Why model? And Why participatory?</td>
<td>The decision rationale for modelling Diabetes in pregnancy (DIP) for ACT Health was as follows. DIP is a complication of pregnancy that is defined as carbohydrate intolerance resulting in hyperglycaemia (abnormally high blood sugar). It includes women for whom the first recognition or onset of the condition occurs during pregnancy, as well as women with pre-existing type 1 and type 2 diabetes mellitus [40]. There has been a dramatic increase in the prevalence of DIP both in Australia and internationally [41] alongside increases in identified risk factors including high maternal body weight, physical inactivity, increasing maternal age, increasing parity and ethnicity [42-44]. There are short- and long-term health risks for both mother and baby, including increased risk of birth injury in the short term and development of diabetes later in life [45-48]. The available evidence does not definitively guide health services on how best to prevent and manage DIP with policy and program questions crossing the spectrum from population health interventions to complex clinical management issues [49-52]. Sophisticated analytical tools, developed using an interdisciplinary approach, such as participatory DSM, are needed to inform policy and health service planning decisions.</td>
</tr>
<tr>
<td>Component</td>
<td>Questions / Dimensions</td>
<td>Application to DIP model</td>
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<tr>
<td>-----------</td>
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</tr>
<tr>
<td>Process</td>
<td>How were stakeholders involved in the model development?</td>
<td>The participatory process centred around three face-to-face workshops where participants interacted to collaboratively map a qualitative conceptualisation of the focus issue; prioritised and mapped interventions to be tested in the model; prioritised and defined the outcomes to be measured; and reviewed and refined iterations of the model. Multiple additional forums e.g. web meetings, emails, and small group meetings, were used to engage participants throughout the process. A diagrammatic overview of the activities involved in the participatory process was included in Chapter 5. The activities were fully described in Chapters 3, 4 and 5. The model was developed to test policy intervention scenarios.</td>
</tr>
<tr>
<td>Partnerships</td>
<td>Who participated and why?</td>
<td>A diverse range of domain experts, including clinicians, public health specialists, researchers, and computer scientists engaged in the participatory process to collaboratively conceptualise the complex issues relating to diabetes in pregnancy and to co-produce a DSM to support decision making. The members of the participatory modelling consortium were listed in Chapter 7.</td>
</tr>
<tr>
<td>Products</td>
<td>What was produced by the modelling process?</td>
<td>The core product was a multi-scale DSM of diabetes in pregnancy in the ACT that can explore policy and health service scenarios to prevent and manage DIP. The model incorporated the complex and interrelated causal factors that contribute to the development of DIP and explored intervention options and combinations, spanning the spectrum from clinical to population health interventions. The model brought together the best available evidence and data with integrated complex systems modelling approaches to inform policy decision making for diabetes in pregnancy and is described in Chapter 7. Associated products were developed to facilitate communication of model results to a broader non-technical audience. These included a plain language factsheet about the model, a podcast and an interactive results dashboard (Chapter 7).</td>
</tr>
<tr>
<td>Component</td>
<td>Questions / Dimensions</td>
<td>Application to DIP model</td>
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<tr>
<td>ImPact</td>
<td>What was the impact of the modelling process?</td>
<td>Process impact: Capacity building and knowledge exchange was a key impact of the participatory modelling. The process enabled significant knowledge about both dynamic simulation modelling and diabetes in pregnancy to be combined to develop a decision support tool for policy and practice decision making. Professional academic, clinical and information sharing networks were established through the process. The model and the participatory process have been presented in multiple clinical, simulation modelling and knowledge mobilisation forums. Forecast impact: High weight status is an important and modifiable risk factor for DIP, and the impact of prevention interventions targeting weight were prioritised for first testing in the model. Model results forecasted that population level interventions would be necessary to make an impact on DIP incidence in the ACT. Targeted interventions for high risk women delivered either pre- or post-pregnancy were simulated to have a positive impact for individuals but would not substantially impact on population DIP incidence. The model also demonstrated that prevention interventions need to overcome BMI increases associated with increasing maternal age and parity. Policy impact: These findings are currently being used to support and inform a diabetes prevention and management plan for the ACT. The model findings have been used to emphasise the importance of including diabetes in pregnancy as a central focus for the service plan.</td>
</tr>
<tr>
<td>Prioritising</td>
<td>What future research priorities arose from the process and/or the model?</td>
<td>Two research priorities that arose from the process included firstly, improving knowledge about the dynamics and heterogeneity in the aetiology of glycemic dysregulation and diabetes mellitus development and secondly, understanding the impact of glycemic control during pregnancy for women diagnosed with DIP on maternal and perinatal outcomes.</td>
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</table>
Research in a real-world context – reflections on the challenges, strengths and limitations of this participatory action research

In this section I will reflect on the participatory action research (PAR) approach employed as a conceptual framework to investigate the research objectives, and discuss the associated challenges, strengths and limitations. PAR differs from conventional research in three ways [53]. Firstly, the focus of PAR is to both study and enable action. As described in the Chapter 1, the action is decided through a reflective cycle, whereby participants collect and analyse data, then determine what action should follow. The resulting action is then further researched, and an iterative reflective cycle perpetuates data collection, reflection, and further action [53]. Secondly, participants become partners in the research process: including selecting the research topic, data collection, and analysis and deciding what action should happen as a result of the research findings [53, 54]. Thirdly, PAR contrasts with less dynamic approaches that separate data and information from their contexts, PAR is embedded within the research context [53]. The PAR framework of action orientation, collaboration, reflection, iteration and involvement of researchers as participants was applied on two levels in this thesis. Firstly, within the core research cycle investigating the development of the DSMs for diabetes in pregnancy; and secondly, as part of the reflective research cycle examining the participatory approach to model development in both the primary and the two additional case studies.

Researcher position is critical to consider in participatory action research as the action researcher impacts on the process being examined and exerts influence on the study [53, 55]. My position in the participatory action research was as a participant observer; I both enabled and examined the process of developing the DIP dynamic simulation model using participatory methods and studied the value and utility of the participatory modelling process as perceived by end-user decision makers. As outlined in Chapter 3, my role in the primary case study (DIP model) was highly visible as the project lead, core modelling team coordinator, and primary conduit between the technical modellers and the stakeholder participants. My central role as both project enabler and PhD candidate / researcher was an important consideration when interviewing the end-user decision makers to elicit their perceptions of the value and utility of participatory modelling for decision support. Firstly, I was explicit about seeking participants true perceptions of the process and invited them to
genuinely reflect on both pros and cons. Secondly, the participants were all senior research, policy and practice professionals who were also aware of my status as a PhD candidate and less likely to feel the pressure of providing a socially desirable response than perhaps less experienced study participants may have been. Finally, the potential for interviewees to limit the disclosure about negative aspects of the process was further mitigated in the research design with the inclusion of two additional case studies. This allowed me to collect data from projects where I had not played a visible role in facilitating workshops and developing the model. The additional interviews provided opportunity to compare across interviews to examine whether there was some caution among participants from the primary case study to fully disclose their views on the value of the process. The level of interviewee openness was found to be similar across all case studies. The senior policy makers and clinicians interviewed were comfortable to openly discuss both the negative and positive aspects of their experience with the participatory model development process and the benefits and limitations of using the models to inform decision making (Chapter 6).

A core characteristic of participatory action research is that it is embedded in a real-world context [53]. As described above and in Chapters 4 to 6, this can strengthen the research by providing opportunities for it to be directly applied to addressing real issues. However, real-world policy making can also result in challenging and unexpected circumstances that delay or impact on the implementation of the research [55]. This thesis examined the in-depth collaboration of senior clinicians, policy makers and researchers from multiple Australian jurisdictions that addressed priority public health issues. Engaging the very senior and highly busy participants in the model development processes provided access to a significant knowledge base, and opened doors to opportunities for the models to be applied in practice. However, these senior domain experts also had many competing commitments and a significant challenge of implementation was ensuring that interactions with them were focused and efficient, met their expectations, minimised the risk of overburdening them and therefore facilitated their ongoing engagement in the process. An additional, practical challenge was finding suitable times to bring all the participants together. For the DIP case study for example, it became apparent as the project progressed that long lead times would be essential when booking workshops and meetings to ensure that as many key participants as possible were able to attend. It was therefore necessary to estimate when each development stage of the model would be ready for presentation to participants well in advance. Most times, these estimations were reasonably accurate, and meetings went ahead
as scheduled, however sometimes unexpected delays occurred and some meetings had to be postponed resulting in further, lengthy negotiations regarding scheduling.

The core modelling team for the primary case study also had other priorities to balance during the study period. For example, the head of the technical modelling team based in Canada, Professor Nathaniel Osgood, a highly skilled and experienced modeller with substantial teaching and research commitments, relied on much of the detailed programming being completed by his post-graduate students, working under his supervision. All these modellers needed to balance their time on the DIP model development with other commitments. There were also two personnel changes among the student modellers as each person primarily responsible for model development moved on in their own studies. The DIP model is a highly sophisticated and complex model and each new modeller required time to become familiar with it and learn the next steps for its development under the guidance of Professor Osgood. The development of an Australian-based programming workforce who specialise in health sector modelling has been an ongoing challenge and priority for The Australian Prevention Partnership Centre and other agencies who aim to expand the usage of these technologies for policy decision support.

Finally, it is important to reflect on my own position as an employee within ACT Health – which I believe was invaluable in enabling and facilitating the implementation of this collaborative project. While undertaking this research I also continued to work part-time as a Manager within the Epidemiology Section in ACT Health. In this capacity I was embedded within the health service, which provided invaluable opportunities to use my established professional relationships to establish the project within ACT Health, and to engage participants in the model development process. My work context also enabled me to subsequently apply the findings of the research to inform ACT Health policy development for diabetes in pregnancy. Fortuitously, the completion of the DIP model coincided with the timing of the ACT Health Minister’s interest in diabetes, and diabetes in pregnancy in particular, as an important health issue. To facilitate communication of the model and engagement with the Minister and her advisers, a suite of knowledge translation products was developed, including a fact sheet, an interactive dashboard and a podcast (Chapter 7). However, just prior to the date scheduled for the model to be presented to the Minister, other priorities subsumed her attention. These included a major organisational restructure in which ACT Health was a split into two agencies, and intense, negative local media interest in
her portfolio (for example https://www.canberratimes.com.au/canberra-news/health-split-not-a-fix-but-good-step-forward-fitzharris-20181002-p5079a.html). These issues resulted in the postponement of the presentation to, and engagement with, the Minister. However, at the time of writing she remains interested in the model as a new analytical method for informing policy and it is intended that the meeting will proceed – although after the submission of this thesis. It is important to note that whilst these matters were specific to the context of the ACT at the time of this thesis, similar fast moving events are the norm in the modern political context. They need to be considered when embarking on complex modelling projects and to guide realistic expectations about the timing and likelihood of successful impact.

Recommendations and next steps:

Recommendation 1: Develop strategies to share knowledge and support interdisciplinary modelling collaborations

One of the most important determinants of the successful policy modelling projects examined in this thesis was the collaboration and communication among those involved: the modellers themselves, the participants and stakeholders and the end-users of the model outputs. This cross-disciplinary collaboration was essential to yield useful policy models that were actually used by decision makers [13, 56]. However, because of the diversity of professional backgrounds among those involved, it was challenging to navigate the differences in terminology, methodological approaches and domain understanding for each discipline [7, 56, 57]. In all of the case studies included in this thesis, “translators” played a pivotal role in working between the disciplines to facilitate communication and understanding [56]. Further development of strategies and methods to support interdisciplinary modelling collaborations, and communication forums to share knowledge across disciplines (e.g. [7]) is recommended to facilitate ongoing advances in cross-disciplinary participatory modelling research.
Recommendation 2: Incorporate strategies derived from this participatory action research in the implementation of future participatory modelling projects

There were also many challenges associated with the practical implementation of the participatory aspects of the modelling. It was time consuming, intellectually demanding and required effective and patient coordination and facilitation skills. However, the benefits outweighed the challenges, providing opportunity to develop useful, policy-relevant models that were truly grounded in rigorous evidence and the significant knowledge base of the participants. Participant interest and engagement remained high across the three case studies and opportunities to utilise the models to inform decision were facilitated through their professional network. Detailed recommendations and procedural guidance for the implementation of participatory DSM were reported in Chapters 4 to 6. The key recommendations are summarised below:

**Emphasise co-production** – co-production of knowledge was reported by all participants as a highly valued outcome. It is recommended that a diverse group of expert participants be engaged as equal partners in all phases of the project from negotiating a focus topic, to engaging in the model development activities, actively contributing expert knowledge, refining the models, reviewing the model results and identifying and facilitating opportunities to communicate policy and program insights. Ensuring that the participant group includes representation of groups who have an important stake in the focus topic is recommended to facilitate the acceptance and use of the model.

**Focus on a current priority topic** – Participatory modelling processes are time consuming and resource intensive. Therefore, it is recommended that future modelling projects include a planning phase in which the focus topic is considered and negotiated with policy partners prior to commencement.

**Recruit key project roles** – It is recommended that the two key project roles that facilitated effective engagement of expert participants in these case studies be utilised in future modelling projects. These are the Domain expert, a well-respected authority on the focus issue and who can play a lead role in the project planning and workshop facilitation; and the Translator, a person who can translate the characteristics of the policy environment and data
for the modelling team and the model requirements and development process for the participants.

**Encourage openness and transparency in the process** – The participatory process provides a valuable opportunity to leverage significant knowledge in the development of policy decision support models. A challenging, but rewarding, aspect of the process was openly engaging with participants to iteratively critique, refine and ultimately improve the model. It is recommended that openness and transparency in the process be encouraged in future modelling projects to increase trust with participants and achieve policy relevant and useful DSMs.

**Communicate** – Communication was critical in all phases of the modelling project. It is recommended that background briefing material about the participatory process is developed prior to the commencement of the participatory process to enable participants to prepare. It is recommended that frequent concise and targeted communication and project updates be provided to participants to facilitate their ongoing engagement without overburdening them. Simple, clear and concise key messages about insights from the model should be derived and tools developed to facilitate communication to a variety of audiences.

**Recommendation 3:** Build dynamic simulation modelling capacity among public health professionals and expand research into the application and comparison of modelling methods for health policy questions

Many of the participants who engaged in the modelling projects had limited experience with DSM methods at the outset [56]. They were therefore unable, for example, to contribute to decisions about the methods used to represent causal pathways, or strategies to overcome gaps in the evidence base. As participant experience with and knowledge of DSM methods increases, further research into end-user or policy makers’ views about different systems science methods will be possible and is highly recommended. For example, the perceived value of agent-based modelling compared with system dynamics modelling in terms of conceptual design, model structure and usefulness for decision making would be of value to explore, along with the preferences for one modelling method over another for different policy questions. These insights would help inform future modelling projects and target areas requiring development. Incorporating DSM concepts and their application to public health
issues into public health professional, biostatistics and epidemiologist training programs is also recommended to increase awareness and adoption of these methods in the health sector.

Recommendation 4: Develop and test methods to facilitate interdisciplinary communication

A key challenge identified in this thesis was the design of communication methods that were effective across disciplines. Methods were required, firstly, to communicate model structure and logic in a way that was transparent and understandable for participants, and secondly, to communicate the model results to a broader policy audience. The lack of effective, transdisciplinary communication methods is a barrier to the uptake of modelling for public health [4] and the challenge will increase as more complex and sophisticated policy models are developed. Storytelling was one strategy utilised in this research to both communicate the model structure (Chapter 5) and the model findings (Chapter 7), however further research will be required to explore the effectiveness of this communication approach in other settings and whether other strategies are equally or more effective. Observational and experimental study designs could be utilised to investigate this issue drawing on participatory action research, communications, psychology and organisational behaviour research.

Recommendation 5: Test the novel participatory methods utilised in these case studies in other settings

The case studies investigated in this thesis were based in Australian jurisdictional health departments. Further exploration is necessary to determine if the novel collaborative methods used in these case studies would be as effective in other international settings. However, the in-depth analysis identified themes that were generalisable across the three case studies and can be utilised by multiple disciplines, including researchers, modellers, health service planners and policy makers, to inform future participatory modelling projects.
Next steps for the diabetes in pregnancy model

Dynamic simulation models mature over time. Further model development and modification can occur post-commissioning as new knowledge and evidence becomes available or new policy questions arise (Chapter 6) [9]. Further development work is planned for the DIP model developed in the primary case study to leverage its ability to explore intergenerational effects of diabetes in pregnancy on health outcomes. The use of agent-based modelling methods allows for individual agents to “inherit” a maternal history of diabetes in pregnancy. The effect of this on the individual agent’s risk of developing childhood overweight or obesity, diabetes in pregnancy, or early onset type 2 diabetes mellitus will be incorporated into the next version of the model.

Conclusion

This thesis explored the use of participatory DSM to inform health policy discourses, and it is the first empirical research specifically focused on understanding and elaborating the participatory method in applied health policy settings. This aim was achieved through the application and study of a novel participatory modelling approach in one primary and two secondary case studies. The in-depth analysis demonstrated that participatory DSM is feasible, useful and valuable to apply to priority public health issues with global significance [58]. The novel participatory activities utilised in these case studies successfully elicited and mobilised detailed and comprehensive knowledge and evidence about the focus issues which was synthesised and incorporated into the models. The process utilised in the primary case study was examined in detail to uncover the core analytic processes, activities and decisions involved in developing a DSM for diabetes in pregnancy using participatory methods. The analysis identified the common motivators for participation, the highly valued co-production elements and the unique benefits of DSM from the perspective of senior end-user policy makers who engaged in the case studies. The DSMs developed in these case studies are being used to provide policy insights and to inform decision making in Australian health services. The systematic data collection and analysis in this thesis identified key elements required for successful implementation of participatory DSM projects and provided valuable insights and practical guidance for implementing future projects in applied health settings.


34. Investigator grants [https://nhmrc.gov.au/funding/new-grant-program/investigator-grants]


58. Ten threats to global health in 2019 [https://www.who.int/emergencies/ten-threats-to-global-health-in-2019]
APPENDICES

Appendices for Chapter 3


2. Ethics approval letters from:
   - ACT Health Human Research Ethics Committee; and
   - University of Notre Dame Australia Human Research Ethics Committee.

3. Participant Information Sheets and Consent Forms

4. Participatory workshop one report – Diabetes in Pregnancy in the ACT

5. The Australian Prevention Partnership Centre news article: Workshop unpicks causes of gestational diabetes as part of simulation modelling project. [Article Link]

6. Participatory workshop two report – Diabetes in Pregnancy in the ACT

7. The Australian Prevention Partnership Centre news article: Project expanded to tackle all forms of diabetes in pregnancy. [Article Link]

Appendix for Chapter 6

8. Indicative questions for semi-structured interviews

Appendices for Chapter 7

9. Prevention Works Podcast Transcript

10. Diabetes in Pregnancy model documentation
Appendix 1: ACT Public Health Bulletin article

Case Study

Harnessing new technologies to inform health decision making: Dynamic simulation modelling as a decision support tool for diabetes in pregnancy

Louise Freebairn, Epidemiology Section and Dr Paul Kelly, Chief Health Officer & Deputy Director General, Population Health Protection & Prevention Division, ACT Health

There is mainstream acceptance that decision making for health programs and policies should be evidence-based; however, this can be difficult to achieve. The concept of “evidence informed decisions” is particularly challenging in population health policy and practice, where many of the current “big questions” are complex and not easy to address. These problems have multiple interacting causal factors with competing possible courses of action for decision makers to choose between, each course of action potentially resulting in complex and unintended consequences.1,2 Many factors, including availability and diversity of information, opinion and experience, timing, the political cycle, local norms, the influence of external players, and the availability of funds all influence decision-making.3,4

Research methods in prevention science have traditionally taken a reductionist approach focusing on detail of components of a system.5,6 For example, many studies have looked at the effectiveness of specific interventions on specific target groups. These studies have contributed and will continue to contribute significantly to our knowledge; however, these methods have difficulty accounting for the complexity of population health where there are delays between cause and effect and unanticipated consequences of interventions.7 New approaches, such as dynamic simulation modelling, provide insights into broader system behaviour in population health and enhance the evidence available for decision making.

Dynamic simulation modelling

Dynamic simulation modelling is a systems science method that recreates complex systems and human behaviours as a computer or mathematical model. These models can answer “what if” questions about the likely impacts over time of different policy and intervention options and combinations so that they can then be considered more broadly before implementation in the real world.1,8 Dynamic simulation modelling has been used to map health system components and their interactions, bring together evidence, examine and compare the potential outcomes of interventions, and guide more efficient investment and conscientious disinvestment of resources.8 This is important for preventive health policy and practice where decision support tools must have the capacity to steer a course through the complexity of interactions that give rise to real-world public health problems such as the global epidemic of chronic disease.1,8,9

Advances in technology have made modelling methods more user-friendly and allow for greater participation in model development. Participatory model development engages multidisciplinary stakeholders in a group model building process where participants share their knowledge about the causal pathways for the focus issue and where and how interventions have an impact on outcomes. Through a series of participatory workshops, the model building group, informed by evidence and data, collaboratively identify and map the key risk factors and likely causal pathways leading to outcomes of interest. The map is then used to construct, quantify and test a computer modelled representation of the causal pathways and intervention effects for the focus issue.1,8,10-12

The Population Health Protection & Prevention, ACT Health, in partnership with The Australian Prevention Partnership Centre, has brought together local, national and international researchers, clinicians and policy makers (see modelling participant group description below) to collaboratively develop a dynamic simulation model for Diabetes in Pregnancy in the ACT.13 More information about this process is available here: http://preventioncentre.org.au/our-work/research-projects/gestational-diabetes-through-a-systems-science-lens/.

