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Simulation modelling in mental health: A systematic review

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ABSTRACT

While mental illness is one of the leading causes of international disease burden, within fifteen identified reviews of healthcare simulation only three included papers are in mental health. Here we systematically review the use of simulation modelling in mental healthcare, identifying 160 papers. There were widespread and innovative applications of simulation in the areas of medical decision making and epidemiology, with health system planning and optimisation relatively underrepresented. Markov modelling was the preferred method across area and illness. However, the literature is currently undermined by a lack of coherence and evidence of implementation, and we acknowledge an ongoing issue of accessing unpublished models from healthcare and government organisations. To advance, the field requires a shared knowledge base. We propose that this may be facilitated by the use of existing epidemiological models as the basis of modelling in all other areas.

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Systematic review; simulation modelling; mental health; healthcare

1. Introduction

The healthcare sector is characterised by complexity. At each service level, clinicians and managers strive for balance between: evidence-based practice and innovation; client choice and clinical judgement; and patient outcomes and fiscal constraints. To aid them in balancing these competing interests, researchers have increasingly looked to apply simulation models to healthcare decisions.

Simulation models can be defined as simplified abstractions of real systems (Brailsford, Harper, Patel, & Pitt, 2009). They allow the user to predict future states by tracking changes in the system over time, with these changes determined by: probabilities and attributes assigned to individuals or entities (agent-based modelling; ABM); time-specific state transitions (Markov models); events (Discrete Event Simulation; DES); or system flows (System Dynamics; SD). This provides decision makers with an opportunity to experiment in ways impossible in the real world, removing barriers such as cost, risk, limited time and limited participant sampling. Models can also be built iteratively, providing flexibility in scope and detail as problems and users' understanding evolve. They make visible hidden system interactions and emergent properties, often leading to profound insights for the user (Gogi, Tako, & Robinson, 2016; Thompson, Howick, & Belton, 2016).

Early work in healthcare simulation (England & Roberts, 1978; Fries, 1976) focussed on patient flows in outpatient clinics and hospitals, using SD to solve resource-allocation problems. Later increases in computing power allowed for more complex approaches, with ABM often used for epidemiological models of disease transmission, and DES now being the recommended technique for cost-utility analysis, over the more simplistic Markov approach (Afzali, Karnon, & Gray, 2012; Heeg et al., 2008).

Since Fries' bibliography in 1976, fourteen additional reviews have been published that discuss the application of different types of modelling methods to components of the healthcare system (Brailsford et al., 2009; England & Roberts, 1978; Fone et al., 2003; Forsberg, Aronsson, Keller, & Lindblad, 2011; Günal & Pidd, 2010; Jun, Jacobson, & Swisher, 1999; Klein, Dittus, Roberts, & Wilson, 1993; Lehaney & Hlupic, 1995; Mielczarek & Uziałko-Mydlikowska, 2012; Mustafee, Katsaliaki, & Taylor, 2010; van Sambeek, Cornelissen, Bakker, & Krabbendam, 2010; Smith-Daniels, Schweikhart, & Smith-Daniels, 1988; Tunnicliffe-Wilson, 1980, 1981). However, in these fifteen reviews, only three papers on mental health were listed (Bernard, Amir, Hosios, & Rousseau, 1977; Bodin, Carroll, Lee, & Stout, 1972; Kuno, Koizumi, Rothbard, & Greenwald, 2005). This paper provides an advance then, by systematically reviewing the use of simulation models in mental healthcare.

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Mental illness is one of the leading causes of disease burden, accounting for an estimated 14% of disability-adjusted life years worldwide (World Health Organisation, 2008). The chronicity, heterogeneity and comorbidities of mental illness present a complex challenge for healthcare managers, policy makers and clinicians. Increasing public awareness has created a demand for services largely unmet by healthcare providers worldwide (World Health Organisation, 2008). It is this challenge of providing patient-centred and evidence-based mental health services that offers a unique opportunity for the application of simulation modelling.

In this review we aim to identify, in a way more focused on this specific field and so hopefully more comprehensive than previously achieved, the range of developments and uses of simulation modelling in mental healthcare. In the paper we will firstly outline the search strategies used, then provide an overview of the literature. Then we will move into profiling modelling methods in four different areas of application: epidemiology, disease prevention & screening; medical decision making and treatment evaluation; healthcare system operations; and healthcare system design and planning. This comprehensive profile of the state of the art in this specific field will then allow us to make recommendations about future directions for mental health simulation.

