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"TURNING MIRRORS INTO WINDOWS":

A STUDY OF PARTICIPATORY DYNAMIC SIMULATION MODELLING TO INFORM HEALTH POLICY DECISIONS

Louise Anne Freebairn BSc (Hons) MClinPsych

Submitted in fulfillment of the requirements for the degree of

Doctor of Philosophy



School of Medicine University of Notre Dame, Sydney Australia

August, 2019

"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 indepth 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 coproduce 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 feasibiliy 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

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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:

- Freebairn L. Atkinson J, Kelly P, McDonnell G, and Rychetnik L. Simulation modelling as a tool for knowledge mobilisation in health policy settings: a case study protocol. Health Res Policy Syst 2016;14:71 doi: 10.1186/s12961-016-0143y. <u>https://health-policy-systems.biomedcentral.com/articles/10.1186/s12961-016-0143-y</u>
- Freebairn L, Rychetnik L, Atkinson J, Kelly P, McDonnell G, Roberts N, Whittall C, and Redman S. Mobilising Knowledge for Policy Development: implementing systems approaches through participatory dynamic simulation modelling. Health Res Policy Syst 2017; 15:83. https://doi.org/10.1186/s12961-017-0245-1
- 3) <u>Freebairn L</u>, Atkinson J, Osgood N, Kelly P M, McDonnell G, and Rychetnik L. 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. *PloS one*, *14*(6), e0218875. <u>https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0218875</u>
- 4) <u>Freebairn L</u>, Atkinson J, Kelly P M, McDonnell G, and Rychetnik L. Decision maker's experience of participatory dynamic simulation modelling methods for public health policy. BMC Health Informatics and Decision Making 2018; 18(1):131. <u>https://doi.org/10.1186/s12911-018-0707-6</u>
- 5) <u>Freebairn L</u>, Qin Y, Atkinson J, Nolan C, Kent A, Kelly P M, McDonnell G, and Osgood N on behalf of the modelling consortium. 'Turning the tide' on diabetes in pregnancy: Insights from dynamic simulation modelling. Under clinical review prior to submission

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.

Presentions

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

<u>Freebairn L</u>. 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

<u>Freebairn L</u>, 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

<u>Freebairn, L</u>. 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

<u>Freebairn L</u>, Atkinson J, Osgood N, Kelly P, Safarishahrbijari A, Qian W, McLean A, Nolan C, Kent A, McDonnell G and Rychetnik L. Dynamic Simulation Modelling to Inform Decision Making for Diabetes in Pregnancy in the ACT. MODSIM 2017 – 22nd International Congress on Modelling and Simulation. 3-8 December 2017. Hobart

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<u>Freebairn L</u>. Simulation modelling as a tool for knowledge translation in health policy settings: a case study protocol. School of Medicine, University of Notre Dame, Research Conference 2016. 23 March 2016. Sydney.

<u>Freebairn L</u>. Gestational diabetes through a systems science lens. Centre for Health Stewardship Research Group. Australian National University. 19 November 2015. Canberra.

<u>Freebairn L</u>. Simulation modelling: A systems approach to optimising the use of evidence to inform decision making in gestational diabetes care. MODSIM – 21st International Congress on Modelling and Simulation. 29 November 2015. Gold Coast.

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

Additional publications

During my candidature I also contributed to the following publications on topics related to my research.

- a) <u>Freebairn L</u> and Kelly P. Harnessing new technologies to inform health decision making: Dynamic simulation modelling as a decision support tool for diabetes in pregnancy. ACT Population Health Bulletin. Volume 6, Issue 2, May 2017, p, 31-32.
- b) Atkinson J, O'Donnell E, Wiggers J, McDonnell G, Mitchell J, <u>Freebairn L</u>, Indig D, Rychetnik L. Dynamic simulation modelling of policy responses to reduce alcoholrelated harms: rationale and procedure for a participatory approach. Public Health Res Pract. 2017;27(1):e2711707.
- c) O'Donnell E, Atkinson JA, <u>Freebairn L</u>, Rychetnik L. Participatory simulation modelling to inform public health policy and practice: Rethinking the evidence hierarchies. J Public Health Policy. 2017; May;38(2):203–215. doi: 10.1057/s41271-016-0061-9.
- d) Atkinson J, Knowles D, Wiggers J, Livingston M, Room R, Prodan A, McDonnell G, O'Donnell E, Jones S, Haber P, Muscatello D, Ezard N, Phung N, <u>Freebairn L</u>, Indig D, Rychetnik L, Ananthapavan J, Wutzke S on behalf of the alcohol modelling consortium. Harnessing advances in computer simulation to inform policy and planning to reduce alcohol-related harms. *International Journal of Public Health*, 2018; 63: 537. https://doi.org/10.1007/s00038-017-1041-y
- e) Roberts N, Li V, Atkinson J, Heffernan, M, McDonnell G, Prodan A, Lung T, Lloyd B, Mitchell J, Nieuwenhuizen S, <u>Freebairn L</u>, Wiggers J, Can the target set for reducing childhood overweight and obesity be met? A system dynamics simulation study in New South Wales, Australia. *Systems research and behavioural science*, 2018, https://doi.org/10.1002/sres.2555
- f) Qin Y, <u>Freebairn L</u>, Atkinson J, Qian W, Safarishahrbijari A, Osgood N. Multi-scale simulation modeling for prevention and public health management of diabetes in pregnancy and sequelae. In SBP-BRiMS 2019: International Conference on Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling and Simulation (pp.256-265). Springer, Cham.

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 "quasisupervisors", 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.

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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 (<u>https://help.anylogic.com/index.jsp</u>).

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].

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