Diabetes in Pregnancy in the ACT

Diabetes in pregnancy (DIP) is increasing both in the ACT and Australia,14,15 and this is challenging the capacity of diabetes services. The increase in DIP is associated with an increasing prevalence of risk factors such as overweight and obesity, older maternal age and increasing numbers of women from high-risk ethnic groups.14 Diagnostic screening guidelines were modified in 2015 to address the changing characteristics of women becoming pregnant and the increasing prevalence of type 2 diabetes mellitus.16 The new guidelines recommend that women who are high risk for developing diabetes in pregnancy should be screened in the first trimester of pregnancy.16 Consequently, these women are diagnosed with DIP earlier in their pregnancy and require services for a longer period of time. With increasing prevalence of risk factors, service providers report that women are more frequently presenting with a combination of risk factors resulting in more complex diabetes care needs.
Harnessing new technologies to inform health decision making: Dynamic simulation modelling as a decision support tool for diabetes in pregnancy

The rising prevalence of DIP is having a significant impact on health service demand and resources, and the need to “do things differently” was identified by participants. The model can inform investments for intervention in DIP, spanning the spectrum from clinical to population health interventions. Workload and resource use have been incorporated into the model to enable it to act as a resource allocation decision support tool. Prevention of risk factors was also prioritised in the model as small delays in the development of diabetes will have large implications for the longer-term burden of disease and costs to the health system. The model considers the short, intermediate, and long term implications of the increasing prevalence of risk factors for DIP. At the time of publication, this model was being finalised.

Dynamic simulation modelling is a decision support tool allowing for policy and practice scenarios to be simulated and explored. This “what if” capacity can be used to compare interventions alone or in combination before they are implemented. Examples of “what if” questions that can be explored in the ACT Diabetes in Pregnancy model include: What if we implemented population health interventions to reduce modifiable risk factors for diabetes in pregnancy? What if we targeted particular sub-groups with these interventions? How should the intervention be delivered? What if we modified the model of care for diabetes in pregnancy services? What is the likely impact on resource use?

Diabetes in Pregnancy ACT Modelling Group Participants
The Diabetes in Pregnancy Modelling group participants included policy and program officers, endocrinologists, a neonatologist, a general practitioner, diabetes educator, public health professionals, medical and population health researchers and dynamic simulation modelling experts. Participants included local, national and international experts in the field travelling from South Australia, Northern Territory, New South Wales and Saskatchewan, Canada to participate in the workshops.

Conclusion
Participatory dynamic simulation modelling provides opportunity for diverse health stakeholders to collaborate and explore policy and health service scenarios for priority public health topics and support decision making. Technological advances in modelling software combined with participatory modelling methods place the decision maker at the centre of the process in the development of dynamic decision support tools. Research into the impact of these methods on decision making is ongoing.

References
Appendix 2: Ethics approval letters

Ethics approval letters from:

- ACT Health Human Research Ethics Committee; and
- University of Notre Dame Australia Human Research Ethics Committee.
Ms Louise Freebairn
Manager
Health Outcomes and Knowledge Translation
Epidemiology Section
Health Improvement Branch
PO Box 825
Canberra City ACT 2601

Dear Ms Freebairn

ETHLR.15.160

The ACT Health Human Research Ethics Committee’s Low Risk Sub-Committee received notification of the proposed study:

Simulation modelling: A systems approach to supporting the use of evidence to inform decision making for gestational diabetes at its meeting of 11 August 2015.

I am pleased to inform you that, following further correspondence, your application has been approved.

The Sub-Committee agreed that the application is for low risk research and determined that the research meets the requirements of the National Statement on Ethical Conduct in Human Research and is ethically acceptable.

I attach for your records an Outcome of Consideration of Protocol form.

I confirm that the ACT Health Human Research Ethics Committee is constituted according to the National Statement on Ethical Conduct in Human Research 2007 and is certified for single review of multi-centre clinical trials. ACT Health HREC operates in compliance with applicable regulatory requirements and the International Conference on Harmonization Guidelines on Good Clinical Practice.

Yours sincerely

L. Morauta

Louise Morauta PSM PhD
Chair
ACT Health Human Research Ethics Committee
Low Risk Sub-Committee

9 September 2015
ACT HEALTH HUMAN RESEARCH ETHICS COMMITTEE

Outcome of Consideration of Protocol

Submission No: ETHLR.15.160 Date of Approval: 9 September 2015

Project Title: Simulation modelling: A systems approach to supporting the use of evidence to inform decision making for gestational diabetes

Submitted by: Ms Louise Freebairn

Your project was considered by the ACT Health Human Research Ethics Committee and Approved for a period of 3 years.

First Annual Review due: 1 September 2016

The Ethics Committee require as part of the review process that:

- At regular periods, and not less frequently than annually, Principal Investigators are to provide reports on matters including:
  - security of records
  - compliance with approved consent procedures and documentation
  - compliance with other approved procedures.
  - as a condition of approval of the protocol, that Investigators report immediately:
    - adverse affects on subjects
    - proposed changes in the protocol
    - unforeseen events that might affect continued ethical acceptability of the project.
- All published reports to carry an acknowledgement stating:
  - Approved on 9 September 2015 by the ACT Health Human Research Ethics Committee’s Low Risk Sub-Committee.

Louise Morauta PSM PhD
Chair
ACT Health Human Research Ethics Committee
Low Risk Sub-Committee
9 September 2015
Ms Louise Freebairn
Manager
Health Outcomes and Knowledge Translation
Epidemiology Section
Health Improvement Branch
PO Box 825
Canberra City ACT 2601

Dear Ms Freebairn

ETHLR.15.150

Thank you for your letter of 2 August 2016, requesting amendments relating to:
Simulation modelling: A systems approach to supporting the use of evidence to inform decision making for gestational diabetes

The following has been approved out of session:
- Audio recordings to be transcribed by external transcription company Rev
- Participant Information Sheet, model development group, revised August 2016

This correspondence has been recorded on the Committee’s file and will be reported to the next available meeting.

Yours sincerely,

August Marchesi
Director
Human Research Ethics
25 August 2016
Ms Louise Freebairn  
Manager  
Health Outcomes and Knowledge Translation  
Epidemiology Section  
Health Improvement Branch  
PO Box 825  
Canberra City ACT 2601  

Dear Ms Freebairn  

ETHLR.15.150  

Thank you for your letter of June 2017, requesting amendments relating to:  

Simulation modelling: A systems approach to supporting the use of evidence to inform decision making for gestational diabetes  

At its meeting of 12 July 2017, the Committee approved:  

- To include participants from modelling projects that are further advanced and have used the same participatory processes in the post-workshop interviews  
- Participant Information Sheet, model application group, version 1.4 dated June 2017  
- Consent Form, version 1.3 dated June 2017  
- Indicative questions for the semi-structured interviews  

This information is now recorded on the Committee’s files.  

Yours sincerely,  

A/Professor Paul Crauf MPH FRACP  
Acting Chair  
ACT Health Human Research Ethics Committee  
Low Risk Sub-Committee  
12 July 2017
8 October 2015

Associate Professor Lucie Rychetnik & Ms Louise Freebairn
School of Medicine
The University of Notre Dame Australia
PO Box 944
Broadway NSW 2007

Dear Lucie and Louise,

Reference Number: 015119S

Project Title: “Evaluation of simulation modelling to inform policy and program options for gestational diabetes in the ACT.”

Your response to the conditions imposed by a sub-committee of the university’s Human Research Ethics Committee, has been reviewed and assessed as meeting all the requirements as outlined in the National Statement on Ethical Conduct in Human Research (2014). I am pleased to advise that ethical clearance has been granted for this proposed study.

All research projects are approved subject to standard conditions of approval. Please read the attached document for details of these conditions.

On behalf of the Human Research Ethics Committee, I wish you well with your study.

Yours sincerely,

Dr Natalie Giles
Research Ethics Officer
Research Office

e: Prof Christine Bennett, Dean, School of Medicine Sydney;
   Prof George Manda, SRC Chair, School of Medicine Sydney.
19 September 2016

A/Prof Lucie Rychetnik & Ms Louise Freebairn  
School of Medicine  
The University of Notre Dame Australia  
P.O Box 944  
Broadway NSW 2007

Dear Lucie and Louise,

Reference Number: 0151198  
Project Title: “Evaluation of simulation modelling to inform policy and program options for gestational diabetes in the ACT.”

Your response to the conditions imposed by a sub-committee of the university’s Human Research Ethics Committee, has been reviewed and based on the information provided has been assessed as meeting all the requirements as mentioned in National Statement on Ethical Conduct in Human Research (2007). Therefore, I am pleased to advise that your request for an amendment has been granted for this approved study.

All research projects are approved subject to standard conditions of approval. Please read the attached document for details of these conditions.

On behalf of the Human Research Ethics Committee. I wish you well with your study.

Yours sincerely,

[Signature]  
Dr Natalie Giles  
Research Ethics Officer  
Research Office  

[Signature]

Prof George Merrett, SRC Chair, School of Medicine Sydney
11 July 2017

Associate Professor Lucie Rychetnik & Ms Louise Freebairn
School of Medicine
The University of Notre Dame Australia
PO Box 944
Broadway NSW 2007

Dear Lucie and Louise,

Reference Number: 0161198

Project Title: “Evaluation of simulation modelling to inform policy and program options for gestational diabetes in the ACT.”

Your response to the conditions imposed by a sub-committee of the university’s Human Research Ethics Committee, has been reviewed and assessed as meeting all the requirements as outlined in the National Statement on Ethical Conduct in Human Research (2007, updated May 2015). I am pleased to advise that ethical clearance has been granted for this proposed amendment to your study.

Other researchers identified as working on this project are:

<table>
<thead>
<tr>
<th>Name</th>
<th>School/Centre</th>
<th>Role</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dr Paul Kelly</td>
<td>ACT Health</td>
<td>Co-Supervisor</td>
</tr>
<tr>
<td>Dr Jo-An Atkinson</td>
<td>Sax Institute</td>
<td>Co-Supervisor</td>
</tr>
</tbody>
</table>

*All research projects are approved subject to standard conditions of approval. Please read the attached document for details of these conditions.*

On behalf of the Human Research Ethics Committee, I wish you well with your study.

Yours sincerely,

[Signature]

Dr Natalie Giles
Research Ethics Officer
Research Office

cc: Prof George Manled, SIRC Chair, School of Medicine Sydney
Appendix 3: Participant information and consent forms

Participant information form and consent forms are included for: firstly, the model development group who participated in the diabetes in pregnancy case study and secondly, the end-user participants from the additional case studies who were interviewed.
Evaluation of simulation modelling to inform policy and program options for gestational diabetes in the ACT

Project Overview:

This project is an evaluation of the use of simulation modelling as a systems science tool to support decision making for gestational diabetes programs and policies in the ACT.

Simulation modelling provides policy makers with a unique tool for synthesizing and leveraging existing data, evidence and expert and local knowledge to examine in a robust, risk-free and low cost way, the likely impact of different policy scenarios prior to implementation. Recent advances in modelling software capability and more user-friendly interfaces have meant that simulation modelling is now more broadly accessible, enabling a transparent and participatory approach to be used for the development of more complex models.

The outputs of such models can be used to inform broader policy dialogues to determine which policy and program options can and should be pursued.

As you have agreed to participate in the gestational diabetes model development workshops, you are now eligible to participate in this evaluation.

Investigators:

The Principal Investigator for this project is Louise Freebairn from the Epidemiology Section, ACT Health, and PhD student at University of Notre Dame. The investigator team includes Dr Paul Kelly, ACT Chief Health Officer; Associate Professor Lucie Rychemnik, Dr Jo-An Atkinson and Eloise O’Donnell from The Australian Prevention Partnership Centre; and Professor Alison Kent and Professor Chris Nolan from the Canberra Hospital and Health Services.

Participant Information:

You are invited to take part in this evaluation based on your participation in the gestational diabetes simulation modelling project. Before you decide to take part in this evaluation it is important for you to understand why the evaluation is being done and what it will involve. Please take time to read the Evaluation of simulation modelling policy and program options to manage gestational diabetes in the ACT, April 2016.
following information carefully. Please ask the study team any questions you have and request any further information you need.

**Why is this study being done?**
The purpose of this study is to evaluate a systems modelling approach to understand the factors associated with gestational diabetes and its treatment and to optimise the use of evidence to inform policy and program decisions.

**What is involved in the study?**
Participants of this evaluation will participate in model development workshops. Evaluation of the modelling process will involve audio recording of workshops. The focus of the audio recording is on group interactions rather than the contribution of any one individual. In addition, you will be asked to complete surveys before and after the workshops and may be invited to participate in recorded interviews with the researcher before and after the workshops.

Participants will:
- Attend model building workshops which involve group discussion and will be audio recorded for the evaluation
- Be invited to participate in semi-structured interviews - this will be interviews with yourself and a member of the research team before and after the model development process. They are expected to take less than one hour and will be scheduled for a mutually convenient time and place

**Why have I been chosen?**
You have been chosen to participate in this evaluation because you have been identified as a clinical, policy or research expert in the field of systems modelling or gestational diabetes who has agreed to attend the model development workshops.

**Do I have to take part?**
Participation in this evaluation is voluntary. It is completely up to you whether or not you participate. If you decide not to participate, it will not impact on your employment or your relationship with the researchers or other participants in the research.

You can refuse to take part in this evaluation or withdraw from it at any time without giving a reason and without consequence. If you choose to withdraw, the information you have provided prior to the point of withdrawal will be included in the study analysis unless you request removal of the information where feasible. From the point of withdrawal no further information will be collected from you or included in the study.
Are there any risks?
There are no anticipated risks from participating in the evaluation. Your involvement will not impact on your employment or your relationship with the researchers or other participants in the research.

Are there any benefits?
The evaluation may provide benefits to decision making for gestational diabetes diagnosis and treatment, however it may or may not directly benefit you. Your participation may help others in the future.

What are the costs?
There will be no cost to you for participating in this evaluation. Travel costs associated with your participation will be covered by The Australian Prevention Partnership Centre. Please contact the Louise Freebairn on louise.freebairn@act.gov.au if this applies to you.

Access to the results of the study
Results will be used in a Doctor of Philosophy research thesis by the principal investigator listed above. They will also be published in journal articles and conference papers. In any publication, information will be provided in such a way that you cannot be identified. Results will be provided to you, if you wish.

What about confidentiality?
Any identifiable information that is collected about you in connection with this study will remain confidential and will be disclosed only with your permission, or except as required by law. Only the researchers named above will have access to your details and results that will be held securely at ACT Health.

If you have any questions please contact the research team

Louise Freebairn, Epidemiology Section, ACT Health,

Phone: 02 6205 2608 or email: louise.freebairn@act.gov.au

Should you have any problems or queries about the way in which the study is conducted, and do not feel comfortable communicating with the staff conducting this survey, please contact: ACT Health Human Research Ethics Committee (ACTH-HREC), Level 6, Building 10, Canberra Hospital, Telephone: (02) 6174 7968 or acthealth-hrec@act.gov.au
Consent Form for Participation in a Research Project

I, _____________________________ (name of participant)
of ______________________________ (address)

have been asked to consent to participation in a research project entitled:

Modelling policy and program options to manage
gestational diabetes in the ACT

In relation to this study I have read the Participant Information Sheet and have been informed of the following points:

1. Approval has been given by the ACT Health Human Research Ethics Committee (ETHLR:15.150) and the University of Notre Dame Human Research Ethics Committee (015119S).

2. The aim of the study is to apply and evaluate a systems modelling approach to understand the factors associated with gestational diabetes and its treatment and to optimise the use of evidence to influence policy and program decision making.

3. The results obtained from the study may or may not be of direct benefit to me.

4. The study procedure will involve completion of surveys, audio-recorded model development and engagement workshops and audio-recorded evaluation interviews.

5. Should I have any problems or queries about the way in which the study was conducted, and do not feel comfortable contacting the research staff, I am aware that I may contact the ACT Health Human Research Ethics Committee Secretariat, Canberra Hospital, Yamba Drive, Garran ACT 2605 (ph: 6174 7968)

6. I can refuse to take part in this project or withdraw from it at any time without giving a reason and without consequence. If I choose to withdraw, the information I have provided prior to the point of withdrawal will be included in the study analysis unless I request removal of the information where feasible. From the point of withdrawal no further information will be collected from me or included in the study.

7. I understand that while the results of the research will be made accessible my involvement and my identity will not be revealed.

After considering all these points, I accept the invitation to participate in this study.

Name: (please print) __________________________ Date: __________

Signature (Participant) __________________________

Investigator: (please print) __________________________ Date: __________

Signature (Investigator) __________________________

Modelling policy and program options to manage gestational diabetes in the ACT, version 1.2, July 2015
Evaluation of participatory simulation modelling to inform policy and program decision making for complex health issues

Project Overview:

This project aims to investigate the use of participatory dynamic simulation modelling as a tool to support decision making for health sector programs and policies.

Simulation modelling provides policy makers with a unique tool for synthesizing and leveraging existing data, evidence and expert and local knowledge to examine in a robust, risk-free and low cost way, the likely impact of different policy scenarios prior to implementation. Recent advances in modelling software capability and more user-friendly interfaces have meant that simulation modelling is now more broadly accessible, enabling a transparent and participatory approach to be used for the development of more complex models.

The outputs of such models can be used to inform broader policy dialogues to determine which policy and program options can and should be pursued.

Investigators:

The Principal Investigator for this project is Louise Freebairn from the Epidemiology Section, ACT Health, and PhD student at University of Notre Dame. The investigator team includes Dr Paul Kelly, ACT Chief Health Officer; Associate Professor Lucie Rychetnik from the University of Notre Dame and Dr Jo-An Atkinson from The Australian Prevention Partnership Centre.

Participant Information:

You are invited to take part in this study. Before you decide to take part it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully. Please ask the study team any questions you have and request any further information you need.

Why is this study being done?

The purpose of this study is to apply and evaluate a systems modelling approach to understand the factors associated with complex health issues and to optimise the use of evidence to inform policy and program decisions.
What is involved in the study?

Participants will be invited to participate a recorded interview with the researcher. The interview is expected to take approximately one hour.

Why have I been chosen?

You have been chosen to participate in this study because you have been involved in a participatory dynamic simulation modelling project, for example the NSW Premier’s Priorities Project – reducing childhood overweight and obesity by 5% project or the Model behaviour – a systems approach to reducing alcohol related harms project.

Do I have to take part?

Participation in this study is voluntary. It is completely up to you whether or not you participate. If you decide not to participate, it will not impact on your employment or your relationship with the researchers or other participants in the research.

You can refuse to take part in this project or withdraw from it at any time without giving a reason and without consequence. If you choose to withdraw, the information you have provided prior to the point of withdrawal will be included in the study analysis unless you request removal of the information where feasible. From the point of withdrawal no further information will be collected from you or included in the study.

Are there any risks?

There are no anticipated risks from participating in the study. Your involvement in the project will not impact on your employment or your relationship with the researchers or other participants in the research.

Are there any benefits?

The study may provide benefits to decision making for complex health issues, however it may or may not directly benefit you. Your participation may help others in the future.

What are the costs?

There will be no cost to you for participating in this study.

Access to the results of the study

Results will be used in a Doctor of Philosophy research thesis by the principal investigator listed above. They will also be published in journal articles and conference papers.

Evaluation of simulation modelling for policy and program decision making, version 1.4, June 2017
In any publication, information will be provided in such a way that you cannot be identified. Results will be provided to you, if you wish.

What about confidentiality?

Any information that identifies you in connection with this study will remain confidential and will be disclosed only with your permission. An external company, Rev, will assist with transcribing the audio-recordings. Files are securely stored and transmitted using 128-bit SSL encryption, will never be shared with anyone outside of Rev and will only be visible to the transcribing professionals who have signed strict confidentiality agreements. The Rev confidentiality statement can be found on the website: https://www.rev.com/

Any identifiable information that is collected about you in connection with this study will remain confidential and will be disclosed only with your permission, or except as required by law. Only the researchers named above will have access to your details and results that will be held securely at ACT Health.