2. Methods

2.1. Search strategy

We searched Business Source Complete, Cumulative Index to Nursing and Allied Health Literature (CINAHL), Embase, OVID Medline and In-Process and Other Non-Indexed Citations, Proquest Central, PsycINFO, Scopus and Web of Science for papers published before September 2016. The abstract, title and keywords of articles were searched using ("simulation model*" OR "discrete event simulat*" OR microsimulat* OR "markov model*" OR "system dynamic model*" OR "agent based model*") AND ("mental health*" OR "psychiatr*"). Table 1 contains the search strategy and results for PsycINFO. The conference proceedings of the Winter Simulation Conference (1968 to 2014) were manually searched using the search terms "mental health" and "psychiatry".

2.2. Inclusion criteria

We included papers published in peer-review journals, full papers in conference proceedings, and dissertations. Review papers were excluded, after inspection of their reference lists to identify additional publications.

Abstracts and then articles were screened against the following criteria:

(1) The *application* of simulation modelling (as previously defined);
(2) To the epidemiology, treatment or prevention of a mental illness as defined in the International Classification of Diseases (ICD-10; World Health Organisation, 1992) or Diagnostic and Statistical Manual of Mental Disorders (DSM-V; American Psychiatric Association, 2013) or components of the mental healthcare system.

Papers with a primary focus on method or with less than a paragraph description of the simulation process were excluded, as were neurological simulations of disease states and investigations of subclinical issues (e.g. moderate cognitive impairment, risky drinking behaviour and public tobacco use policy).

2.3. Data extraction

Information for each remaining article was extracted using a standardised form (Table 2). We chose a broad classification scheme for area of application, derived from Lagergren (1998) and previously used in Melczark and Uziałko-Mydlikowska's (2012) healthcare simulation review. Articles were classified as addressing issues of: Epidemiology, disease prevention & screening; Medical decision making and treatment evaluation; Healthcare system operations (Resource optimisation); or Healthcare system design and planning. The level of model implementation was classified using the scheme from Brailsford et al.'s (2009) healthcare simulation review, as: theoretical (proposed by the authors); conceptualised (discussed with a client organisation); or implemented (used in practice). Articles were by default classified as theoretical unless consultation with a healthcare organisation was reported (conceptualised implementation) or organisational changes were attempted as a result of the modelling results (implemented).

3. Results

The search strategy flow chart is shown in Figure 1. Of 490 articles screened, 160 met inclusion criteria. A data extraction table containing details of all included articles is provided as an online supplement.

Table 1. Search strategy for PsycINFO.

	Searches	Results
1	(simulation model or discrete event simulat* or microsimulat* or markov model* or system dynamic* or agent based).mp. [mp = title, abstract, heading word, table of contents, key concepts, original title, tests & measures]	3692
2	(mental health* or psychiatr*).mp. [mp = title, abstract, heading word, table of contents, key concepts, original title, tests & measures]	379,496
3	1 and 2	94

Table 2. Data extraction sheet.

1	Reference
	Author, year, title, journal, database
2	Aim/Research question
3	Mental Illness/Issue
4	Modelling method
	DES/SD/ABM/Monte Carlo/Markov/Combination/Other
5	Area
	Epidemiology, disease prevention & screening
	Medical decision making and treatment evaluation
	Healthcare system operations (Resource optimisation)
	Healthcare system design and planning
6	Level of implementation
	Theoretical (theoretically proposed by authors)
	Conceptualised (discussed with client organisation)
	Implemented (used in practice)
7	Model function
	Descriptive (simulates a single scenario)
	Comparative (simulates C2 scenarios and compares outputs)
	Directed interactive (modeller derives scenarios and inputs from client)
	Interactive (scenarios and inputs manipulated directly by clients)
8	Model validation method

3.1. Overview

Articles were published between 1955 and September 2016 inclusive, with the number of publications increasing significantly since 1995 (Figure 2). The majority of articles were journal articles (93.1%), with five conference papers and six dissertations.

Research was conducted in 21 countries, with the USA accounting for 43% of all articles (Table 3). Articles were published in 101 journals, from 16 countries. Table 4 summarises the five most frequent journals, and six most frequent authors. Articles addressed a wide range of mental illnesses across areas (Figure 3). A summary of article methods by area is provided in Table 5. Note that interactive and directed interactive models are combined in Table 5, as only one article, Elazari, Bar-Chi, and Sinuany-Stern (1985), described a model that provided users direct and unassisted interaction.

3.2. Healthcare system operations

Nineteen articles addressed healthcare system operations. The primary foci were patient flow (n = 8) and service configuration (n = 5). The remaining six articles explored service reconfiguration attempts (n = 3), funding models, staff knowledge management and menu planning. Unlike other areas, general mental health services (84.2%) were the predominant focus. System dynamics models were used more frequently in this area than any other, but Markov modelling was still the most-used approach.

The majority of articles included some form of stakeholder engagement, generally at the conceptualised level. However, this did not translate into interactive models, with the largest proportion of articles providing only descriptive functions. Model validation was reported by only 8 articles.

