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LEADING ARTICLE

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

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Abstract

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

1 Introduction

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

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Key Points for Decision Makers

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

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

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

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

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

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

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

2 Box 1 Definition of key terms

2.1 Agent-Based Modelling (ABM)

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

2.2 Clinical Staging

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

2.3 Complexity

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

2.4 Discrete Event Simulation (DES)

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

2.5 Dynamic Simulation Modelling (DSM)

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

2.6 Markov Cohort Modelling

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

2.7 Participatory Systems Modelling

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

2.8 Simulation Modelling

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

2.9 System Dynamics Modelling (SDM)

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

3 Dynamic Simulation Modelling as a Planning Tool in Health

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

3.1 Types of Dynamic Simulation Modelling

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

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

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

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

3.2 When and How to Use System Dynamics Modelling

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

Table 1 Key characteristics of modelling techniques

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

Table 1 (continued)

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

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

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

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

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

3.3 Existing Studies of Simulation Modelling for Mental Health

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

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

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

4 Contemporary Mental Health Prevention and Treatment Paradigms

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

7 Future Research Directions

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

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

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

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

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

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

8 Conclusion

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

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

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Consent to Participate Not applicable.

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

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