If you have any questions please contact the research team

Louise Freebairn, Epidemiology Section, ACT Health,

Phone: 02 6205 2608 or email: louise.freebairn@act.gov.au

Should you have any problems or queries about the way in which the study is conducted, and do not feel comfortable communicating with the staff conducting this survey, please contact: ACT Health Human Research Ethics Committee (ACTH-HREC), Level 6, Building 10, Canberra Hospital, Telephone: (02) 6174 7968 or acthealth-hrec@act.gov.au
Consent Form for Participation in a Research Project

I, ___________________________________________ (name of participant)
of ___________________________________________ (address)
have been asked to consent to participation in a research project entitled:

Evaluation of participatory simulation modelling to inform policy and program decision making for complex health issues

In relation to this study I have read the Participant Information Sheet and have been informed of the following points:

1. Approval has been given by the ACT Health Human Research Ethics Committee (ETHLR.15.150) and the University of Notre Dame Human Research Ethics Committee (015119S).
2. The aim of the study is to apply and evaluate a system modelling approach to understand the factors associated with complex health issues and to optimise the use of evidence to influence policy and program decision making.
3. The results obtained from the study may or may not be of direct benefit to me.
4. The study procedure will involve audio-recorded evaluation interviews which will be provided to and transcribed by Rov transcription services.
5. Should I have any problems or queries about the way in which the study was conducted, and I do not feel comfortable contacting the research staff, I am aware that I may contact the ACT Health Human Research Ethics Committee Secretariat, Canberra Hospital, Yamba Drive, Garran ACT 2605 (ph: 6174 7968)
6. I can refuse to take part in this project or withdraw from it at any time without giving a reason and without consequence. If I choose to withdraw, the information I have provided prior to the point of withdrawal will be included in the study analysis unless I request removal of the information where feasible. From the point of withdrawal no further information will be collected from me or included in the study.
7. I understand that while the results of the research will be made accessible my involvement and my identity will not be revealed.

After considering all these points, I accept the invitation to participate in this study.

Name: (please print) __________________________ Date: ____________

Signature (Participant) __________________________

Investigator: (please print) __________________________ Date: ____________

Signature (Investigator) __________________________

Evaluation of simulation modelling for policy and program decision making, version 1.3, June 2017
The following report was provided to participants from the model development group for the diabetes in pregnancy case study following workshop one.
Summary of Gestational Diabetes
Modelling Workshop One

5 May 2016

Background

The purpose of The Australian Prevention Partnership Centre (TAPPC) is to develop and use systems thinking and systematic ways of preventing lifestyle related chronic disease. People from a range of disciplines, backgrounds and countries have gathered together to come up with practical ways to support decision making and research translation to address these issues.

This project will develop a dynamic simulation model that will look at gestational diabetes mellitus (GDM) from an ACT perspective and will be using ACT data. However, the national context will be considered in the model development and the model will be a proof of concept with the potential to expand much more broadly.

The model will consider the short, middle and long-term implications of the current food culture, overweight and obesity and GDM and Type 2 diabetes mellitus. Small delays in the development of diabetes will have large implications for the longer-term burden of disease and costs to the health system. This long-term vision is important as the model is built collaboratively.

Increasing demand for health services due to the rising prevalence of GDM is having a significant impact on resources and the need to “do things differently” was identified by several workshop participants. Workload and resource use will be incorporated into model to enable it act as a resource allocation decision support tool.

This workshop brings together practitioners, policy makers and researchers and allows for greater accessibility of data and expertise. This partnership also allows for research to be translated into policy and program decisions more readily.
Model purpose

The following purposes for the model were synthesised from the key modelling questions contributed by participants at the workshop. Full responses are included in Appendix A.

- Determine the best investments for intervention in GDM. E.g. “I’m here to see if modelling can help determine the right interventions, at the right times, by the right people, in the most efficient and effective way (to make a difference).” Interventions in the model to include both clinical and population health interventions.

- Examine GDM within a context or system e.g. Food environment, personal environment such as stress and coping.

Determining model structure: interventions and outcomes

Participants were divided into two groups to identify priority interventions and outcomes. Interventions and outcomes will be the focus of workshop 2, however it is important to understand the types of interventions and outcomes that will be incorporated into the model when commencing the model build. Workshop 2 will focus on identifying the causal mechanisms for the interventions and outcomes.

Each group identified interventions and outcomes and then all participants voted on those interventions and outcomes they considered to be most important for inclusion in the model (see images below).

Interventions:

This group discussed interventions based on a life course (from pre-pregnancy right through to college, Image A below). It was discussed that the biggest benefit at the population level is achieved when targeting people going from normal weight to overweight.

Most of the interventions that were mentioned were around education and primary prevention around physical activity and healthy eating.
**Top 5 prioritised interventions:**

1. Weight and height measurement pre pregnancy - having ongoing education about what is a healthy BMI, for pre pregnancy in particular. This would be a combination of awareness and education and measurement. Include a feedback mechanism.

2. Targeted preconception programs for high risk - women who are considered very high risk for GDM, come to program that works on getting them into the right shape before they conceive. (Subset of the first program)

3. Inter pregnancy - lifestyle change targeted at this stage of a woman's life course. Trying to reduce women who have had GDM gain for overweight and obese

4. Early screening at booking for the pregnancy. (Clinically based intervention). Not just for when they come to the hospital, but also when they come to GP - and what that would involve.

5. Incentives for lifestyle change.
Outcomes:

This group identified outcomes for the mother and outcomes for the baby separately and divided them into short term, medium term and long term outcomes (see Images B and C below).

Top 5 prioritised outcomes:

1. Incidence of GDM
2. Maternal diabetes
3. Childhood obesity
4. Early onset diabetes
5. Diabetes complications

Image B: Outcomes for Mother identified by participants
Image C: Outcomes for baby identified by participants

Mapping causal factors to the model infrastructure

Image D: Participants mapping factors to the agent based modelling infrastructure
A “strawman” model infrastructure for three agent state charts was laid out on a large table.

The three state charts were as follows:
- Pregnancy state chart: States = not pregnant, 1st pregnancy, subsequent pregnancy
- GDM state chart: States = Low risk for GDM, high risk for GDM, GDM diagnosed (with sub states indicating that the GDM was well controlled or not)
- Weight state chart: States = normal/underweight, overweight, obese

Participants were asked to identify factors that contribute to people moving between the states in each state chart.

Image E: Detail of mapped factors

Refining the priority causal factors for inclusion in the model

A sub-group of participants met subsequent to the workshop to refine and synthesise the factors identified. A process of grouping the factors identified the
following themes (listed in no particular order) which will be represented in the model.

1. Family history/genetic factors
   a. Family history of diabetes
   b. Family history of obesity
   c. Epigenetics
   d. Genes

2. Food
   a. Unhealthy diet
   b. Food security
   c. Food environment

3. Physical Activity
   a. Level of physical activity
   b. Level of sedentary behaviour
   c. Physical environment

4. Health state
   a. Previous pregnancy with GDM
   b. Multiple pregnancy
   c. Previous still birth
   d. Previous macrosomic baby
   e. Previous pregnancy with fetal growth restriction
   f. Personal history of macrosomia

5. Health care system
   a. Type of screening test
   b. Universal or selective screening
   c. Access to health care – rurality/remoteness
   d. Health bureaucracy
   e. Government policy
   f. Infrastructure/environment
   g. Market/trade

6. Metabolic functioning
   a. Weight status
   b. Gestational weight gain

7. Non-modifiable factors
   a. Age
   b. High risk ethnic group
   c. Migration
   d. Polycystic Ovary Syndrome (PCOS)

8. Psychosocial
   a. Education level
b. Social network
c. Cultural norms
d. Occupation
e. Inequality
f. Psychological factors
g. Poverty

Next steps:

• Workshop 2 will focus on interventions and outcomes. Participants will identify the causal mechanisms for interventions and pathways for measuring outcomes.
• Participants have been invited to be involved in model development meetings and discussions between workshops.
• Workshop 2 – 19 August 2016.
Appendix A Key questions identified by participants

- I’m interested in the food environment and the impact this has on the problem of GDM. How can we link the acute management of GDM with population level management? How do we measure outcomes that occur at the systems level?
- How do we manage GDM, particularly in the second half of pregnancy?
- How does GDM fit into the broader problem of diabetes and obesity prevention?
- I’m concerned with the continuum of pre-pregnancy, during pregnancy and after pregnancy. Here to see if modelling can help determine the right interventions, at the right times, by the right people, in the most efficient and effective way (to make a difference).
- Consideration of personal and contextual factors that contribute to stress.
- Better ways to assess models of care for managing GDM.
- Interested in looking at different approaches before and after prevention, and how the model can help decide where to invest for intervention.
- Different models of care provision and testing better ways to prevent GDM.
- The risk for the next generation and prevention as early as possible for the next generation.
- What is the best bang for buck for population interventions and clinical management interventions? Also, long term considerations in terms of health services costs and burden of disease.
Appendix 5: News article – Workshop unpicks causes of gestational diabetes as part of simulation modelling project.

Archived: Simulation modelling helps to unpick causes of gestational diabetes

1 June 2016

A multi-disciplinary group of clinicians, policy makers, researchers and modellers have worked together to map the risk factors and causes of gestational diabetes in the ACT.

The team included international guests, Mr Allan McLean, Associate Professor Nate Osgood and Professor Roland Dyck, who are world leaders from Canada in simulation modelling for gestational diabetes.

This was the first of a series of workshops for a PhD project led by Louise Freebairn involving ACT Health, Prevention Centre and the University of Saskatchewan.
Ms Freebairn, Manager of the Knowledge Translation and Health Outcomes Team at ACT Health, said the project aimed to tackle the growing problem of gestational diabetes against the backdrop of increasing interest in systems science methods to examine complex problems.

Simulation modelling is one method under the umbrella of systems science, and can be used as a unique ‘what if’ tool to test the likely impact of a range of possible solutions before implementing them in the real world.

Ms Freebairn said a key outcome of the day was that workshop participants agreed on the importance of a population health approach to address the increasing rates of gestational diabetes.

“One participant used the analogy of current diabetes services rescuing people who have fallen into a river. They don’t have the capacity to run upstream and see why people are falling in because they are too busy pulling people out,” she said. “What they need is somebody to go upstream and stop people falling into the river in the first place. This is where population health approaches can play an important role.”
Ms Freebairn said the project optimised the collaborative nature of the Prevention Centre, not only because of the multidisciplinary group of participants, but also its policy relevance.

"If the model can inform even small effects in the delay of the onset of diabetes, this will have huge impact in terms of the long-term benefits for health service costs and the burden of disease in individuals and the population," she said.

The next workshop, to be held in August, will explore the likely effect of a range of interventions.

• By [Boise O’Donnell], Research Officer
Appendix 6: Summary report – Gestational diabetes modelling workshop two

The following report was provided to participants from the model development group for the diabetes in pregnancy case study following workshop two.
Summary of Gestational Diabetes Modelling Workshop Two

19 August 2016

Background

The purpose of The Australian Prevention Partnership Centre (TAPPC) is to develop and use systems thinking and systematic ways of preventing lifestyle related chronic disease. People from a range of disciplines, backgrounds and countries have gathered together to come up with practical ways to support decision making and research translation to address these issues.

This project will develop a dynamic simulation model that will look at gestational diabetes mellitus (GDM) from an ACT perspective and will be using ACT data. However, the national context will be considered in the model development and the model will be a proof of concept with the potential to expand much more broadly.

The model will consider the short, middle and long term implications of the current food culture, overweight and obesity and GDM and Type 2 diabetes mellitus. Small delays in the development of diabetes will have large implications for the longer term burden of disease and costs to the health system. This long term vision is important as the model is built collaboratively.

Increasing demand for health services due to the rising prevalence of GDM is having a significant impact on resources and the need to “do things differently” was identified by a number of workshop participants. Workload and resource use will be incorporated into model to enable it act as a resource allocation decision support tool.

This workshop series brings together clinicians, policy makers and researchers and allows for greater accessibility of data and expertise. This partnership also allows for research to be translated into policy and program decisions more readily.
Model purpose

The following purposes for the model were synthesised from the key modelling questions contributed by participants at the workshop. Full responses are included in Appendix A.

- Determine the best investments for intervention in GDM. E.g., “I’m here to see if modelling can help determine the right interventions, at the right times, by the right people, in the most efficient and effective way (to make a difference).” Interventions in the model to include both clinical and population health interventions.

- Examine GDM within a context or system e.g. Food environment, personal environment such as stress and coping.

Reporting back and presenting the current version of the model

An overview of the model architecture was presented showing the three model levels as follows:

- **Population level**
  - System Dynamics model
  - Population level – people in this model are mostly homogeneous
  - Characteristics of the population influence how people move through the model e.g. Demographics
  - The population moves through stocks and flows

- **Individual level**
  - Agent based model (agent = person)
  - People have individual characteristics that impact on how they transition between states
  - Statecharts capture the state of a person e.g. Normal weight, overweight or obese

- **Service level**
  - Discrete Events Model
  - Modeling of GDM services in ACT broadly. The model is not specific to individual services
  - Select agents from ABM flow through various services as appropriate
  - Service provision influences health outcomes
  - Allows us to look at staffing and workload
A simplified model conceptualisation was presented, as shown below and case examples were used to demonstrate how people would “move through” the model levels.

Image A: Gestational Diabetes Mellitus model conceptualisation

Participants were shown screenshots of the model in the AnyLogic software and the model running.

Intervention mapping

The top 5 prioritised interventions from Workshop 1 (see below) were reviewed and discussed.

Top 5 prioritised interventions:

1. Weight and height measurement pre pregnancy - having ongoing education about what is a healthy BMI, for pre pregnancy in particular. This would be a combination of awareness and education and measurement. Include a feedback mechanism.

2. Targeted preconception programs for high risk - women who are considered very high risk for GDM, come to program that works on getting
them into the right shape before they conceive. (Subset of the first program)

3. Inter pregnancy - lifestyle change targeted at this stage of a woman's life course. Trying to reduce women who have had GDM gain for overweight and obese

4. Early screening at booking for the pregnancy. (Clinically based intervention). Not just for when they come to the hospital, but also when they come to GP - and what that would involve.

5. Incentives for lifestyle change.

Other potential interventions suggested for inclusion in the model were:

- Interventions targeting prevention of people transitioning into higher weight categories.
- GP screening for type 2 diabetes opportunistically or pre-pregnancy
- Transgenerational interventions from birth – evidence base is limited
- App based intervention – providing service information, risk calculators for GDM, information about timing of visits to health services etc

The following four interventions were agreed on to be the focus during this workshop.

- Weight and height measurement pre-pregnancy,
- Targeted pre-conception lifestyle program for high risk women,
- Changing models of care for women with diagnosed GDM,
- Inter-pregnancy lifestyle change.

Participants were “walked through” an example of intervention mapping using early screening for GDM as an example intervention as shown below.
Image B: Gestational Diabetes Mellitus model conceptualisation with example intervention

“Early screening” mapped
INTERVENTION MAPPING ACTIVITY:

Participants worked in two groups, each group working on two interventions.

**Intervention 1: Transgenerational intervention - Monitoring peoples’ weight across their life course.**

This intervention targets “everybody” from a “whole of life” perspective. People have their BMI measure to identify those who are overweight and obese. These people can then be referred to services.

**Delivery:**

- Awareness campaign plus GP standard practice – also in schools? (height and weight could be done in vaccination program). Though potential stigma from mass weighing. Discussion of potential opt-out for height and weight as part of immunisation consent.
- Need to coach GPs in this to make it routine, like taking BP.
- Getting men involved- possibly at football. Discussion of interventions at barbers (US model).

**Target risk factor:**

- It targets risk factors of diet and PA, therefore weight states.

**Effectiveness**

- Little evidence available

**Differential effects:**

- Differential effects: It would affect the ‘worried well’ differentially, it is easier to target children, cultural perceptions of weight, geographic location.
- Delivery mechanism would have an effect on the effectiveness, e.g. if it was conducted in a school hall (overweight kids would not go to school that day).
- Providing varied settings for different ethnic groups, need to approach through AMSs for Indigenous people.
• Slow cultural shifts (e.g. with smoking), however legislative change is necessary as well for large societal change.

Unintended consequences:

• stigma, and also potential for encouraging eating disorders (though eating disorders are less of a risk than Overweight and obesity).
• Similar to smoking being made socially unacceptable, it could be similarly unacceptable to make poor food choices (including fast food, restaurants, supermarkets etc).
• Acceptability of running the school based program.

Resources:

• Resources used include GPs, dieticians, practice nurses.

Image C: Transgenerational intervention mapped to model conceptualisation
Intervention 2: Inter-pregnancy lifestyle change

GDM makes you higher risk for diabetes and getting GDM again therefore there is an opportunity between pregnancies to intervene with women to reduce their risk.

This intervention aims to change their weight status to reduce diabetes risk. noting that not everyone who has had GDM is considered pre-diabetic.

Risk factors targeted:

- weight status,
- diet,
- history of GDM

Delivery:

- Target is at the individual level.
- Counselling: If a woman has had GDM, had lifestyle interventions, in between they will need postnatal testing, discuss results and what they mean with the woman and impact on lifestyle. General recommendation is if test result is normal, should be re-tested in 1-2 years (normally 5 years if you aren’t planning on becoming pregnant again). If you have pre-diabetes, then it’s yearly test recommendation. NDSS reminder system will include letter for this. Follow up rates vary across Australia.
- App based delivery may be appropriate particularly for young adults - research shows differential effect by age.

Barriers:

- There is no Medicare number for diet and lifestyle intervention targeted at obstetrics, GDM wouldn’t be considered a chronic condition.
- People may not attend GP. It might be better to make interventions available through mothers’ groups or Maternal and Child Health clinics
- Maternal guilt – another responsibility for mothers (to keep fit)

Differential effects:

- Age, SES, Indigenous status would be relevant for this.
- SES and geographic location – effects ability to afford a healthy diet, so dietary advice may need to be targeted according to this.
- Exercise advice – targeted to individual preferences.
• Is obesity individual or societal responsibility?

Image C: Interpregnancy intervention mapped to model conceptualisation
**Intervention 3: Targeted pre-conception lifestyle program for women**

The intervention discussed was an app based intervention supported by a social media campaign. The app would include:

- Information for localised pregnancy services and resources e.g. GP recommendations, include GIS location information, information about shared care GP program, location of obstetricians, scan reminders for genetic conditions etc.
- Embedded risk calculators (for GDM and other high risk pregnancy conditions). If a high score is calculated – advised to see GP
- Simple lifestyle messages
- Goal setting
- Prompts based guidelines – e.g. Are you taking folic acid? Have you seen your GP (based on predetermined visit schedule)?

**Pre-pregnancy GP visit:**

- Immunisation
- Folic acid
- Risk identification
- Pre-pregnancy glucose tolerance
- BMI
- Blood pressure
- Advice re: lifestyle
- Contraception advice

**Target group:**

This intervention targets the population of reproductive age people. It is primarily targeted at women.
Risk Factors targeted:

- Lifestyle behaviours e.g. Physical activity and diet
- Providing information about risk

Impact

Effectiveness estimates from app implementation studies could be used in the model e.g. Canadian app, behavioural intervention apps.

Increased demand for GP services

Differential effects:

- Uptake may vary by SES, literacy, ethnicity, geographic location.
- People with a family history of diabetes may be more motivated to access information
- Unplanned pregnancies – women who have unplanned pregnancies are unlikely to be impacted by this intervention

Unintended consequences:

- Shifting health spending to pre-conception care.
- Undernutrition to avoid high glucose levels.
Image D: Pre-conception intervention mapped to model conceptualisation
Intervention 4: Comparing different models of care.

This group discussed step up and step down models of care. In step up model, women receive usual antenatal care, and don’t see the endocrinologist unless required. In step down models women see the full multidisciplinary team and then services are reduced if their diabetes is being managed. The traditional model is for women to see the multidisciplinary team for every visit.

Intervention:

Compare models of care. E.g. Provide training to midwives, GP’s, and obstetricians so they can provide GDM care in usual antenatal pathways instead of immediately referring to endocrinologist. Guidelines to be developed to outline the criteria for escalation of care. Therefore, only a small proportion would need to go to multidisciplinary clinics freeing up endocrinology services for people with Type 1 and Type 2 diabetes.

Effectiveness:

Outcome studies if available.

Cost analysis of different models

Barriers

Health professionals reluctant to change practice.

Unintended consequences

Some providers who get paid per episode of care may not refer to a multidisciplinary clinic because they wouldn’t get end of care payments, leading to perverse incentives. We need to be aware of what each provider will gain or lose.

This intervention assumes that there will be no loss of funding due to the changed model of care.
Image E: Models of care comparison intervention mapped to model conceptualisation
INTERVENTION MAPPING ACTIVITY REPORTING BACK:

All four intervention maps were transferred onto a large diagram of the model architecture to promote group discussion and feedback.