3.3. Healthcare system design and planning

Healthcare system design and planning was addressed by 21 articles, and accounts for much of the earlier work as part of the deinstitutionalisation of mental health in America (Bernard et al., 1977; Bodin et al., 1972; Bremner & Eicker, 1969; Kennedy, Wright, Anderson, & Cooley, 1972; McCollom & Harris, 1982). Articles focussed on similar issues as the healthcare system operations literature, covering service configuration, funding and policy decisions. The primary difference between the two areas was the level of analysis. While the operations area focussed on discrete organisational

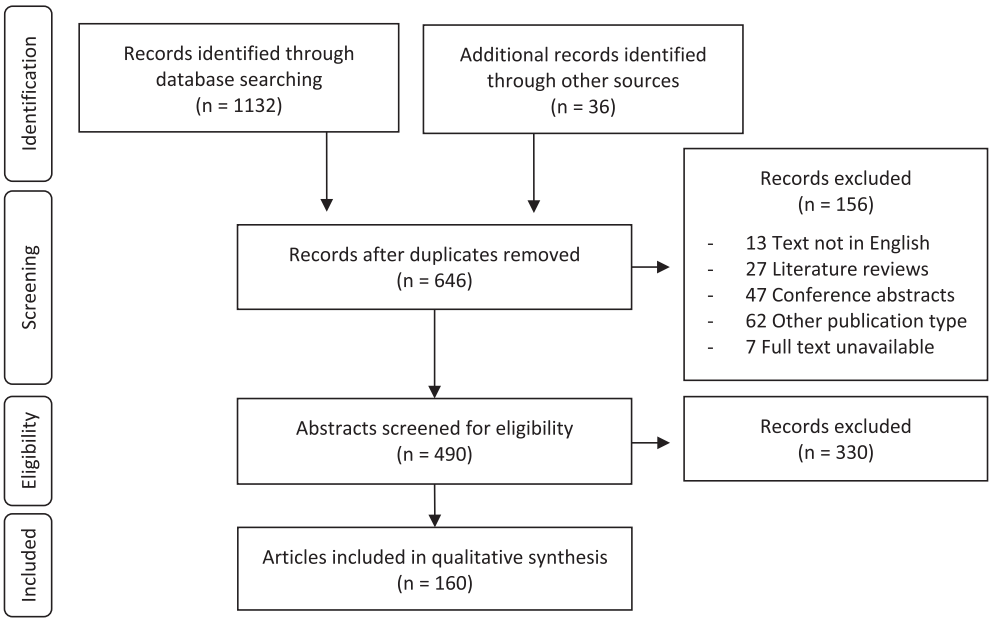

Figure 1. Flow chart of search strategy and included studies.

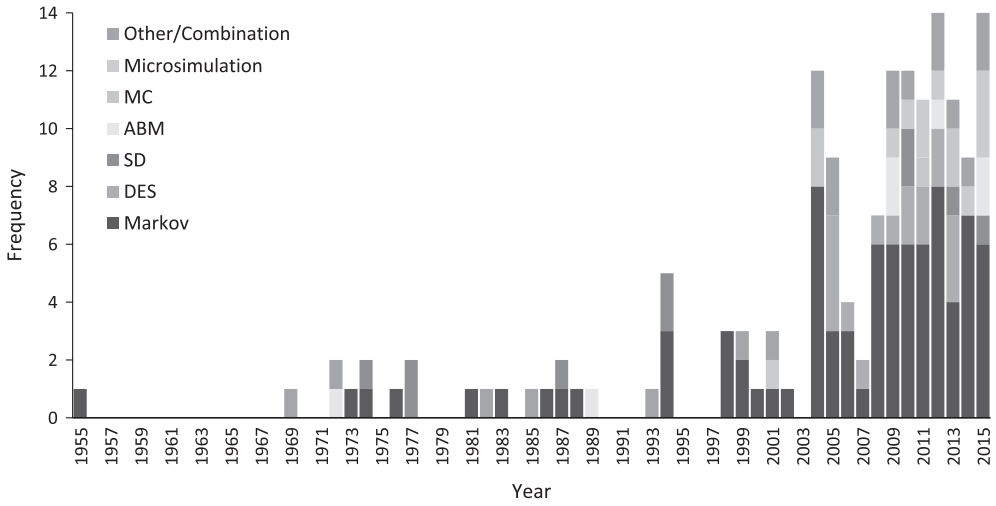

Figure 2. Publication frequency by complete years and model type.

Table 3. Country of origin by publication count.

Country	Number of articles
USA	69
UK	22
Canada	20
Australia	9
The Netherlands	9
Spain	5
Sweden	4
Thailand	2
Belgium	1
China	1
Czech Republic	1
France	1
Germany	1
Israel	1
Mexico	1
New Zealand	1
Norway	1
Switzerland	1
Taiwan	1
Uganda	1
Vietnam	1
Unspecified	7

Table 4. Top journals and authors by publication count.