Image C: Four interventions mapped to large model conceptualisation
OUTCOMES:

Top 5 prioritised outcomes:

The following outcomes were prioritised at workshop 1:

1. Incidence of GDM
2. Maternal diabetes
3. Childhood obesity
4. Early onset diabetes
5. Diabetes complications

The group agreed that the following outcomes should be added to the model:

- **Premature births** should be added (though extreme prematurity is rare with GDM), so we will count it as pre-37 weeks.
- **Large for gestational age** – birthweight to be added as an outcome
- **NICU admission**
- **Type of birth** – caesarean section, normal birth, instrumental birth
- **Health economics** – Cost of the outcomes considered in the model, including cost of birth (e.g. emergency Caesarean)
- Short term outcomes: **quality of life for mother** – literature shows QoL weights for different types of birth. And **quality of life weights for infants** with low birthweight etc. A challenge identified for using this outcome is how long do you apply these- i.e. If someone has caesarean birth how long does it affect them? Quality of life can fluctuate, however mortality and morbidity can be combined as **quality adjusted life years (QALY)** which can provide a standard measure
- Some women who change their lifestyle after GDM, although many will revert to previous lifestyle after pregnancy. The influence of the partner will impact on women’s ability to maintain lifestyle changes – women cook two meals during pregnancy then change back after pregnancy to just cooking unhealthy food.
NEXT STEPS:

- The model architecture will be finalised
- Data will be sourced and used to populate the model
- Validation and verification of the model against historic data
- Workshop 3 will be held in November 2016 to allow the group to interact with and critique the functioning model.
Appendix 7: News article – Project expanded to tackle all forms of diabetes in pregnancy

Project expanded to tackle all forms of diabetes in pregnancy

15 May 2017

Dynamic simulation modelling will be used to examine the growing problem of all diabetes in pregnancy, as a Prevention Centre PhD project expands due to pressing interest from clinicians and policy makers.

The PhD project is being undertaken by Louise Freebairn, a manager with the Epidemiology Section in the population division of ACT Health. Ms Freebairn was initially looking at gestational diabetes, or diabetes that develops during pregnancy. However, after input from a group of senior clinicians, systems modellers and academics, the project has expanded to incorporate all forms of diabetes in pregnancy.

Obesity and childbearing later in life mean more women already have glucose intolerance or diabetes before they become pregnant. This makes their management more complex and has greater long-term health implications for both them and their babies.

The risk factors for gestational and type two diabetes overlap so introducing population-level interventions such as encouraging women to lose weight before conception could significantly
reduce the burden of diabetes.

**Huge impact**

"Expanding the project means we can really look at the spectrum of opportunities to intervene for prevention – the impact is potentially huge," Ms Freebairn said.

"Babies are at increased risk of developing diabetes later in life if their mother has had diabetes in pregnancy. Our model is looking at these inter-generational effects to see if we can prevent or delay the onset of diabetes in pregnancy, and what impact this would have on their children and future generations," Ms Freebairn said.

Dynamic simulation models bring together a variety of evidence sources such as research, expert knowledge, practice experience and data to create a ‘what-if’ tool to test various policy scenarios over time.

Ms Freebairn is conducting her research while being embedded in a senior role in ACT Health. This has provided her with direct access to key clinicians working in the health service.

**Building connections**

Through the Prevention Centre network, she has also made connections with international leaders in systems modelling as well as with academic experts, policy makers and clinicians from across Australia.

"The support that’s come from the Centre and beyond the Centre for this work has been quite extraordinary,” said ACT Chief Health Officer, Dr Paul Kelly.

"It’s about not just the high level policy people and professors, but underneath that is the next level of really practical people on the ground and young people who are really learning from this. I have great hope that they are the ones that will change the paradigm in the future.”

The group modelling workshops have been completed, and
Canadian health data science expert Professor Nate Osgood and his team are building the dynamic simulation model.

Once the model is complete, scenarios to be tested include the use of an app containing health recommendations for women to use pre-conception and during pregnancy.

Ms Freebaim’s project forms part of a larger body of work at the Prevention Centre using dynamic simulation modelling to inform policy decisions in complex public health problems.

Read more

– Helen Signy, Senior Communications Officer
Appendix 8: Indicative questions for semi-structured interviews

The following interview schedule was published as supplementary material for the manuscript included in Chapter 6.

Indicative questions for pre-modelling workshop interviews

Introduction

Thank you very much for agreeing to be interviewed for this project. I am going to ask you some questions about challenges that gestational diabetes health services are facing, about your experience of evidence based decision and making and your experience with simulation modelling processes.

GESTATIONAL DIABETES SERVICES

1. Based on your experience, what are the current challenges that GDM services are facing?
2. What do you think is driving these challenges?
3. What changes do you think GDM services need to make to cope with these challenges?
4. Which interventions would you prioritise to prevent and manage GDM?

EVIDENCE BASED DECISION MAKING

The next questions are about evidence-based decision making.

1. Could you talk a little about your thoughts on evidence-based decision making in the health policy context?
2. What factors have you found to be useful to support its use? What are the main challenges?
3. Have you had experience using results of evidence synthesis methods such as systematic reviews, meta analyses? Did they meet your needs for evidence to
inform your decision making? From your experience, what are the strengths and limitations of these methods?

4. What other forms of evidence do you use in decision making?

**SIMULATION MODELING**

The following questions are about any experience you have had with simulation modeling processes

1. Have you participated in any form of dynamic simulation modeling process before?  
   *(Only continue if reply yes)*

2. Could you tell me about the modelling process and your experience of it?

3. In your opinion what are the benefits and limitations of simulation modelling as an evidence synthesis tool?

**FINAL QUESTION**

Finally, we are interested in your goals for participating in the project.

What do you hope to get out of participating in this modeling process?

Thank you very much for agreeing to be interviewed. Just before we finish, do you have any questions that you would like to ask about this project?
Indicative questions for post modelling semi-structured interviews.

Introduction:

- I am interested in hearing about your experience of participating in the XX dynamic simulation modelling project.

- We have several projects that have used similar methodology and are at different stages of maturity. I would like to talk to you about your experiences with the XX modelling projects so we can collect information on impact in different settings and at different stages of maturity.

- I am keen to hear your honest appraisal of the pros and cons of this method.

1. How did you come to be involved in the project? When you were first approached, what were your thoughts? Why did you agree? What were your expectations at the beginning of the modelling project? Were those expectations met?

2. Were there aspects of the workshops that you found useful? [Prompt as needed - What were these and why?]

3. I’d like to ask you a bit about some of the different aspects of the participatory process. Could you tell me about your experience of:

   a. The activities at the workshops

   b. The interactions with professionals from a range of disciplines
c. The model outputs

(prompt as needed – what do you feel you gained from these)

4. We are interested in exploring the value of using a participatory approach to develop the model. In your view, what were the benefits of using this approach? And what were the challenges?

5. One key aspect of group model building is to bring together a diverse group of experts to discuss and compare their “mental models” (by that I mean their individual understanding of an issue and its context). The aim of this is to enable the modellers to learn about the issue from a range of perspectives, and for the expert participants to compare their own perspectives to that of others in the group. What are your thoughts about this aspect of the workshops? In your opinion, how successful were the workshops in enabling this to occur?

6. Having been through the experience of the workshops, what are your thoughts now on how dynamic modelling can facilitate evidence being used to inform decision making?

7. Have you been able to apply any insights gained from the modelling process to your work? If so, could you talk about some examples? In your opinion, were your insights based on your involvement in the workshops or from the results generated by the model?

8. Could you talk a bit about the purpose for which the model was developed and the broader context? I’m interested to hear whether this has had any influence on its subsequent use.
9. Since you participated in the modelling process, have you been able to use the model outcomes or insights you gained from the process to build an argument for prevention programs?

10. Would you like to see this work developing into the future? Would you be interested in being involved?
Appendix 9 Prevention Works podcast

I was invited to speak about the DIP modelling project for the Prevention Works podcast series commissioned by The Australian Prevention Partnership Centre. The Prevention Works podcast presents a series of interviews with policy makers, practitioners and researchers discussing the work of Prevention Centre to find new approaches to the prevention of lifestyle-related chronic disease. The transcript of the interview with Professor Chris Nolan and myself is included below and the interview is available on the Prevention Centre website: https://preventioncentre.org.au/resources/tackling-the-pandemic-of-diabetes-in-pregnancy/
Tackling the pandemic of diabetes in pregnancy

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Transcript

Episode: Tackling the pandemic of diabetes in pregnancy

Louise Freebairn: So, short-term risks include preterm birth, being born early before 37 weeks gestation; being large for gestational age, so having a large baby, and that’s associated with more risk of interventional birth. You’re more likely to actually be admitted to an intensive care unit, a neonatal intensive care unit as well.

Gretchen Miller: Diabetes and pregnancy today on Prevention Works. A pandemic, in fact, of diabetes is rocking the country, and it’s having a profound effect on prenatal care.

Chris Nolan: So we’re not really getting in and intervening before these women become pregnant, and once they have their baby, we don’t have the resources to have follow-up.

Gretchen Miller: Now, pregnancy’s meant to be a joyful
experience. And, of course, it is. But it does bring with it a host of health risks. Pregnancy can trigger diabetes, and, our changing lifestyles mean there are more and more entering pregnancy who already have it, putting both themselves and the health of their baby at risk. The figures will surprise you. They've jumped by 10 per cent in a very short time, and medicos are having a hard time keeping up and following up.

I'm Gretchen Miller, bringing you the podcast of The Australian Prevention Partnership Centre in Canberra today. We're with Louise Freebairn, who manages the Knowledge Translation and Health Outcomes Team in epidemiology at ACT Health. Louise is running a study for the Prevention Centre. And with her, Professor Chris Nolan from the ANU Medical School, who's acting director of the ACT Diabetes Service. He's seen the rising tide of diabetes in pregnancy firsthand. Let's start by looking at why pre-existing and diabetes that develops during pregnancy are both on the rise.

Louise Freebairn: That's right, there are two different types of diabetes in pregnancy. Gestational diabetes is diabetes that's first detected during pregnancy and the other forms of diabetes are pre-existing diabetes, and so that could be type 1 or type 2 diabetes. What we're seeing is a rise in gestational diabetes, as well as type 2 diabetes that is pre-existing before pregnancy. We're seeing that rise in association with increases in a number of risk factors for both of those conditions.

Gretchen Miller: Why is that?

Louise Freebairn: We're now seeing women having babies at an older age, so in the last 15, 20 years we've really seen a dramatic increase in the number of women or the proportion of women who are aged over 35 who are having babies. We are also seeing an increase in the percentage of women who are overweight or very overweight or obese before they become pregnant, and so both of those are quite important risk factors for diabetes alone and for gestational diabetes. We’re also seeing an increase in Australia in the number of women from some of the higher risk ethnic groups giving birth, so that’s also adding to the increasing rates. Actually, many of the women don’t possess just one of those risk factors. We’re actually seeing more women who have more than one risk
factor, and when they interact that can significantly increase your risk.

**Gretchen Miller:** I had no idea that having a baby older was likely to expose you to more risk of developing gestational diabetes.

**Louise Freebairn:** Having a baby older means that you’re actually having your babies at a time in your life when you’re more at risk of developing type 2 diabetes. It’s actually just that age-related change in your metabolism and your physiology that’s leading to the increase there.

**Chris Nolan:** That’s exactly right. The rate of gestational diabetes at age 20 is actually very low, but for women having babies into their late 30s, it’s highly prevalent.

**Gretchen Miller:** So, Chris, we might ask you about working in the hospital. You’re a doctor working in the hospital with these women every day. What are you actually seeing?

**Chris Nolan:** Our clinic at the Canberra Hospital, I started our diabetes in pregnancy clinic about 13 years ago and initially, the clinic was just a morning and we managed to finish in time for lunch. Now it’s actually consumed the whole day and we struggle to get out by 6:00pm. There’s been an increase particularly in women with gestational diabetes, but also women with type 2 diabetes. There has been a dramatic increase in those for the reasons that Louise has already discussed, but type 1 diabetes and pregnancy seems to be increasing as well. Type 1 diabetes is the type of diabetes that younger people get and you need to go straight onto insulin therapy with type 1 diabetes.

**Gretchen Miller:** Why are younger people getting type 1 diabetes?

**Chris Nolan:** Type 1 diabetes, it’s an autoimmune disease where the immune system attacks the insulin-producing cells in the pancreatic beta cells. The big question is, what triggers that autoimmune attack? We know that there’s genetic factors that contribute that we can’t change. There may be environmental factors that also are difficult to change such as certain viral infections. But, in parallel with the increase in type 2 diabetes, which is usually related to increasing overweight and obesity, this is
also having an effect on, we believe, triggering type 1 diabetes more often than it used to. Whereas, we have a sort of a pandemic, really, of type 2 diabetes. At the same time, type 1 diabetes is gradually increasing as well.

Louise Freibairn: We’ve gone from 6 per cent in about 2005 to about 16 per cent of women who have babies in the ACT are diagnosed with diabetes in pregnancy. We’ve gone from numbers that were around 200 per year to numbers that are sort of getting over 800 and creeping close to 1,000 women per year. For a small jurisdiction like the ACT, that takes up a lot of resources. That’s a really significant increase. Larger jurisdictions might be able to absorb that, but for a smaller jurisdiction with limited resources, that places a lot of demand on our services that we’re possibly not able to cope with as easily.

Gretchen Miller: It’s extraordinary to hear you call it a pandemic, Chris. What do you mean by that?

Chris Nolan: Diabetes, it’s increasing in pandemic proportions. That means that it’s a global phenomenon. In Australia, we’re probably lucky with diabetes and we’re seeing a dramatic increase, but in countries such as India, such as China, the Middle East, the rates of diabetes are increasing much faster.

Gretchen Miller: Is that because of increasing wealth?

Chris Nolan: It’s certainly related to changes in lifestyle and moving from country rural areas into cities where the access to the types of food available are different. It’s changes in work-life balance and people working longer hours and then making poor choices on food on the way home, as we see in countries like Australia, and less opportunity for exercise than there used to be. All of those factors are contributing.

Gretchen Miller: What does diabetes in pregnancy look like for the woman? How might she become aware that she’s developed it?

Chris Nolan: Diabetes is screened for in pregnancy.

Gretchen Miller: So there’s no symptoms beforehand?

Chris Nolan: There’s usually no symptoms for gestational
diabetes. It’s a diagnosis from laboratory tests and the standard test is the oral glucose tolerance test. Many women having pregnancies now are very aware that they’re going to have a glucose tolerance test sometime through their pregnancy. It’s usually between 24 and 26 weeks, so relatively late in the pregnancy. Many women are surprised by the diagnosis when it happens. It does cause them a lot of concern and challenges for them in actually needing to look after something they were not expecting.

**Gretchen Miller:** If you’re already diabetic with type 1 or type 2, what risk does pregnancy add to your illness? Apart from the risk to the baby, what about you when you’ve had the baby and you’re back to relatively normal life?

**Chris Nolan:** The experience of pregnancy for women with pre-existing diabetes is a challenge because the management of the diabetes and the associated factors such as high blood pressure impact on the outcomes of the pregnancy, so that’s a real challenge. If women do have underlying other complications of their diabetes like renal disease, that renal disease can accelerate through pregnancy. Eye disease, the retinopathy of diabetes, can accelerate through pregnancy and they need to be monitored very closely as well.

But one of the good things about pregnancy and women with pre-existing diabetes, it often is an opportunity for them to improve the way that they look after their own diabetes. Often having, for example, type 1 diabetes through adolescence is a real challenge, and adolescent kids struggle to look after their diabetes well. Sometimes it’s not until a major change in their life happens like a pregnancy, they learn for the first time how to look after it well, and so we’ve had many women come through our clinic that didn’t look after their diabetes very well before but through pregnancy because they’re looking after a baby as well, they change, and those changes continue often after pregnancy.

**Gretchen Miller:** There is implications, of course, for the baby?

**Louise Freebairn:** That’s right. Women with diabetes in pregnancy have a high risk of having a large baby, a large for gestational age
baby. There are higher risk of birth complications and there are also longer-term risks. There’s longer-term risks for both mother and baby, where the mum is at higher risk of developing type 2 diabetes later in life, as is the baby. The child is also at risk of having childhood overweight and obesity. Preterm birth is another one of the risks for women with diabetes in pregnancy, and as we understand it, the different groups have different risks at different levels of weight. If you’re from an ethnicity that has a higher risk profile, then your risk as actually higher at a lower BMI than somebody from a different group.

Gretchen Miller: I’m wondering whether it’s because of the mandatory testing that we’re picking up.

Chris Nolan: Over the last 20 years, there has been increasing rates of screening for gestational diabetes. Now it is very well accepted that it’s a screen that all pregnant women have, and the majority of pregnant women do get that test. Some of the increase is due to more universal testing, but that’s not the main reason in the last 10 years.

Gretchen Miller: Now, with some chronic diseases, things like, say, prostate cancer, over-testing … There is this notion of over-testing where too much testing sort of discovers disease that you probably wouldn’t have died with otherwise and it’s led to issues of overtreatment as well, which has knock-on side effects. I guess this is absolutely not the case with gestational diabetes or any kind of diabetes? The sooner you get it, the better. Would that be right?

Chris Nolan: We believe so, but it is not as simple as we’d like it to be. To diagnose gestational diabetes there needs to be cut points of glucose levels. What we’re aware of is that there’s actually a continuum from the normal low blood glucose to quite elevated blood glucose. There’s a continuum of increasing risk according to that glucose and where you decide with diagnosis in a test that this is the level above which you’re going to call abnormal and below that’s normal, that’s really artificial.

With a very large study that was performed internationally called the HAPO Study, the Hyperglycaemia Adverse Pregnancy Outcome Study, they studied around 26,000 women and they did glucose tolerance tests on them all and without any treatment and
they determined the pregnancy outcomes. From that study, they showed that the risk of having adverse outcomes such as large for gestational age babies, so big babies at birth, such as hypertension in pregnancy, increased Caesarean section rates. There were cut points for the levels on the glucose tolerance tests that those risks were increased and it’s on the basis of that we make or diagnosis now. For all women at that cut point, whether it really is significant for them or not, is continued to be debated. Certainly, at the upper end of the spectrum, it’s really important those women are diagnosed and treated. At the lower end it becomes a little bit more grey and I think we do need to be careful not to be overtreating women unnecessarily.

Gretchen Miller: Tell me a little bit about this study that you’re doing, Louise. You started studying gestational diabetes but you expanded it after input from clinicians and other stakeholders to include all forms of diabetes and I’m wondering why.

Louise Freebairn: The study actually involves a participatory process. We’re engaging with expert stakeholders and they include endocrinologists, we’ve got obstetricians, we have diabetes educators, public health physicians, experts on the food environment, health economists all coming together to provide input into the logic and the structure that we would include in a dynamic simulation model.

A dynamic simulation model is just … Essentially it’s computer model that can help us explore a complex issue. For many complex issues that we have now, we have a lot of information but we don’t necessarily have the tools to bring that information together into a single picture that we can use to inform decision making. What we’re exploring is how we can actually use dynamic simulation modelling as one of those tools to integrate information and really make best use of the information that we have.

Gretchen Miller: How did you work with the practitioners, with all these experts?

Louise Freebairn: What we do is we get the stakeholders into a room. Yes, we do interviews, so we go through a process of talking to people individually as well as bringing them together into large
group workshops where we actually go through quite practical hands-on activities to map out a conceptual map of the issue. We would be looking at the risk factors that might contribute to a woman developing diabetes in pregnancy, and so we might actually look at each of those risk factors in depth and also map them to a transition in the model.

It might be that where a woman might transition from not having gestational diabetes to having gestational diabetes, and if you think about that process, well, she needs to be tested. She needs to be diagnosed. She needs to have a high blood glucose level in her physiology that needs to be represented in the model. We can also include other factors which could be her weight status. It could be her cultural background and her age and other demographic factors as well. We compile all of the information that they’ve given us into a conceptual map, which we then convert into a mathematical model, essentially, and we have some really sophisticated computer software tools now where we can look at the interaction between risk factors and you can also look at the combined effective different interventions and switch interventions on and off to work out how they interact and what the likely impact will be for those interventions.

**Gretchen Miller:** You started studying gestational diabetes and focusing there on diabetes which develops during pregnancy, but then you expanded it after discussing it with clinicians and other stakeholders to include all forms of diabetes. Now, why did you do that?

**Louise Freebairn:** It did expand to include all forms of diabetes, and that was from the discussions that we had with the expert stakeholders where the increase in pre-existing diabetes was seen to be a really significant factor that we should include in the modelling and would be an important gap if we had left it out. We really wanted to look at lifestyle prevention programs, population health interventions, and those are really relevant to the development of type 2 diabetes, as well as gestational diabetes.

**Gretchen Miller:** This is Prevention Works and we’re talking to Louise Freebairn and Chris Nolan about diabetes in pregnancy. I’m Gretchen Miller.
What are you hoping to learn from your research?

Louise Freebairn: I think there’s lots of things that we’re hoping to learn. This is quite an ambitious model. I think we really are breaking new ground internationally on the methods that we’re using. We’re actually incorporating a number of different types of modelling methods into the one model. That’s allowing us to actually look at the risk factors, as well as some of the underlying physiology right through to clinical service provision, so we’re really wanting to be able to ask questions about the population health type interventions that we can implement. Pregnancy is another one of those opportunities where people start to think about their health and it’s also an opportunity where you can actually have an impact on more than one person with the same intervention.

So you can actually have an impact on mother and baby but also whole families and improve their diet and their level of physical activity. It’s quite an effective time to intervene with people, so we’re really interested in exploring some of those intervention options and some of the questions around timing or perhaps target groups. Do we actually target an intervention to all of the people Canberra who are considering having a baby, or would you actually target women who already have some of the risk factors? Would you time an intervention for pre-pregnancy or would you time the intervention for between pregnancies? Would you target women who’ve had diabetes in pregnancy in their first pregnancy before they contemplate a second pregnancy? Those are the types of population health questions that we can ask in the model. We can also some questions around models of care. Can we implement a different way of providing services and what impact would that have on resources?

Gretchen Miller: That’s really significant because what you’re talking about there, going from what was it? 8 per cent to 16 per cent, that is an enormous increase. 10 per cent. You’re talking about services being stretched, so when I think about it I think, “Well, you’ve done the test. You’ve got to provide the service.” But how might you address providing services differently?

Louise Freebairn: Some of the options that we’ve talked about and are looking to test in the model might be things like providing
group services rather than individual. If you can have a group education session rather than actually having a one-on-one with every woman, and how does that impact on resources. It might be around triaging care, for some of the lower risk women, perhaps they can actually be managed in normal antenatal services rather than needing to be seen by the specialist service.

Gretchen Miller: So perhaps a midwife or nurse might be able to say, “Yes, you’re at risk,” or, “You’ve got low-level diabetes. These are the things you can do”?

Louise Freebairn: That’s right. It might be a midwife under the supervision of an obstetrician with sort of regular check-ups.

Gretchen Miller: I think actually group therapies or group education sessions could be really good because then you’re less … When you’re a pregnant woman you often feel very much alone.

Louise Freebairn: Absolutely. I think sharing ideas and sharing resources could be a very useful thing. I don’t know if you want to add anything because you have already implemented some of these changes.

Gretchen Miller: Have you, Chris? Tell me about that.

Chris Nolan: With an increase from 6 per cent to 18 per cent over the years we’ve had to increase efficiencies of how we run the clinics. We already do run group sessions in pregnancy as an initial education for women who develop gestational diabetes. Then they go on to an individual appointment with a dietitian, and from that point, they either go back to their usual antenatal care pathway if they’re traveling well. If their sugars are elevated they come to our high-risk diabetes and pregnancy clinic and join us on Tuesdays.

We already have implemented some changes. But I think a key point is that implementation of our service is from the time of diagnosis to the time of delivery, so we’re not really getting in and intervening before these women become pregnant, and, once they have their baby, we don’t have the resources to have follow-up appointments with them. We’re very keen to be able to have another group session after pregnancy for these women to sort of debrief and to plan for the future for them and talk about ongoing
lifestyle modifications. We’re very keen, this is about women predominantly, but partners are at risk as well, and to actually get to the partners and assist them.

**Gretchen Miller:** Why are they at risk?

**Chris Nolan:** Often they come from groups that have the same risk factors for diabetes whether it’s ethnic group, age, family histories, etc.

**Gretchen Miller:** Or even just eating habits I imagine because you eat the same sorts of foods.

**Chris Nolan:** And it’s the same lifestyles. If we’re able to, after pregnancy, introduce lifestyle changes that is family-based. I think preventing the women themselves, their partners, and their children from being a future risk of diabetes and diabetes-related problems, I think that would be a major plus for public health.

**Gretchen Miller:** If you’re already implementing some of these ideas, you’re able to feed that experience, I guess, into your dynamic modelling system, yeah? How is that playing out? What are you seeing in the crystal ball?

**Louise Freebairn:** Yes, we can implement and have those different clinical pathways implemented in the model and look at the resourcing that’s required for those. Unfortunately, it’s too early for me to talk about results from the model, but we’re hoping over the next couple of months that we’ll but putting those results out there for discussion and for people to learn, including us.

**Gretchen Miller:** Of course, the issue here, as we’re alluding to, is, aside from health and provision of service to look after these women who we’re now discovering to have diabetes through this mandatory testing, the other issue is cost, of course, and what this is doing to service provision.

**Chris Nolan:** Cost of services is a major issue in this space and with a dramatic increase we need to look at how that service is provided. If there’s a rate of 16 per cent, it is a common condition in pregnancy and we need to really look at for the usual clinicians that work within midwifery and obstetric care that they learn to manage
that themselves without needing quite so much input from specialist diabetes services. In specialist diabetes services, we have to look after children with type 1 diabetes and people with complex diabetes at all different stages of life, we need to look after women that have pre-existing diabetes in pregnancy. If we can teach the obstetricians and midwives to look after that as a common condition in pregnancy, I think that’s certainly a direction for us to go towards.

Another key is prevention in public health and to get that message across. I really don’t believe that women planning their pregnancies are really tuned in to how common gestational diabetes is and what risk they might be at. I think public health messages to women before pregnancy and aimed at trying to get these women to optimise their lifestyle etc before pregnancy, in planning their pregnancies, would be a major plus.

Gretchen Miller: That is really interesting, the idea of saying, “Actually, you do need to look after yourself more than you think.” It’s not just about stopping alcohol, for example, because you want to get pregnant and you don’t want to potentially affect the baby. There’s more than that. It’s not just about getting fit in order to maximise your chances of conceiving. It’s actually about more than that too.

Louise Freebairn: I think that’s quite a common picture is people are just not aware, women are not necessarily aware of how high their risk could be. They’re also not aware of the things they could be doing to actually decrease their risk such as improving their diet, really thinking about eating healthily with fibre and vegetables, having their two and five, and making sure that they’re getting enough physical activity just to really reduce their weight status before, so losing some weight before you become pregnant so that hopefully you’re at a healthy weight before you actually conceive.

Short-term risks include preterm birth, so being born early before 37 weeks gestation. Being large for gestational age, so having a large baby, and that’s associated with more risk of interventional births. You’re much more likely to actually be admitted to an intensive care unit, a neonatal intensive care unit as well.

Gretchen Miller: Where’s your point of contact on this? Are you
going to be targeting, for example. GPs on this issue?

**Louise Freebairn:** Potentially there could be a GP intervention and it might be around educating GPs to highlight gestational diabetes as one of the risks when they’re having a preconception discussion with a woman or her partner. Other things might be using new technology, so it might be actually creating something like an app or extending a current app to actually include more information about the things that people can do to reduce their risk.

**Chris Nolan:** Women often use apps to track their pregnancy and to remember how many weeks they are and when the baby’s due, and what happens when through the pregnancy. To have an app that women actually find useful and add into that extra things such as a risk score for their risk for gestational diabetes to bring it to pre-pregnancy and what sort of things they have to tick off before they actually conceive. Do they need to go to their GP for a pre-pregnancy health check? To add all of that into an app that is truly useful, then it might be used.

**Gretchen Miller:** Chris, being a doctor, as these programs are already being introduced for women in the ACT or you’re already sort of trying out some of these ways of dealing with low-risk diabetes, what do you think the implication and the outcome will be for women in the ACT and also for the ACT health budget?

**Chris Nolan:** The value of this model is that we when we have a set budget, we can work out from the model how we might best spend that budget. For example, at the moment, we spend that budget really between around 24 weeks of pregnancy and the delivery of the baby. If we shifted some of that budget to pre-pregnancy with a public health campaign to increase awareness of gestational diabetes and the need for a healthy lifestyle, would we actually achieve better outcomes or should we use those same dollars after pregnancy in following up these women and their families to improve their long-term health?

Women with gestational diabetes, we know that they’re at very high risk of developing permanent diabetes later in life and if we could prevent that diabetes or even delay it by a decade or two decades, then it has a dramatic impact on the whole health system and the
quality of life for the people involved. If we’re able to intervene early with the children at those first years of life, probably the most important for their long-term health, and to be able to spend their health dollar on them, that might be the best bang for our buck within this space. The model will be able to help us to determine where we should be focusing our health dollar.

**Gretchen Miller:** Hard decisions though, I mean, really, to choose between, okay, dealing with the kids who are already born, or dealing with the mother while she’s in this very vulnerable state of pregnancy, or waiting until … The either-or scenario there is pretty tough.

**Louise Freebairn:** It is really tough, but those decisions are being made now and what we’re looking to do is actually to improve the tools that are being used to guide those decisions.

**Gretchen Miller:** What should women who listen to this podcast who want to get pregnant be doing and what should the government be doing to actually support them in that?

**Chris Nolan:** For women planning pregnancies, I think it’s a really important time in life to have the best healthy lifestyle, and that means being active. That means looking at the sort of foods that we’re eating, and I guess my strongest advice is to try and avoid junk food. I think junk food, fast foods, a lot of takeout foods are very poor quality and are contributing a lot to this increasing prevalence of gestational diabetes. I think that’s the simplest message that would have the biggest impact.

**Gretchen Miller:** Louise?

**Louise Freebairn:** I agree. I think Chris is spot on. You really need to be thinking about your health when you’re contemplating pregnancy. Gestational diabetes is, as Chris has said earlier, often a surprising outcome from the oral glucose tolerance test for many women, so just being aware that it could affect you and to really make as many changes as you can to be as healthy as you possibly can when you become pregnant to try to reduce your risk.

**Gretchen Miller:** That’s Prevention Works for today. Thanks to Louise Freebairn, managing the Knowledge Translation and Health
Appendix 10  Model documentation

The detailed documentation of the model structure and associated parameters, functions and data sources are included in this section. I was the primary author of this document with input from Ms Yang Qin and Professor Nathaniel Osgood, from the University of Saskatchewan. Ms Qin and Professor Osgood provided information about the model components and structure, parameter values and equation functions used in the model. As noted at this start of this chapter, the computer science members of the modelling team are leading a technical paper, on which I am a contributing co-author, in which some of the material in this section will also be included. That paper will describe the validation, calibration and sensitivity analyses conducted during the model development. At the time of submission, the technical manuscript was in draft format and is not presented here as it is not core to my thesis.
A dynamic simulation model

Prevention and management of diabetes in pregnancy in the ACT
Dynamic simulation model documentation: Prevention and management of Diabetes in Pregnancy in the ACT

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Executive summary

**Purpose of this guide:** This document describes the dynamic simulation model developed to explore prevention and clinical management options for diabetes in pregnancy in the ACT.

**The challenge:** Diabetes in pregnancy (DIP) is increasing in the ACT, in Australia and internationally and diabetes services are having difficulty meeting demand with existing resources. The increase in DIP in the ACT is associated with increasing prevalence of risk factors such as overweight and obesity, older maternal age and increasing numbers of women from high-risk ethnic groups. Changes to diagnostic screening have resulted in women being diagnosed with DIP earlier in their pregnancy and therefore requiring services for a longer time. Women are also more frequently presenting with multiple risk factors resulting in more complex care needs.

**A systems approach:** The Australian Prevention Partnership Centre, in partnership with ACT Health and the University of Saskatchewan, adopted a participatory dynamic simulation modelling approach to explore how best to prevent and manage diabetes in pregnancy. The process of model development included mapping the complex problem, model conceptualisation, quantification, testing and validation and drew on existing systematic reviews, meta analyses, research evidence, available data, and the expert knowledge of a broad range of multidisciplinary stakeholders working in the area of diabetes in pregnancy in the ACT, in other states and territories and internationally.

**The model:** is a logically consistent framework that integrates disparate data sources. It can be used as a ‘what if’ tool to test the likely impacts over time of a range of policies and programs to see what combination of interventions are likely to be effective for the prevention and management of diabetes in pregnancy.

**Structure of this document:** This document describes the process of model development, provides detail on the components of the model, and the data and evidence sources used to inform its design and parameterisation. The model can be updated over time to ensure it remains current and continues to produce outputs that are consistent with observed data. The model can also be used as an interactive tool to inform policy and program decisions relating to diabetes in pregnancy.
Acronyms used

BMI     Body mass index  
DIP     Diabetes in Pregnancy  
EI      Early intervention  
GDM     Gestational Diabetes Mellitus  
GP      General practitioner  
IGR     Impaired Glucose Regulation  
LT      Less than (this phrase has been used within age ranges)  
NICU    Neonatal Intensive Care Unit  
Ow      Overweight  
Ob      Obese  
OGTT    Oral Glucose Tolerance Test  
OwO     Overweight or obese  
PA      Physical activity  
T1DM    Type 1 Diabetes Mellitus  
T2DM    Type 2 Diabetes Mellitus  
TAPPC   The Australian Prevention Partnership Centre
Background and rationale

The challenge of diabetes in pregnancy

Diabetes in pregnancy (DIP) is increasing in the ACT, in Australia and internationally. The increase in DIP in the ACT is associated with increasing prevalence of risk factors such as overweight and obesity, older maternal age and increasing numbers of women from high-risk ethnic groups. Changes to diagnostic screening has resulted in women being diagnosed with DIP earlier in their pregnancy and therefore requiring services for a longer time. Women are also more frequently presenting with multiple risk factors resulting in more complex care needs.

The model considers the short, middle and long-term implications of impaired glucose regulation and the increasing prevalence of risk factors for DIP. Prevention of risk factors was prioritised in the model as small delays in the development of diabetes will have large implications for the longer-term burden of disease and costs to the health system.

Alternative models of care for DIP were also considered in the model. The rising prevalence of DIP is having a significant impact on health service demand and resources, and the need to “do things differently” was identified by participants. The model informs the investments for intervention in DIP, including both clinical and population health interventions. Workload and resource use has been incorporated into the model to enable it to act as a resource allocation decision support tool.

The value of dynamic simulation modelling

Dynamic simulation modelling is a term given to quantitative systems science modelling methods, including:

- *System dynamics*, which captures feedbacks delays and accumulations at an aggregate level,
- *Agent-based modelling*, which represents individual heterogeneity and social network influences
- *Discrete event simulation*, which captures service delivery and implementation processes and can be used to explore optimal resource distribution.

These methods have long been used successfully in the engineering, business and industry sectors, but more recently are being used to support the design of efficient and effective responses to complex population health and health care problems [1-5]. These tools represent a significant advance in traditional epidemiological methods and are particularly valuable for exploring the complexity of multiple interacting risk factors and the dynamics of populations and their behaviours over time [6, 7]. They can also be used to explore the potential impact of interventions, individually or in combination, over time for populations or specific target groups.

System dynamics represents complex problems at an aggregate / macro level using three core components: 1) stocks (key variables, like population BMI, that increase or decrease over time); 2) flows (rates of change in a stock); and 3) feedback loops (which can connect stocks and flows over time). System dynamics is underpinned by well-established mathematical theory of nonlinear dynamics [8-10].

Further information regarding the mathematics behind system dynamics can be found at: https://www.wpi.edu/Pubs/E-project/Available/E-project-052812-144829/unrestricted/MathematicsBehindSystemDynamics.pdf.
Agent based modelling (ABM) methods have been enhanced more recently and allow for representation of individuals or agents within the system. The model can be built from the ground up by defining agents, their behaviours and their interactions [11, 12]. ABM is a computational method used to examine the actions of agents (e.g., individuals) situated in an environment (e.g., neighbourhood). ABMs specify decision rules controlling dynamics, such as If-Then statements and mechanistic interactions among agents. When the program is run, agents interact with one another and their environment often resulting in counterintuitive insights about behaviour of agents and the system [13]. Incorporating ABM components allows flexibility to incorporate the dynamics of people making decisions affecting population health outcomes, and thus efficient planning of health care interventions [14].

Discrete event simulation (DES) methods represent processes, that is, as a sequence of operations or events performed across entities [12]. For example, discrete event methods are frequently used to represent and improve efficiency of health services, for example, emergency departments. This modelling method represents complex systems at a low level of abstraction. The core concepts in DES are events, entities, attributes, and resources. An event happens at a certain time point in the environment and can affect resources and/or entities. Entities have attributes and consume resources while experiencing events, but consumption is not affected by individual-level behaviour. Attributes are features or characteristics unique to an entity. They can change over time or not. Resources are objects that provide a service to an entity. Queues are another important concept in DES and occur when several entities compete for a specific resource for which there is a constraint [14]. DES modelling is useful to analyse resource utilisation, throughput of services and the impact of varying policy decisions [14].

Advances in modelling software technology now enable multiple modelling methods to be integrated [12]. This allows for modellers to represent the many interacting components of a system and the complex interplay between individual behaviour and social connections across populations [11]. All three modelling methods have been utilised in this tripartite DIP model.

**Project aim**

The overall aim of the project was to develop a dynamic simulation model to inform the best investments for intervention in diabetes in pregnancy, including both clinical and population health interventions. This project includes:

- Synthesis of diverse evidence sources into a “what if” tool to be used to inform policy and program decision making,
- Analysis and forecasting of the likely impacts of intervention options in the short and long term for mother and baby,
- Extending dynamic simulation methodologies to successfully integrate agent based, system dynamics and discrete event simulation methods into a logically consistent representation of diabetes in pregnancy, and
- Facilitating focused and constructive stakeholder participation in model building and strategy dialogues.
Scope

To develop a dynamic simulation model to inform the best investments for intervention in diabetes in pregnancy for the ACT, including both clinical and population health interventions.

This dynamic simulation model focuses on diabetes in pregnancy (DIP) from an ACT perspective. However, the national context was also considered in the model development with the model being considered a proof of concept with potential to be applied in different contexts.

It is noted that interventions may have differential effects on various socio-economic, geographic or cultural groups. However, due to the lack of available data at this stage, stratification of effects on subgroups (other than age) has not been incorporated into this model.

Models as repositories for best evidence, data and local knowledge

The following perspective is attributed to Professor Nate Osgood, Department of Computer Science, University of Saskatchewan

Models are far from static tools used to support strategic decisions at a given point in time. Instead, they can be updated, refined and expanded as new questions arise and as resources are available to delve deeper into particular components of a model. Models capture our best understanding about a complex problem and improve as our knowledge deepens. As new evidence comes to light and as new interventions are tested and evaluated, the results can be integrated into an existing model to help us derive actionable policy and practice recommendations. As such, simulation models allow us to further leverage investment in research, the collation of big data, the evaluation of policies and programs, and in infrastructure improvements for reporting of administrative data. Furthermore, dynamic simulation models are moving away from being technocratic artefacts built in back rooms and are increasingly being used as tools for improving communication, stakeholder engagement, consensus building, teaching and learning, and for elucidating research priorities.
Method

Model development process

The dynamic simulation model was developed using a participatory and transparent evidence synthesis process. A multi-disciplinary group of domain experts from academia, policy, public health and clinical practice, as well as health economists and national and international leaders in dynamic simulation modelling were invited to contribute to this work as part of the expert model building group (see Appendix A).

Three participatory workshops were held (on 5 May and 19 August 2016 and 9 March 2017), during which facilitated sessions were conducted. The expert group collaboratively mapped the key risk factors and pathways for developing diabetes in pregnancy, and the mechanisms by which selected interventions have their effect. This has been described in detail elsewhere [15, 16].

A causal map of the problem produced by the expert group in the first workshop was developed into a computational simulation model through an iterative process of model conceptualisation, quantification of parameters and representation of the mathematical relationships among the components of the logical structure. Iterative consultation and validation took place, to ensure the final model would be detailed where required for the application of interventions, but sufficiently streamlined to keep the model manageable. The conversion to a computational model drew on published conceptual understandings of the problem, available data sources, published research and expert guidance to arrive at a plausible and testable representation. The behaviour of the system over time is displayed graphically by the computer modelling software (AnyLogic®). The model was progressively refined over multiple iterations with domain and policy experts (through subsequent workshops and stakeholder meetings) and investigation of differences between the predicted and observed historical behaviours. The model was calibrated and validated against historical data. The product of this process is an interactive dynamic simulation model capable of forecasting the likely impact of interventions over time, either individually or in different combinations.
Overview of the model

Overview of model components

The hybrid model incorporates system dynamics, agent based and discrete event representations using AnyLogic® software (http://www.anylogic.com/), and consists of the following components:

A. Pregnancy representation
B. Dysglycemia classification representation
C. Glycemic regulation representation
D. Population structure
E. Weight status representation
F. Service representation
G. Interventions for scenario testing

Each of these components is shown in Figure 1: Overview of model components and is described below.

The model is initialised on 1 January 2010 and model time units are in years. This retrospective feature contributes to validation of the model, through comparing model outputs from 2010 to 2015 with real world data.

Please refer to Appendix C for an explanation of the model symbols used in the subsequent figures.
A. Pregnancy representation

Pregnancy is represented using a statechart indicating the individual agent’s pregnancy status. Women initially enter the model in a not-pregnant state and men to the not-possible state. Pregnancy occurs according to an age specific fertility rate. Pregnant women are divided two categories: planning pregnancy and not planning pregnancy. The women who do not plan their pregnancy will enter pregnant state directly. Alternatively, women who planned their pregnancy will stay in the planningPregnancy state for six months, then enter the pregnant state, as shown in Figure 2. After entering the pregnant state, the women will transition between a set of states representing the trimesters of pregnancy. While duration of pregnancy is indicated using the trimester states, the model also collects the precise duration of pregnancy in continuous time. The pregnancy statechart is shown in Figure 2.

The model includes a set of parameters associated with the pregnancy, for example parity, BMI, age, history of diabetes, and family history of diabetes, that are relevant as risk factors for the occurrence of dysglycemia in the current pregnancy. These parameters are described in
When a woman gives birth, there is a birth event in which a baby is introduced into the model. This birth event is associated with a variety of types of outcomes, information that is passed on to the new child for example, the mother’s DIP status and history of diabetes, weight status and ethnicity is passed onto the baby. Outcomes including birthweight, type of birth e.g. Caesarean section, NICU admission and Apgar scores are recorded at birth.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Type</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>getFertilityRate(currentAge(),ethnicity)</td>
<td>getFertilityRate(currentAge(),ethnicity) / 1000</td>
<td>function return double</td>
<td>age and ethnicity specific fertility rate of age 15 - 50</td>
<td>ACT Maternal Perinatal Data Collection and ABS Census 2011</td>
</tr>
<tr>
<td>planningPregnancy</td>
<td>0.4</td>
<td>boolean</td>
<td>Rate of planned pregnancies</td>
<td>[17]</td>
</tr>
<tr>
<td>probOfBF</td>
<td>0.75</td>
<td>double</td>
<td>randomTrue(), used in condition determine who is NOT in breastFeeding</td>
<td>Assumption</td>
</tr>
<tr>
<td>dipTestTime</td>
<td>Uniform(8, 12) or Uniform (26, 28)</td>
<td>double</td>
<td>= Service.assignDiPTestTime(agent: Person) normally test time is 26 - 28 week of pregnancy. For high risk group (e.g. obese, age &gt; 35) they will have the test at 8 - 12 weeks</td>
<td>Clinical guidelines</td>
</tr>
<tr>
<td>mothersDiabetesStatus_atBirth</td>
<td>NormoglycemicDiabetesStatus / GestationalDiabetes / Type1DM / Type2DM</td>
<td>DiabetesStatus</td>
<td>getDiabetesStatus() mother’s glycemia status at delivery</td>
<td></td>
</tr>
<tr>
<td>mothersWeight_atBirth</td>
<td>Not_Overweight_or_Obese / Overweight / Obese</td>
<td>Weight</td>
<td>mother’s weight status at delivery</td>
<td></td>
</tr>
<tr>
<td>mother</td>
<td>this</td>
<td>Person</td>
<td>Reference to mother</td>
<td></td>
</tr>
<tr>
<td>maternalPreviousLiveBirths</td>
<td>parity</td>
<td>int</td>
<td>How many children did the mother give birth to before this delivery?</td>
<td></td>
</tr>
<tr>
<td>Parameter</td>
<td>Value</td>
<td>Type</td>
<td>Description</td>
<td></td>
</tr>
<tr>
<td>----------------------------</td>
<td>--------------------------------------------</td>
<td>------</td>
<td>----------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>maternalAgeAtBirth</td>
<td>currentAge()</td>
<td>double</td>
<td>Current age of the mother</td>
<td></td>
</tr>
<tr>
<td>timeUntilNaturallyFertile</td>
<td>max (0.0, normal(0.15, 0.15));</td>
<td>double</td>
<td>time unit is year, this is the time that agent is in postpartum state (either in breastfeeding or in not breastfeeding state)</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Functions in pregnancy state chart

<table>
<thead>
<tr>
<th>function name</th>
<th>parameters</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>probilityVarCalculation</td>
<td>(p_normalGlocuse: double, oddRatio: double, normalGlycemia: double, g_average: double)</td>
<td>$P = \frac{1}{1 + \left( \frac{1 - P_N}{P_N} \right)^{\beta_1 \cdot \left( \frac{G_N - G}{0.4mM} \right)}}$ [1,2]</td>
</tr>
<tr>
<td>earlyLatePregnancyInsulinSensitivityByWeight</td>
<td>(weight:Weight)</td>
<td>At the beginning of pregnancy, calculate $K_{gI-EarlyPreg}$ and $K_{gI-LatePreg}$ of this agent according to their weight status, for linear interpolation in function linearInterpInPregnancy(timeDuringPregnancy)</td>
</tr>
</tbody>
</table>
B. Dysglycemia classification representation

The dysglycemia classification representation relates to the underlying glycemic regulation of the individual as shown in Figure 1.
Figure 3.

Awareness of their glycemic status and/or being diagnosed with a dysglycemia condition are important factors influencing an individual’s access to lifestyle and pharmacological interventions. The dysglycemia classification statechart separates the underlying glycemic status from the diagnosis of T2DM and GDM, as the point of diagnosis is dependent on clinical service and screening regimens.

There are four states in the dysglycemia classification statechart representing the range of possible categories for an individual’s glycemic status. These are: normoglycemic and impaired glucose regulation (IGR), Type 1 diabetes mellitus (T1DM), Gestational diabetes mellitus (GDM), and Type 2 diabetes mellitus (T2DM). Individuals transition between the classification states depending on whether their underlying glycemic level exceeds the criteria for each state as indicated in Table 3.

Case example: An individual may start in a normoglycemic state and then develop, without her awareness, an impaired glucose regulation state, as her glycemia level increases. The increases may be caused by ageing or weight increase. For simplicity of the representation of underlying glycemia status, we use one state to represent normoglycemic state and IGR state.

Both normoglycemic and IGR agents, at the time of a pregnancy, may transition to a GDM state. Post pregnancy, depending on the agent’s degree of glycemic control, there are two possible transitions (Figure 3). If the agent adheres to lifestyle intervention changes and maintains a degree of control over her dysglycemia, she may return to the IGR and normoglycemic state. In the absence of effective glycemic control and further decline of her condition, she might proceed to T2DM immediately.

There are currently no transitions from diagnosed T2DM to normoglycemic and IGR. These transitions are possible; however, it is rare for people to move between states in this direction and often this only occurs with bariatric surgery, which is not a priority intervention for inclusion in this model.
Figure 3: Dysglycemia classification representation structure

Table 3: Parameters in dysglycemia classification state chart

<table>
<thead>
<tr>
<th>parameter</th>
<th>value</th>
<th>description</th>
<th>source</th>
</tr>
</thead>
<tbody>
<tr>
<td>hazardOfT1DMAmongstThoseSusceptible</td>
<td>0.04</td>
<td>Among susceptible people, there are 4% chance to develop into T2DM</td>
<td>Clinical estimate</td>
</tr>
<tr>
<td>isGeneticallyPredisposedToT1DM</td>
<td></td>
<td>(self.ethnicity == Australian_Born) &amp;&amp; randomTrue(prevalenceType1DM_Australiaborn)</td>
<td></td>
</tr>
<tr>
<td>prevalenceType1DM_AustralianBorn</td>
<td>0.01</td>
<td>used to give value for isGeneticallyPredisposedToT1DM</td>
<td></td>
</tr>
<tr>
<td>fastingBloodGlucoseThreshold_before2015</td>
<td>5.504</td>
<td>the glycemia standard before 2015</td>
<td>calibrated</td>
</tr>
<tr>
<td>thresholdCoefficientToT2DM</td>
<td>1.636</td>
<td>used to calculate the standard of T2DM, the T2DM standard after 2015 = 1.636*5.504</td>
<td>calibrated</td>
</tr>
<tr>
<td>coeffRatesToGDM</td>
<td>0.642</td>
<td>used to calculate the standard of GDM state, the GDM standard after 2015 = 1.636<em>5.504</em>0.642</td>
<td>calibrated</td>
</tr>
</tbody>
</table>
C. Glycemic regulation representation

The model incorporates a representation of the underlying physiological regulation associated with an individual's glycemic status based on mathematical models of diabetes progression by De Gaetano, Hardy and colleagues [18-20]. The mechanism for glycemic regulation included in the model is referred to as an endogenous dynamic mechanism. This means that the model represents over time the evolution in certain factors related to the level of dysglycemia and metabolic load a woman experiences in pregnancy. Glycemic regulatory capacity is represented as a stock, allowing the level of an individual’s regulatory capacity to increase and decrease over time. Therefore, the factors that influence glycemic regulatory capacity such as increased metabolic load due to pregnancy, changes to diet and physical activity and pharmacological interventions can be modified within the model and the impact measured over time and between generations.

Glycemic regulatory capacity is a function of two factors in the model. Firstly, it is a function of biologic regulatory capacity, that is, the internal regulatory capacity associated with underlying physiology. Secondly, there is a component of external regulatory ability of the individual, that is, their conscious regulation through adherence to blood testing, medication regimens and lifestyle interventions including diet and physical activity. The model mechanism allows for changes in an individual’s adherence over time.

As glucose levels rise, a well-regulated person’s physiology absorbs the blood glucose levels. However, in the event of insulin resistance, as caused by pregnancy, high weight or other factors [21], the body’s direct regulatory mechanisms for lowering glucose are impaired (i.e., lower insulin sensitivity). The body normally responds to this by increasing the replication rate of beta cells, thereby producing more beta cells ($\beta$) to output more insulin and lower the blood glucose level. The increase in the replication rate of beta cells (here, $\lambda$), depends on a reasonably high pancreatic reserve (here, represented by $\eta$). Over time, the pancreatic reserve is drained faster with high glucose levels, meaning that the ability to replicate beta-cells quickly is impaired. As a result, the body may be unable to further increase beta cells in response to high glucose levels thereby further lowering the pancreatic reserve $\eta$. Eventually the cycle of beta cell loss (with $\lambda<0$), results in further high levels of glucose, causing in turn more damage in terms of loss of beta cells. In short, with high glucose levels, the body can initially respond through normal mechanisms. When those mechanisms fail, it turns to expanding beta cell levels. However, if that is insufficient to bring down the blood glucose levels to safe levels, the ability to further expand beta cell levels is impaired because of a drained and insufficient pancreatic reserve. As a result, the blood glucose becomes even higher, eventually causing beta cells to decrease, and further worsening blood glucose levels.

The model incorporates the impact of beta cell decline associated with exposure to dysglycemia. Exposure to dysglycemia results in a decline of beta cell function over time and this eventually limits the individual’s regulatory capacity. Reduced beta cell function decreases the effectiveness of lifestyle interventions on
glucose regulation meaning that, even if an individual with reduced beta cell function makes significant changes to their diet and activity levels, the impact on the blood glucose regulation will be minimised. As well as capturing the duration of time that an individual is exposed to dysglycemia, the model also captures episodes of diabetes in pregnancy with poorly controlled blood glucose levels that have exposed a baby to dysglycemia prenatally. The glycemic regulation representation is shown in Figure 4.
Figure 4: Glycemic regulation representation
### Table 4: Parameters from the diabetes progression models by De Gaetano, Hardy et al.

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Notation</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beta0_initialBetaParameter</td>
<td>B0</td>
<td>initial β-cell mass</td>
<td>1000</td>
<td>Table 2 in [18] 1 in the table of [20]</td>
<td>Mci in [19]</td>
</tr>
<tr>
<td>I0_initialInsulinemia</td>
<td>I0</td>
<td>insulinemia at age t0, t0 is 18 yr in the model, but in here is age 0</td>
<td>50</td>
<td>[18]</td>
<td>pM</td>
</tr>
<tr>
<td>G0_initialGlycemia</td>
<td>G0</td>
<td>glycemia at age t0, t0 is 18 yr in the model, but in here is age 0</td>
<td>GDistribution</td>
<td>[20]</td>
<td>mM</td>
</tr>
<tr>
<td>Glambda_glycemiaOfMaximalSensitivity</td>
<td>Gλ</td>
<td>glycemia of maximal sensitivity of regulation of β cells G0 in model, right now we use 5, should change to G0, assuming the subjects to be in a perfect state of health at t0.</td>
<td>5</td>
<td>[20]</td>
<td>mM</td>
</tr>
<tr>
<td>Tgl_LiverGlucoseOutputVariable</td>
<td>Tgl</td>
<td>liver glucose output, represents the net difference of zero-order liver production and zero-order brain uptake of glucose.</td>
<td>see equations</td>
<td></td>
<td>mM/min</td>
</tr>
<tr>
<td>Kxg_1stOrderInsulinIndependentGlucoseTissueUpdateRate</td>
<td>Kxg</td>
<td>1st order insulin independent glucose tissue uptake rate, “glucose effectiveness”,</td>
<td>9.504*12</td>
<td>Table 2 in [18]</td>
<td>min-1</td>
</tr>
<tr>
<td>KxiStart_BaseLine1stOrderInsulinEliminationRate</td>
<td>KxiStart</td>
<td>1st order elimination rate for insulin at baseline (e.g. at 18 yr)</td>
<td>0.05 * 60 <em>24</em>365 due to model unit</td>
<td>Table 2 in [18]</td>
<td>min-1</td>
</tr>
<tr>
<td>KxiEnd_EndOfLife1stOrderInsulinEliminationRate</td>
<td>KxiEnd</td>
<td>1st order elimination rate for insulin at the end of life (e.g. at 90 yr)</td>
<td>0.035 * 60 <em>24</em>365 due to model unit</td>
<td>Table 2 in [18]</td>
<td>min-1</td>
</tr>
<tr>
<td>Parameter name</td>
<td>Notation</td>
<td>Description</td>
<td>Value</td>
<td>Source</td>
<td>Unit</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>----------</td>
<td>-----------------------------------------------------------------------------</td>
<td>---------------</td>
<td>--------------</td>
<td>------------</td>
</tr>
<tr>
<td>KxgI0</td>
<td>KxgI0</td>
<td>value of KxgI at t0</td>
<td>4.32*12</td>
<td>Table 2 in [18]</td>
<td>min−1 /pM</td>
</tr>
<tr>
<td>tI</td>
<td>tI</td>
<td>Elapsed time after adulthood (t0) of midpoint KxgI (0.5 × KxgI ) decrease</td>
<td>120</td>
<td>Table 2 in [18]</td>
<td>mo</td>
</tr>
<tr>
<td>vI_HillDecement</td>
<td>vI</td>
<td>steepness of hill-function decrement in insulin sensitivity</td>
<td>18</td>
<td>Table 2 in [18]</td>
<td>1</td>
</tr>
<tr>
<td>LambdaMinParameter</td>
<td>λmin</td>
<td>minimum value of λ (β cell replication rate), the maximum net apoptosis rate</td>
<td>-0.02*12</td>
<td>Table 2 in [18]</td>
<td>mo-1</td>
</tr>
<tr>
<td>eta0_InitialPancreaticReservationParameter</td>
<td>η0</td>
<td>value of η (baseline pancreatic reserve at t0 (determined)</td>
<td>0.04*12</td>
<td>Table 2 in [18]</td>
<td>mo-1</td>
</tr>
<tr>
<td>K_ethaG_ConstantRateOfpancreaticGlucoseToxicity</td>
<td>Kηg</td>
<td>pancreatic glucose toxicity coefficient, expressing the effect of (hyper)glycemia on the pancreatic reserve. This parameter embodies an operational definition of glucose toxicity as the relationship between (prevailing) glucose concentration and</td>
<td>0.02*12</td>
<td>Table 2 in [18]</td>
<td>mo−1 (mM)−1</td>
</tr>
<tr>
<td>Gh_glucoseConcentrationForHillShapedGlycemicEffectOnPancreaticInsulinRelease</td>
<td>Gh</td>
<td>centering glucose concentration for Hill-shaped glycemia effect on pancreatic insulin release</td>
<td>9</td>
<td>Table 2 in [18]</td>
<td>mM</td>
</tr>
<tr>
<td>vh_PowerCoefficientForHillShapedGlycemicEffect</td>
<td>vh</td>
<td>power coefficient for Hill-shaped glycemia effect on pancreatic insulin release</td>
<td>4</td>
<td>Table 2 in [18]</td>
<td>1</td>
</tr>
<tr>
<td>A0_initialGlycosylatedHaemoglobin</td>
<td>A0</td>
<td>A(t0), initial condition on glycosylated Haemoglobin(HbA1c)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parameter name</td>
<td>Notation</td>
<td>Description</td>
<td>Value</td>
<td>Source</td>
<td>Unit</td>
</tr>
<tr>
<td>Kxa_eliminationRateOfGlycosylatedHaemoglobin</td>
<td>Kxa</td>
<td>the spontaneous elimination rate of (glycosylated) Haemoglobin(Hb A1c), The elimination rate of Hb A1c is assumed to reflect the elimination of red blood cells.</td>
<td>0.238*12</td>
<td>E1467 [20]</td>
<td>mo-1</td>
</tr>
</tbody>
</table>
### Table 5: Parameters sourced from other papers

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Notation</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>tMax</td>
<td>tmax</td>
<td>Maximum age for aging in insulin first-order eliminate rate in a person</td>
<td>90</td>
<td>E1467 [20]</td>
<td>mo</td>
</tr>
<tr>
<td>x0</td>
<td>x0</td>
<td>Initial value of x</td>
<td>1</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>BetaMaxParameter</td>
<td>Bmax</td>
<td>maximal β – cell population</td>
<td>4000</td>
<td>Table 2 in [18, 20]</td>
<td>Mc</td>
</tr>
<tr>
<td>t0</td>
<td>t0</td>
<td>Starting age, with system at equilibrium, in month</td>
<td>18yr</td>
<td>p E1465 in [20]</td>
<td></td>
</tr>
<tr>
<td>dt</td>
<td></td>
<td>time interval for events</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>dtPregnancy</td>
<td></td>
<td>time interval for equationSolverEvent during pregnancy</td>
<td>0.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>dtNonPregnancy</td>
<td></td>
<td>time interval for equationSolverEvent during NOT pregnancy</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>InsulinSensitivityFractionEarlyPregnancyNorm</td>
<td></td>
<td>in earlyLatePregnancyInsulinSensitivityByWeight(weight), calculate KxgI-EarlyPreg for normal weight person</td>
<td>0.95</td>
<td>[21]</td>
<td></td>
</tr>
<tr>
<td>InsulinSensitivityFractionEarlyPregnancyObese</td>
<td></td>
<td>in earlyLatePregnancyInsulinSensitivityByWeight(weight), calculate KxgI-EarlyPreg for obese person</td>
<td>1.27</td>
<td>[21]</td>
<td></td>
</tr>
<tr>
<td>InsulinSensitivityFractionEarlyPregnancyOverWeight</td>
<td></td>
<td>in earlyLatePregnancyInsulinSensitivityByWeight(weight), calculate KxgI-EarlyPreg for overweight person</td>
<td>0.89</td>
<td>[21]</td>
<td></td>
</tr>
<tr>
<td>Parameter name</td>
<td>Notation</td>
<td>Description</td>
<td>Value</td>
<td>Source</td>
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</tr>
<tr>
<td>---------------------------------------------</td>
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<td>-------------------------------------------------------------------------------</td>
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</tr>
<tr>
<td>InsulinSensitivityFractionLatePregnancyNormal</td>
<td></td>
<td>in earlyLatePregnancyInsulinSensitivityByWeight(weight), calculate KxgL-LatePreg for normal weight person</td>
<td>0.54</td>
<td>[21]</td>
<td></td>
</tr>
<tr>
<td>InsulinSensitivityFractionLatePregnancyObese</td>
<td></td>
<td>in earlyLatePregnancyInsulinSensitivityByWeight(weight), calculate KxgL-LatePreg for obese person</td>
<td>0.77</td>
<td>[21]</td>
<td></td>
</tr>
<tr>
<td>InsulinSensitivityFractionLatePregnancyOverWeight</td>
<td></td>
<td>in earlyLatePregnancyInsulinSensitivityByWeight(weight), calculate KxgL-LatePreg for overweight person</td>
<td>0.43</td>
<td>[21]</td>
<td></td>
</tr>
<tr>
<td>NewtonRaphsonEpsilon</td>
<td></td>
<td>Newton–Raphson method</td>
<td>0.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>tau_CompleteRecoveryTime</td>
<td></td>
<td>used in creating event recentlyDeliveredBaby_DynamicEvent, set isRecentlyPregnant false.</td>
<td>6.0/12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>tau_RecoveryTime</td>
<td></td>
<td>the time that agent in postpartum period, used in InsulinSensitivityInPostPartum() for the calculation of KxgL in postpatum</td>
<td>3.0/12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>tI</td>
<td></td>
<td>tI for normal weight, used in InsulinSensitivityFromDegatano() to calculate KxgL trajectory</td>
<td>120</td>
<td>[18-20]</td>
<td></td>
</tr>
<tr>
<td>Parameter name</td>
<td>Notation</td>
<td>Description</td>
<td>Value</td>
<td>Source</td>
<td>Unit</td>
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</tr>
<tr>
<td>tl_Obese</td>
<td></td>
<td>tl for obese, used in InsulinSensitivityFromDegae tano() to calculate Kxgl trajectory</td>
<td>25.5</td>
<td>Derived from [18-20]</td>
<td></td>
</tr>
<tr>
<td>tl_overWeight</td>
<td></td>
<td>tl for overweight, used in InsulinSensitivityFromDegae tano() to calculate Kxgl trajectory</td>
<td>29</td>
<td>Derived from [18-20]</td>
<td></td>
</tr>
<tr>
<td>insulinDose</td>
<td></td>
<td>used when insulin treatment is applied</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>offspringKxglGlycemiaCoefficient</td>
<td></td>
<td>calibrated value</td>
<td>6.649</td>
<td></td>
<td></td>
</tr>
<tr>
<td>alphahVariable</td>
<td></td>
<td>used in rootOfNumericalSolution_N wrph () to calculate G</td>
<td></td>
<td>Ghvh</td>
<td></td>
</tr>
<tr>
<td>isNormalPancreaticRecoveryT_eta</td>
<td></td>
<td>parameter decide if T\eta is declining or not</td>
<td>false</td>
<td></td>
<td></td>
</tr>
<tr>
<td>t_etha_End</td>
<td>T_{\eta_{end}}</td>
<td>T_{\eta} value at the end of the period of observation</td>
<td></td>
<td>calibrated</td>
<td></td>
</tr>
<tr>
<td>maternalInsulinSensitivityCoefficient</td>
<td></td>
<td>represent impaired insulin sensitivity for offspring whose mother is in DIP. we assume the value of first generation is 1</td>
<td></td>
<td>first generation and offspring whose mother has not had DIP is 1, otherwise is insulinSensitivityCoefficientForOffspring(GlycemiaReadings after 26 weeks)</td>
<td></td>
</tr>
<tr>
<td>preGravidInsulinSensitivity</td>
<td>K_{xgl-PreGravid}</td>
<td>K_{xgl}value at the beginning of pregnancy</td>
<td></td>
<td>K_{xgl}(t)</td>
<td></td>
</tr>
<tr>
<td>Parameter name</td>
<td>Notation</td>
<td>Description</td>
<td>Value</td>
<td>Source Unit</td>
<td></td>
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</tr>
<tr>
<td>earlyPregnancyInsulinSensitivity</td>
<td>$K_{xgI-EarlyPregnancy}$</td>
<td>$K_{xgI}$ value at the early pregnancy</td>
<td>normal weight: $\text{InsulinSensitivityFractionEarlyPregnancyNormal} \cdot K_{xgI-Preg}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>overweight: $\text{InsulinSensitivityFractionEarlyPregnancyOverWeight} \cdot K_{xgI-Preg}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>obese: $\text{InsulinSensitivityFractionEarlyPregnancyObese} \cdot K_{xgI-Preg}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>latePregnancyInsulinSensitivity</td>
<td>$K_{xgI-LatePregnancy}$</td>
<td>$K_{xgI}$ value at the late pregnancy</td>
<td>normal weight: $\text{InsulinSensitivityFractionLatePregnancyNormal} \cdot K_{xgI-Preg}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>overweight: $\text{InsulinSensitivityFractionLatePregnancyOverWeight} \cdot K_{xgI-Preg}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>obese: $\text{InsulinSensitivityFractionLatePregnancyObese} \cdot K_{xgI-Preg}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parameter name</td>
<td>Notation</td>
<td>Description</td>
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<td>-------------------------------------------------------------------------------</td>
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</tr>
<tr>
<td>Ro_ratioOf1stOrderTo2ndOrderRateConstant ForTissueGlucoseUptakeFromPlasmaParameter</td>
<td>$\rho$</td>
<td>Ratio of 1st- to 2nd-order (insulin-dependent) rate constants for tissue glucose uptake from plasma</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>gamma_InsulinResistanceAsNoOfmMGlucoseAtWhichGlycemiaStabilizesPerpMInsulinemiaVariable</td>
<td>$\gamma$</td>
<td>Resistance to insulin as the number of mM glucose at which glycemia stabilises for a single pM of insulinemia, is the converse of glucose effectiveness [insulin sensitivity (KxgI)] and expresses resistance to insulin as the concentration at which glucose stabilises for each picomolar of insulin concentration.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I_fastingSerumInsulinConcentrationVariable</td>
<td>$I$</td>
<td>fasting serum insulin concentration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ImaxB_InsulinAttainableLevelVariable</td>
<td>$I_{\text{maxB}}$</td>
<td>insulin-attainable levels expressed as the maximal contribution of 1 million -cells to fasting insulin plasma concentration. Its value is determined by the maximal insulin secretion rate per million -cells $T_{\text{igB}}$ and by the actual first-order apparent rate of elimination of insulin from plasma ($K_{\xi}$), which is considered here to decrease with age.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>betaVariable</td>
<td>$\beta$</td>
<td>initial value is 1000, -cell mass as millions of active -cells</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EthaPancreaticReplicationReserveVariable</td>
<td>$\eta$</td>
<td>the current ability of the pancreas to increase its -cell proliferation rate if sufficiently stimulated by the ambient glucose concentration, depending on the current state of pancreatic health.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T_ethaSpontaneousRecoveryRateOfPancreasVariable</td>
<td>$T_\eta$</td>
<td>spontaneous recovery rate of the pancreas, an impairment in cell replicating reserve has been simulated by forcing a decline in the term reflecting cell recovery from injury, $T\eta$. For the case of normal replicating ability, this parameter is kept fixed throughout life; otherwise the parameter is made to decrease linearly from a normal initial value to a somewhat decreased value at the end of the period of observation.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G_fastingPlasmaGlucoseConcentrationVariable</td>
<td>$G$</td>
<td>fasting plasma glucose concentration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parameter name</td>
<td>Notation</td>
<td>Description</td>
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<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A_{\text{glycosylatedHaemoglobinHbA1cVariable}}$</td>
<td>$A$</td>
<td>just calculate in the model, not used by other function glycosylated haemoglobin, with increase determined by prevailing glycemias and by the concentration of native Hb A0 and decrease linearly determined by the continuous destruction of red blood cells.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$K_{\text{ag_productionRateOfGlycosylatedHaemoglobinFromCirculatingGlucoseVariable}}$</td>
<td>$K_{\text{ag}}$</td>
<td>the rate of production of Hb A1c from circulating glucose.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$h_{\text{glucoseEffectOnPancreasVariable}}$</td>
<td>$h$</td>
<td>Glucose effect on pancreas. In the model, $h$ is calculated, but not used anywhere.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$K_{\text{xi_1stOrderInsulinEliminationRateVariable}}$</td>
<td>$K_{\text{xi}}$</td>
<td>First-order elimination rate constant for insulin and reflects clearance from the plasma, occurs when glycemia exceeds the renal threshold, in which case glucose is eliminated with urine in a linear, plasma concentration-dependent fashion. When glycemia is below the renal threshold, as occurs in most normal or treated subjects, there is difficulty identifying a physiological process to which a linear term for glucose elimination may correspond.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$h(G_{0})_{\text{initialGlucoseEffectOnPancreasVariable}}$</td>
<td>$h(G_{0})$</td>
<td>Value of the $h(G)$ function at $t_0$ (determined)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_{\text{igB}}_{\text{maximumPancreaticInsulinSecretionPerMillionBetaVariable}}$</td>
<td>$T_{\text{igB}}$</td>
<td>maximal insulin secretion rate,</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$I_{\text{maxB}}_{\text{InsulinAttainableLevelVariable}}$</td>
<td>$I_{\text{maxB}}$</td>
<td>maximal insulin secretory capacity, ($I_{\text{maxB}}$) has been defined as the ratio of maximal insulin secretion per million $\beta$-cells per litre of distribution space ($\text{maximal insulin secretion}(T_{\text{igB}})$) and $K_{\text{xi}}$. In other words, we make a distinction between secretion rate ($T_{\text{igB}}$) and the effect, in terms of concentration, that this maximal secretion rate attains ($I_{\text{maxB}}$). The distinction is relevant when (like for the present simulations) the apparent first-order elimination rate ($K_{\text{xi}}$) for insulin is made to decline with age.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda_{\text{maxVariable}}$</td>
<td>$\lambda_{\text{max}}$</td>
<td>Maximum (positive) value of , maximum replication rate of $\beta$-cell, assuming no apoptosis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$x_{\text{GlucoseVariable}}$</td>
<td>$x$</td>
<td>Replaces glucose variations with variations of a scale-free pure number</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parameter name</td>
<td>Notation</td>
<td>Description</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>----------------------------------------------------</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LambdaVariable</td>
<td>$\lambda$</td>
<td>Net rate constant for β-cell growth (or decay) resulting from the difference between production (replication) rate and mortality (apoptosis) rate.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$K_{xgI}$SecondOrderInsulinDependentGlucoseTissueUptakeRate</td>
<td>$K_{xgI}$</td>
<td>This coefficient represents the second-order insulin-dependent glucose uptake rate constant per unit of insulin and therefore reflects insulin sensitivity ($K_{xgI}$) of peripheral tissues.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MetforminInterventionPart1Variable</td>
<td>= getInterventionVariable(currTime, tMetforminPart1, MetfDosePart1, betaMetfPart1, alphaMetfPart1);</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MetforminInterventionPart2Variable</td>
<td>= getInterventionVariable(currTime, tMetforminPart2, MetfDosePart2, betaMetfPart2, alphaMetfPart2);</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LifeStyleInterventionVariable</td>
<td>= getInterventionVariable(currTime, tLifeStyle, adherence() * LiStDose, betaLifeStyle, alphaLifeStyle);</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 7: Equations used in glycemic regulation representation

<table>
<thead>
<tr>
<th>Equations</th>
<th>Unit of state / variable</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>[ \frac{\delta B(t)}{\delta t} = \lambda(G)B(1 - \frac{B}{B_{max}}) ]</td>
<td>( \text{Mc} )</td>
<td>Initially beta cell mass is 1000, then beta cell is either increasing or decreasing, which is determined by net rate constant for -cell growth (or decay) resulting from the difference between production (replication) rate and mortality (apoptosis) rate (lambda variable). If beta cell is increasing due to compensation to G increase, the maximum increase is 4000.</td>
<td>[18, 19]</td>
</tr>
<tr>
<td>[ \frac{\delta \eta(t)}{\delta t} = -K_{\eta}G\eta + T_{\eta}, \eta(t_0) = \eta_0 ]</td>
<td>( \text{mo-1} )</td>
<td>moving from some starting value (0) and then changing [potentially increasing to a maximum (max) or decreasing toward zero] depending on the prevailing glycemia levels. sustained hyperglycemia will lead to a decrease of ( \eta ).</td>
<td>[18-20]</td>
</tr>
<tr>
<td>[ \frac{\delta A}{\delta t} = -K_{\eta}A + K_{\alpha}G\left(\frac{100 - A}{100}\right), A(t_0) = A_0 ]</td>
<td>( % )</td>
<td>To link observable glycated haemoglobin dynamics with the glucose dynamics, a simple linear model of the kinetics of HbA1c has been hypothesised</td>
<td>[18-20]</td>
</tr>
<tr>
<td>isUnderInsulinTreatment ? \rho = \rho + insulinDose * adherence() / Kxi</td>
<td></td>
<td>When insulin treatment is applied, the impact of treatment with insulin on insulin sensitivity has been considered by adding an additional term to the equation describing I in the slow model of DeGaetano and find G and I based on this extra term. The impact of treatment with insulin has been calculated in the body of the function “updateGfastingGlucoseAndFastInsulin”.</td>
<td></td>
</tr>
<tr>
<td>Equations</td>
<td>Unit of state / variable</td>
<td>Description</td>
<td>Source</td>
</tr>
<tr>
<td>--------------------------------------------------------------------------</td>
<td>--------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>--------</td>
</tr>
<tr>
<td>$G = \frac{y}{p-I}$</td>
<td></td>
<td>Equation used to calculate glycemia value</td>
<td>[18-20]</td>
</tr>
<tr>
<td>$h(G) = \frac{(G/G_s)^{i+k}}{1-(G/G_s)^{i+k}}$</td>
<td></td>
<td>Glucose effect on pancreas. In the model, h is calculated, but not used anywhere.</td>
<td>[18-20]</td>
</tr>
<tr>
<td>$K_{yi}(t) = K_{yi}\text{Start} + \frac{t-t_0}{t_{max}-t_0}(K_{yi}\text{End} - K_{yi}\text{Start})$</td>
<td>$\text{min}^{-1}$</td>
<td></td>
<td>[18-20]</td>
</tr>
<tr>
<td>$h(G_0) = \frac{(G_0/G_s)^{i+k}}{1-(G_0/G_s)^{i+k}}$</td>
<td>$\text{min}^{-1}$</td>
<td></td>
<td>[18-20]</td>
</tr>
<tr>
<td>$T_{ig3} = \frac{K_{yi}\text{End} \cdot I_0}{h(G_0) \cdot E_0}$</td>
<td>$\text{pM/min/Mc}$</td>
<td></td>
<td>[18-20]</td>
</tr>
</tbody>
</table>
### Equations

<table>
<thead>
<tr>
<th>Equations</th>
<th>Unit of state / variable</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{m,\text{max}} = \frac{I_{m,\text{max}}}{K_w}$</td>
<td>$pM/Mc$</td>
<td></td>
<td>[18-20]</td>
</tr>
<tr>
<td>$\lambda_{\text{max}} = \lambda_{\text{max1}} + \eta$</td>
<td>$mo^{-1}$</td>
<td></td>
<td>[18-20]</td>
</tr>
<tr>
<td>$\lambda = \frac{\lambda_{\text{max1}}}{G}$</td>
<td></td>
<td></td>
<td>[18-20]</td>
</tr>
<tr>
<td>$\lambda(G) = \lambda_{\text{max1}} + \eta \frac{1}{1+G^{\gamma}}$</td>
<td>$mo^{-1}$</td>
<td>A depends on prevailing glucose concentrations in the sense that it varies from a minimum negative value $(\lambda_{\text{min}})$ to a maximum value that is dependent on both the prevailing pancreatic reserve described here $(\lambda_{\text{max}}=\lambda_{\text{min}}+\eta)$ and glucose level according to a sigmoidal third-degree Hill function, with $\lambda=\lambda_{\text{min}}$ when $G=0$ and $\lambda$ tending to $\lambda_{\text{max}}$ as $G$ tends to infinity.</td>
<td>[18-20]</td>
</tr>
<tr>
<td>$\rho = 0 \times K_{xg}/K_{xgI}$</td>
<td>$pM$</td>
<td>It has been assumed that the insulin-independent glucose tissue uptake rate constant $K_{xg}$ is small (within the range of considered glycemias) compared with insulin-dependent glucose uptake (50) and that, consequently, the $\rho$ is also approximately zero.</td>
<td>[18-20]</td>
</tr>
</tbody>
</table>

### Equations

<table>
<thead>
<tr>
<th>Equations</th>
<th>Unit of state / variable</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{g} = (K_{xg} + K_{xgI} \times I_{0})G_{0}$</td>
<td>$mM/min$</td>
<td></td>
<td>[20]</td>
</tr>
<tr>
<td>$\gamma = \frac{\lambda_{\text{max1}}}{K_{xgI}}$</td>
<td>$mM \times pM$</td>
<td></td>
<td>[18-20]</td>
</tr>
<tr>
<td>Equations</td>
<td>Unit of state / variable</td>
<td>Description</td>
<td>Source</td>
</tr>
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<td>--------</td>
</tr>
<tr>
<td>$K_{28} = \frac{E_{28}(t)}{\sigma_{28}}$</td>
<td>%/mo/mM</td>
<td>this equation is in the function $\text{InsulinSensitivityFromDegaetano}(\text{double } t)$ different $t$ is used for different weight category $t_I$ for normal weight, $t_I_{Obese}$ for obese, $t_I_{Overweight}$ for overweight</td>
<td>[18-20]</td>
</tr>
<tr>
<td>$K_{28} (t) = K_{28}^{(0)} \left(1 - \frac{t}{(t_{0}^{*})^{2}}\right)^{2}, \ t \geq t_{0}$</td>
<td>min$^{-1}$/pM</td>
<td>different $t$ is used for different weight category $t_I$ for normal weight, $t_I_{Obese}$ for obese, $t_I_{Overweight}$ for overweight</td>
<td>[20]</td>
</tr>
<tr>
<td>$T_{n} = K_{n} \times G_{0} \times \eta_{0}$</td>
<td>mo$^{-2}$</td>
<td>This equation reflects the case of normal replicating ability, this parameter is kept fixed throughout life.</td>
<td>[20]</td>
</tr>
</tbody>
</table>
Table 8: Functions used in glycemic regulation representation

<table>
<thead>
<tr>
<th>function name</th>
<th>parameters</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>insulinSensitivityCoefficientForOffspring</td>
<td>GValueList: ArrayList&lt;Double&gt;</td>
<td>averageGlycemia = after 26 weeks of pregnancy, the average value of the difference between the glycemia values which are higher than GDM standard, and GDM standard</td>
</tr>
<tr>
<td>adherence</td>
<td></td>
<td>Beta (2, 5, 0, 1)</td>
</tr>
<tr>
<td>slopeOfDeclineInInsulinSensitivityDueToImpairment</td>
<td></td>
<td>if $T_\eta$ is impaired, we assume it decreases linearly from a normal initial value to a decreased value at the end of the period of observation. The slope of the linear equation is calculated using the following equation.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$Slope = \frac{-K_{\eta}G_0(\eta_0-t_{end})}{t_{end}-t_0}$</td>
</tr>
<tr>
<td>getT_ etaSpontaneousRecoveryRateOfPancreasVariable</td>
<td></td>
<td>calculate $T_\eta = K_{\eta}G_0\eta_0 + isNormalPancreaticRecoveryT_\eta \text{ if } 0$: (</td>
</tr>
<tr>
<td></td>
<td></td>
<td>current age $&gt; t_0 \text{ if } \text{slope } \times (\text{current age } - t_0) : 0$</td>
</tr>
<tr>
<td>function name</td>
<td>parameters</td>
<td>description</td>
</tr>
<tr>
<td>-------------------------------------</td>
<td>-------------------------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| **insulinSensitivityBasedWeight**   | (weight: Weight, kxgIOffspringCoefficient: double) | \[ K_{xgI}(t) = K_{xgI_0} \left( 1 - \frac{(\text{weight})^2}{1+(\text{weight})^2} \right), \quad t \geq t_0 \]
|                                    |                                                 | = K_{xgI_0}, \quad t \leq t_0                                                                                                                                                                      |
|                                    |                                                 | From[18-20], assume Kxgi trajectory based on different weight status (represented by ti), without weight change during the observation. |
|                                    |                                                 | **insulinSensitivityBasedWeight()** calculates kxgi for changing weight status. If weight change to overweight or obese, ti here will use ti_overweight or ti_obese, respectively. |
|                                    |                                                 | \[ K_{xgI} = (K_{xgI} + (\text{InsulinSensitivityFromDegasano}(ti) - K_{xgI}) \times \frac{dt}{tau}) \times \text{maternalInsulinSensitivityCoefficient} \] |
|                                    |                                                 |                                                                                                                                 |
| **linearInterpInPregnancy**         | (timeDuringPregnancy:double)                    | Assumption: kxgi will decrease during pregnancy, after postpartum will back to normal. Here using LinearInterpolator from org.apache.commons.math3. |
|                                    |                                                 | \[ [] x = \{\text{timeOfPregnancy}, \text{timeOfPregnancy}+3*\text{month()}, \text{timeOfPregnancy}+9.3*\text{month()})\}; \]
|                                    |                                                 | \[ [] y = \{Kxgi-PreGravid, Kxgi-EarlyPreg, Kxgi-LatePreg\}; \]
|                                    |                                                 | \[ f = \text{interpolate}(x,y) \]
<p>|                                    |                                                 | [ f(timeDuringPregnancy) ]                                                                                                                                                                       |</p>
<table>
<thead>
<tr>
<th>function name</th>
<th>parameters</th>
<th>description</th>
</tr>
</thead>
</table>
| InsulinSensitivityInPostPartum | \( (K_{xgI} \_ \text{coefficient}: \text{double}) \) | \[
K_{xgI} = K_{xgI-\text{LstP-reg}} \times (K_{xgI}(t) \times K_{xgI-\text{LstP-reg}}) \times \left(1 - e^{-\frac{\text{time}}{\text{time_constant}}}ight)
\]

- **CalculateInsulinSensitivityFunction**
  - during pregnancy: \( K_{xgI} = \text{maternalInsulinSensitivityCoefficient} \times \text{linearInterpInPregnancy}(t) \)
  - postPartum: \( K_{xgI} = \text{maternalInsulinSensitivityCoefficient} \times \text{InsulinSensitivityInPostPartum()} \)
  - non-pregnant: \( K_{xgI} = \text{insulinSensitivityBasedWeight}() \)
  - lifestyle treatment && metformin treatment: \( K_{xgI} = K_{xgI} + K_{xgI} \times (\text{LifeStyleInterventionVariable} + \text{MetforminInterventionPart1Variable} + \text{MetforminInterventionPart2Variable}) \)
  - lifestyle treatment: \( K_{xgI} = K_{xgI} + K_{xgI} \times \text{LifeStyleInterventionVariable} \)
  - metformin treatment: \( K_{xgI} = K_{xgI} + K_{xgI} \times (\text{MetforminInterventionPart1Variable} + \text{MetforminInterventionPart2Variable}) \)

Kxgi is being calculated during pregnancy, postpartum, non-pregnancy, lifestyle interventions and metformin treatment. One very important issue that should be reconsidered is the dose of metformin and insulin. The impact of metformin and lifestyle treatment is based on the work of DeGaetano et al [18, 19].
<table>
<thead>
<tr>
<th>function name</th>
<th>parameters</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>equationSolverFunction</td>
<td></td>
<td>This function finds the integration of all flows using Euler method, replacing the integration process in Anylogic. B, η and A is updated here.</td>
</tr>
<tr>
<td>updateGfastingGlucoseAndIFastinInsulin</td>
<td></td>
<td>This function finds and updates the values for Glucose and Insulin based on Newton–Raphson method. The other import functionality of this function is updating all the components of System-Dynamics including &quot;States&quot; and &quot;Dynamic variables&quot;.</td>
</tr>
</tbody>
</table>
D. Population representation

The model starts with an index population, these are people who start in the model at different ages and are initialised in different states. The index population is based on ACT demographic information taken from the 2011 Australian Census and National Health Survey data. At the birth transition in the pregnancy state chart, individuals are born into the model, and the sex of descendants is determined by a distribution. For simplicity, male descendants are deleted after they transit to the descendantPopulation_Male state. Initial and descendant female population leave the population according to the death rate from the Australian Bureau of Statistics ([http://stat.data.abs.gov.au/Index.aspx?DataSetCode=DEATHS_AGESPECIFIC_OCCURENCEYEAR](http://stat.data.abs.gov.au/Index.aspx?DataSetCode=DEATHS_AGESPECIFIC_OCCURENCEYEAR)). Age is initialised and collected in continuous model time and can be calculated at any point in the model. This allows statistics to be aggregated by any relevant age groupings eg. 1-year, 5-year or, 10-year age groups etc. In this way, the model supports flexible characterisation. The population statechart representation is shown in
Figure 5.

Babies born into the model inherit their mother’s status at time of birth, allowing the model to collect family history information about those children and their descendants. The information available for the descendent population is therefore richer than the initial population. For example, the mother’s glycemia status affects the insulin sensitivity of children. The initial population has imposed assumptions onto the model, for example, for initial population, their insulin sensitivity is assumed not affected by their mother’s status, however for the descendent population this information is generated by the model.
Figure 5: Population representation structure
Table 9: Parameters used in population representation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>initialAgeCategory</td>
<td></td>
<td>AgeGroup</td>
<td>assign age group when enter population state chart</td>
</tr>
<tr>
<td>agentIndexNumber</td>
<td>Determine when agent is created in the model.</td>
<td>int</td>
<td>agent index in the population</td>
</tr>
<tr>
<td>motherIndexNumber</td>
<td>Determine when agent is created in the model.</td>
<td>int</td>
<td>for descendant, its mother's index in the population</td>
</tr>
<tr>
<td>gender</td>
<td>Female/Male</td>
<td>Gender</td>
<td>agent's gender.</td>
</tr>
<tr>
<td>ethnicity</td>
<td>ADiPS/ATSI/Australian_Born/Other</td>
<td>Ethnicity</td>
<td>agent's ethnicity</td>
</tr>
<tr>
<td>descendant</td>
<td>True / false</td>
<td>boolean</td>
<td>the agent is born during model running or not</td>
</tr>
<tr>
<td>ageCreatedinModel</td>
<td>Determine when agent is created in the model.</td>
<td>double</td>
<td>Agent age at start of the model run</td>
</tr>
<tr>
<td>isImmigrant</td>
<td>True / false</td>
<td>boolean</td>
<td>the agent is immigrant or not</td>
</tr>
</tbody>
</table>
E. Weight status representation

BMI categories have been used in this model to categorise an individual’s weight status. The categories used in the statechart are: not overweight/obese; overweight, obese and NA (not applied). However, underlying the statechart, weight status is characterised as a continuous variable based on z score and age specific BMI distributions [22]. Upon entry to adulthood, agents are allocated a z-score representing their position within the population weight distribution. Their position within the distribution is assumed to stay the same as they age. Hayes et al reported that the population weight distributions move toward higher BMI through the life course i.e. people gain weight as they age, therefore an agent with a z score of 1 on entry to adulthood may be healthy weight, however if they maintain the same z score into their 40’s the movement of the population weight distribution may position them within the overweight category. Individuals can transition between weight states as they lose or gain weight. If an agent loses weight due to an intervention a new lowered z-score is assigned and if they gain weight, for example due to pregnancy [23], they are assigned a new higher z-score. The weight status representation is shown in

When an agent is introduced into the model, the BMI of the agent is initialised based on the BMI distribution of the age group that this agent belongs to. The corresponding Z-score is calculated from the BMI value and mean of the BMI distribution. As the agent ages they will transfer from current age group to next age group (e.g. 25 - 35). The BMI distribution also changes from the distribution of current age group to the distribution of next age group. By applying the Z-score to the BMI distribution of the next age group, the BMI will be calculated. The BMI value of the next age group for an agent will
be calculated in an event with cyclic timeout of 10 years. A second event with cyclic timeout of 1 year was used to move the BMI of current age group towards the BMI of next age group gradually.

With this Z-score-BMI mechanism, we also capture the BMI change after pregnancy. After pregnancy, based on a distribution, four types of BMI change can occur. These include decreasing more than 1 BMI unit, no change of BMI, increasing more than three BMI unit and increasing 1 BMI unit. After the BMI value has changed after pregnancy, the new BMI and BMI distribution of current age group of the agent are used to recalculate the agent’s Z-score.

**Figure 6: Weight status statechart**

![Weight status statechart](image)

**Table 10: Parameters used in weight dynamics**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMI</td>
<td>assignInitialBMI(age)</td>
<td>double</td>
<td>BMI value of the agent</td>
</tr>
<tr>
<td>Z-score</td>
<td>getZscore(age, BMI)</td>
<td>double</td>
<td>Representing the position of the BMI value in BMI distribution.</td>
</tr>
</tbody>
</table>
### Table 11: Functions used in weight dynamics

<table>
<thead>
<tr>
<th>Function name</th>
<th>parameters</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>getZscore</td>
<td>(age: double, BMI: double)</td>
<td>Calculate the Z-score of an agent based on age and BMI</td>
</tr>
<tr>
<td>getBMI</td>
<td>(age: double, Z-score: double)</td>
<td>Calculate the Z-score of an agent based on age and Z-score</td>
</tr>
<tr>
<td>getWeightCategory</td>
<td>(BMI: double)</td>
<td>Calculate weight category of an agent</td>
</tr>
<tr>
<td>assignInitialBMI</td>
<td>(age: double)</td>
<td>When model introduced into model, assign initial BMI to the agent based on their age.</td>
</tr>
<tr>
<td>BMIChangeBetweenPregnancy</td>
<td></td>
<td>Based on BMI change type after pregnancy, assign new BMI and Z-score after pregnancy</td>
</tr>
</tbody>
</table>
F. Service representation

Services during pregnancy are represented using discrete events simulation components. Regular primary care is represented in a statechart in Person reflecting that a woman is receiving usual health care services through a general practitioner (Figure 7 (1)). For non-pregnant agents, they are in InPrimaryCare state and receive risk factor check every two years. Agents leave InPrimaryCare state when they become pregnant, when they enter the NotInPrimaryCare state. While in the NotInPrimaryCare state, agents move through the clinical service pathway as follows.

Clinical pathway 1 is shown in Figure 7 below. A pregnant female agent enters the service at the beginning of her pregnancy. She receives an early pregnancy assessment in the earlyPregnancyTest service block (usually performed by her GP). She then waits at delayBeforeTest block for her Diabetes in Pregnancy (DIP) test in dipAssessment block. The DIP test time varies with individuals. In this model, agents who are not categorised as high risk receive the DIP test at 26 - 28 weeks gestation. However, high-risk agents, including obese agents, high risk ethnicities or whose age is over 35 years, have the DIP test at 8 - 12 weeks gestation. At this dipAssessment block, if the woman’s blood glucose level is above the diagnostic threshold (see Table 3) a message transition is triggered in the diagnosis statechart and the agent transitions to a diagnosed state.

The agents whose DIP test result is negative will be referred to standard antenatal care and remain there until delivery. At antenatal care service, resource sets of administrative officers, nurses and physicians are allocated to the queueing agents.

If the DIP test result is positive, meaning the agent has T1DM, T2DM or GDM, the agent first moves to the DIPEducation service block. This service has a resource set of diabeteNurseEducators and delay time of 5 hours. At this time, the agent will start lifestyle intervention. The agent will have lifestyle intervention for 1 week at the delay block underLifestyleAfterEducation. After this delay, agents are referred to the dietitian for a review at dieticianReview service and have their glycemic levels reviewed.

At this point, if the glycemic level does not exceed the GDM criteria, meaning the lifestyle intervention in DIPEducation session is working, the agent continues lifestyle intervention in dietControl delay for 1 week. After dietControl, the agent’s glycemic control is monitored every week until delivery. During this time, if the glycemia result in any week is higher than the GDM criteria in this model, the agent is referred to select-output lifestyleOrInsulinTreatment. If the test results are all negative, the agent will go to delayBeforePostpartumFollowUp delay for postpartum check.

Agents who have high glycemic levels at the dieticianReview service are referred to select-output lifestyleOrInsulinTreatment. Here the agent will be assessed to continue lifestyle intervention or start insulin treatment. The model assumes that if an agent’s glucose level is higher than the criteria of T2DM, the agent will start insulin treatment and continue the insulin treatment until delivery, otherwise she will go back to diet control with continuing lifestyle intervention and ongoing monitoring until delivery.

After delivery, all agents will wait six weeks until they receive postpartum follow-up dip assessment. There are three different conditions in this test. First, if glucose level is higher than GDM criteria but not yet developed into T2DM, the agent will continue lifestyle intervention and leave this service pathway. Second, if the agent is T2DM or T1DM, the agent will start all three treatments: lifestyle intervention, insulin treatment, metformin treatment. Then they also leave this service pathway. Third, if the glucose level of the agent is lower than GDM criteria, the agent will stop lifestyle intervention then leave service.
pathway. After leaving ACT health service pathway, the agents will transition back to InPrimaryCare state in PrimaryCare_Statechart in Person. This representation allows the model to capture resource use and costs associated with service provision to individual agents, and intervention in primary care. Different models of clinical care can be represented and compared in this section of the model.

Figure 7: Service representation

Table 12: Functions used in service representation

<table>
<thead>
<tr>
<th>Function</th>
<th>Return type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>gdmStandard()</td>
<td>double</td>
<td>get model’s criteria for gdm</td>
</tr>
<tr>
<td>T2DMStandard()</td>
<td>double</td>
<td>get model’s criteria for T2DM</td>
</tr>
<tr>
<td>assignDiPTestTime(Person)</td>
<td>double</td>
<td>when enter ACT health service, assign dip test time for different agent, normally test time is 26 - 28. For high risk group (e.g. obese, age &gt; 35) they will start test at 8 - 12 weeks</td>
</tr>
</tbody>
</table>
G. Interventions for scenario testing

Four types of population level interventions are implemented into the model and described as follows.

A. Public health messaging and mobile app support

The intervention is target on the women aged 20-35 years. As a pre-pregnancy intervention, it is applied in InPrimaryCareState of PrimaryCare_Statechart every year. The targeted women will have certain probability to take this intervention, as well as retake the intervention. The intervention achieves healthier pre-pregnancy BMI and optional lifestyle change, by reducing BMI for overweight or obese agent whereas no BMI reduce for healthy weight agent. The lifestyle change resulting from the intervention improves the insulin sensitivity in glycemia regulation representation of the model.

B. Targeted pre-pregnancy support

This intervention takes place at the planning pregnancy state before pregnancy, and works on women with risk factors, including BMI greater than 28, age greater than 30 years and high-risk ethnicity according to the ADIPS criteria [24]. Similarly, with the mechanism of public health message and mobile app support intervention, health professional support also targets weight reduction and optional lifestyle change.

C. Targeted post-pregnancy support

The intervention targets on women how had DIP in previous pregnancy, take places between pregnancy and include both weight reduction and lifestyle change. In this intervention, the target group is the women who were diagnosed with DIP in a previous pregnancy. The lifestyle change intervention with strong adherence allows the intervention to have a stronger effect on insulin sensitivity.
<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>alphaLifeStyle</td>
<td>used in getInterventionVariable() as parameter alphaPart for calculation of LifeStyleInterventionVariable</td>
<td>0.08</td>
<td>[17]</td>
</tr>
<tr>
<td>alphaMetfPart1</td>
<td>used in getInterventionVariable() as parameter alphaPart for calculation of MetforminInterventionPart1Variable</td>
<td>0.015</td>
<td>[17]</td>
</tr>
<tr>
<td>alphaMetfPart2</td>
<td>used in getInterventionVariable() as parameter alphaPart for calculation of MetforminInterventionPart2Variable</td>
<td>0.1</td>
<td>[17]</td>
</tr>
<tr>
<td>betaLifeStyle</td>
<td>used in getInterventionVariable() as parameter betaPart for calculation of LifeStyleInterventionVariable</td>
<td>0.026</td>
<td>[17]</td>
</tr>
<tr>
<td>betaMetfPart1</td>
<td>used in getInterventionVariable() as parameter betaPart for calculation of MetforminInterventionPart1Variable</td>
<td>0.008</td>
<td>[17]</td>
</tr>
<tr>
<td>betaMetfPart2</td>
<td>used in getInterventionVariable() as parameter betaPart for calculation of MetforminInterventionPart2Variable</td>
<td>0.03</td>
<td>[17]</td>
</tr>
<tr>
<td>LiStDose</td>
<td>used in getInterventionVariable() as parameter dose for calculation of LifeStyleInterventionVariable</td>
<td>main.lifeStyleInterventionDoseParameter, [17] = 3.754 can be changed</td>
<td></td>
</tr>
<tr>
<td>tLifeStyle</td>
<td>time starts lifestyle intervention</td>
<td>time()</td>
<td></td>
</tr>
<tr>
<td>isUnderLifeStyleIntervention</td>
<td>default false, change to true when intervention starts</td>
<td></td>
<td></td>
</tr>
<tr>
<td>tMetforminPart1</td>
<td>time starts metformin treatment part 1</td>
<td>time()</td>
<td></td>
</tr>
<tr>
<td>Parameter name</td>
<td>Description</td>
<td>Value</td>
<td>Source</td>
</tr>
<tr>
<td>-------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------</td>
<td>--------</td>
</tr>
<tr>
<td>MetfDosePart1</td>
<td>used in getInterventionVariable() as parameter dose for calculation of MetforminInterventionPart1Variable</td>
<td>main.MetforminInterventionDoseParameter1 = 0.357</td>
<td>[17]</td>
</tr>
<tr>
<td>isUnderMetforminTreatment</td>
<td>default false, change to true when intervention starts</td>
<td></td>
<td></td>
</tr>
<tr>
<td>tMetforminPart2</td>
<td>time starts metformin treatment part 2</td>
<td>time()</td>
<td></td>
</tr>
<tr>
<td>MetfDosePart2</td>
<td>used in getInterventionVariable() as parameter dose for calculation of MetforminInterventionPart2Variable</td>
<td>main.MetforminInterventionDoseParameter2 = 0.568</td>
<td>[17]</td>
</tr>
<tr>
<td>professionSupportRiskFactorBMI</td>
<td>Risk factor to determine whether an agent is eligible to take professional support intervention</td>
<td>28</td>
<td></td>
</tr>
<tr>
<td>professionSupportRiskFactorAge</td>
<td>Risk factor to determine whether an agent is eligible to take professional support intervention</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>professionSupportRiskFactorEthnicity</td>
<td>Risk factor to determine whether an agent eligible to take professional support intervention</td>
<td>ADiPS</td>
<td></td>
</tr>
<tr>
<td>MetforminInterventionPart1Variable</td>
<td>Works on improving insulin sensitivity after agent leave service pathway with T2DM</td>
<td>= getInterventionVariable(currTime, tMetforminPart1, MetfDosePart1, betaMetfPart1, alphaMetfPart1);</td>
<td></td>
</tr>
<tr>
<td>MetforminInterventionPart2Variable</td>
<td>Works on improving insulin sensitivity after agent leave service pathway with T2DM</td>
<td>= getInterventionVariable(currTime, tMetforminPart2, MetfDosePart2, betaMetfPart2, alphaMetfPart2);</td>
<td></td>
</tr>
<tr>
<td>LifeStyleInterventionVariable</td>
<td>Works on improving insulin sensitivity when lifestyle change is enabled in the interventions</td>
<td>= getInterventionVariable(currTime, tLifeStyle, adherence() * LiStDose, betaLifeStyle, alphaLifeStyle);</td>
<td></td>
</tr>
</tbody>
</table>
### Table 14: Functions used in interventions

<table>
<thead>
<tr>
<th>Function</th>
<th>Return type</th>
<th>Description</th>
</tr>
</thead>
</table>
| `getInterventionVariable` | `(curTime: double, t_interv: double, dose: double, betaPart: double, alphaPart: double)` | \[ dose \times \left( e^{-\beta \ln(1 + t_{interv}/\ln(\text{dose} + 1))} - e^{-\alpha \ln(1 + t_{interv}/\ln(\text{dose} + 1))} \right) \]
| `Peak`              | `(alpha: double, beta: double)`                  | \[ e^{\left(-\beta \times \ln(\frac{\alpha}{\beta})\right)} - e^{\left(-\alpha \times \ln(\frac{\alpha}{\beta})\right)} \] |
### Appendix A: Members of the Diabetes in Pregnancy Modelling Consortium

<table>
<thead>
<tr>
<th>Name</th>
<th>Position</th>
<th>Organisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jo-An Atkinson</td>
<td>Lead – Decision Analytics</td>
<td>Sax Institute and The Australian Prevention Partnership Centre</td>
</tr>
<tr>
<td>Tracey Baker</td>
<td>General Practitioner</td>
<td>Chapman Medical Practice</td>
</tr>
<tr>
<td>Lynelle Boisseau</td>
<td>Diabetes Educator</td>
<td>ACT Health Diabetes Service</td>
</tr>
<tr>
<td>Jacqui Davison</td>
<td>Project Officer</td>
<td>The Australian Prevention Partnership Centre</td>
</tr>
<tr>
<td>Roland Dyck</td>
<td>Professor of Medicine</td>
<td>University of Saskatchewan, Canada</td>
</tr>
<tr>
<td>Jeff Flack</td>
<td>Associate Professor, Endocrinology and Medical Informatics</td>
<td>Liverpool Hospital, University of New South Wales</td>
</tr>
<tr>
<td>Louise Freebairn</td>
<td>Manager, Epidemiology Section and PhD Candidate</td>
<td>ACT Health, The Australian Prevention Partnership Centre and University of Notre Dame Australia</td>
</tr>
<tr>
<td>Alison Hayes</td>
<td>Associate Professor, Health Economics</td>
<td>School of Public Health, University of Sydney, and CRE</td>
</tr>
<tr>
<td>Paul Kelly</td>
<td>Chief Health Officer and Deputy Director, General, Population Health Prevention and Protection</td>
<td>ACT Health</td>
</tr>
<tr>
<td>Alison Kent</td>
<td>Professor and Senior Staff Specialist, Neonatology</td>
<td>Australian National University and ACT Health</td>
</tr>
<tr>
<td>Louise Maple-Brown</td>
<td>Associate Professor, Endocrinologist – Diabetes, Kidney and Aboriginal Health</td>
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<td>Name</td>
<td>Position</td>
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</tr>
</tbody>
</table>
Appendix B: Symbols used in modelling diagrams

### System dynamics modelling

<table>
<thead>
<tr>
<th>Stella / iThink symbols</th>
<th>System Dynamics Symbols</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level:</strong></td>
<td><strong>Level</strong></td>
</tr>
<tr>
<td></td>
<td></td>
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<tr>
<td>• also called stock, accumulation, or state variable</td>
<td></td>
</tr>
<tr>
<td>• a quantity that accumulates over time</td>
<td></td>
</tr>
<tr>
<td>• change its value by accumulating or integrating rates</td>
<td></td>
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<tr>
<td>• change continuously over time even when the rates are changing discontinuously</td>
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<tr>
<td><strong>Rate/flow:</strong></td>
<td><strong>Rate</strong></td>
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<tr>
<td></td>
<td></td>
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<tr>
<td>• also called flow, activity, movement</td>
<td></td>
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<tr>
<td>• change the values of levels</td>
<td></td>
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<tr>
<td>• value of a rate is</td>
<td></td>
</tr>
<tr>
<td>• Not dependent on previous values of that rate</td>
<td></td>
</tr>
<tr>
<td>• But dependent on the levels in a system along with exogenous influences</td>
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</tr>
<tr>
<td><strong>Auxiliary:</strong></td>
<td><strong>Auxiliary variable</strong></td>
</tr>
<tr>
<td>• arise when the formulation of a level's influence on a rate involves one or more intermediate calculations</td>
<td></td>
</tr>
<tr>
<td>• often useful in formulating complex rate equations</td>
<td></td>
</tr>
<tr>
<td>• used for ease of communication and clarity</td>
<td></td>
</tr>
<tr>
<td>• value changes immediately in response to changes in levels or exogenous influences.</td>
<td></td>
</tr>
<tr>
<td><strong>Source and sink:</strong></td>
<td><strong>Source/sink</strong></td>
</tr>
<tr>
<td>• <strong>source</strong> represents systems of levels and rates outside the boundary of the model</td>
<td></td>
</tr>
<tr>
<td>• <strong>sink</strong> is where flows terminate outside the system</td>
<td></td>
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</tbody>
</table>
Agent-based modelling

Statechart


Statecharts have states and transitions. The states are “alternative” meaning that objects can only be in one state at a time. A transition execution may lead to a state change that makes a new set of transitions active. The statechart’s states may be hierarchical – a state may contain other states and transitions.

One agent may have several statecharts that describe independent parts of the agent’s behaviour.

References