Journals	Authors
PharmacoEconomics ($n = 11$)	Scott Patten ($n = 10$)
Australian & New Zealand Journal of Psychiatry ($n = 6$)	Theo Vos ($n = 5$)
International Journal of Geriatric Psychiatry ($n = 6$)	Bart Heeg ($n = 4$)
Psychiatric Services ($n = 4$)	Robert Lee ($n = 4$)
Value in Health ($n = 4$)	Cathrine Mihalopoulos ($n = 4$)
	Ben van Hout ($n = 4$)

units (e.g. units/departments, clinics), the planning and design area focussed on state and federal-level changes.

A wide range of modelling approaches were used, but Markov modelling remained the most-used approach. The area accounted for the highest number of implemented and interactive models, but these were still the minority. The implemented models were more likely to also be interactive, with three articles meeting both criteria (Bernard et al., 1977; Bodin et al., 1972; Davies & Goddard, 1994). Interestingly, these three articles were all published pre-2000 when simulation modelling technology was much less advanced.

3.4. Medical decision making and treatment evaluation

Seventy-two articles discussed medical decision making (MDM) and treatment evaluation. The primary foci were pharmaceutical ($n = 43$) and non-pharmaceutical treatment cost-effectiveness ($n = 25$). The remaining four articles explored prediction models for adverse events, and service demand. Papers covered a wide range of illnesses, with a focus on schizophrenia, depression, bipolar disorder and Alzheimer's disease.

Markov modelling was the preferred method, used in two-thirds of the papers. Model validation was almost universally reported (93.1%), with a preference for sensitivity analysis, often in combination with probability sensitivity analysis or Monte Carlo. Models were primarily theoretical and comparative.

3.5. Epidemiology, disease prevention & screening

Forty-eight articles discussed epidemiology, disease prevention and screening. Fifteen articles focussed on disease progression, modelling the effects of comorbidity, social determinants, risk factors and predictors of recovery or relapse. The most sophisticated of these applied the concepts of latent classes (Ciampi, Dyachenko, Cole, & McCusker, 2011; Lopez, 2009) or health states (Sugar, James, Lenert, & Rosenheck, 2004) to create multifactorial profiles of individuals with different disease pathways and prognoses. Patten and colleagues accounted for a further 10 articles, primarily reporting on the prevalence, incidence and duration of depression in British and Canadian contexts. Other significant areas of interest were: lifetime disease cost

Table 5. Article method by research area.

		Method							Implementation			Function			Validation		
Total		ABM	DES	Markov	MC	Micro	SD	Other/comb.	Theor.	Concep.	Impl.	Descriptive	Comparative	Interactive*	None	Single method	≥2 methods
MDM & treatment evaluation																	
N	72	1	7	48	1	7	0	8	55	15	2	9	63	0	5	39	28
%	45.0	1.4	9.7	66.7	1.4	9.7	0.0	11.1	76.4	20.8	2.8	12.5	87.5	0.0	6.9	54.2	38.9
Epidemiology, prevention & screening																	
N	48	3	4	27	3	2	3	6	40	7	1	31	17	0	16	25	7
%	30.0	6.3	8.3	56.3	6.3	4.2	6.3	12.5	83.3	14.6	2.1	64.6	35.4	0.0	33.3	52.1	14.6
Healthcare system operations																	
N	19	1	4	6	0	0	5	3	3	13	3	8	8	3	11	7	1
%	11.9	5.3	21.1	31.6	0.0	0.0	26.3	15.8	15.8	68.4	15.8	42.1	42.1	15.8	57.9	36.8	5.3
Healthcare design & planning																	
N	21	4	3	6	1	1	2	4	10	7	4	6	10	5	5	12	4
%	13.1	19.0	14.3	28.6	4.8	4.8	9.5	19.0	47.6	33.3	19.0	28.6	47.6	23.8	23.8	57.1	19.0
All papers																	
N	166	9	18	87	5	10	10	21	108	42	10	54	98	8	37	83	40
%	100	5.6	11.3	54.4	3.1	6.3	6.3	13.1	67.5	26.3	6.3	33.8	61.3	5.0	23.1	51.9	25.0

Note: * includes directed interactive models. 'ABM' is the Agent-based modelling. 'DES' is the Discrete Event Simulation. 'MC' is the Monte Carlo Simulation. 'Micro' is the Microsimulation. 'Comb' is the Combination of methods. 'MDM' is the Medical decision making. 'Theor.' is the Theoretical; 'Concep.' is the Conceptualised; 'Impl.' is the Implemented.

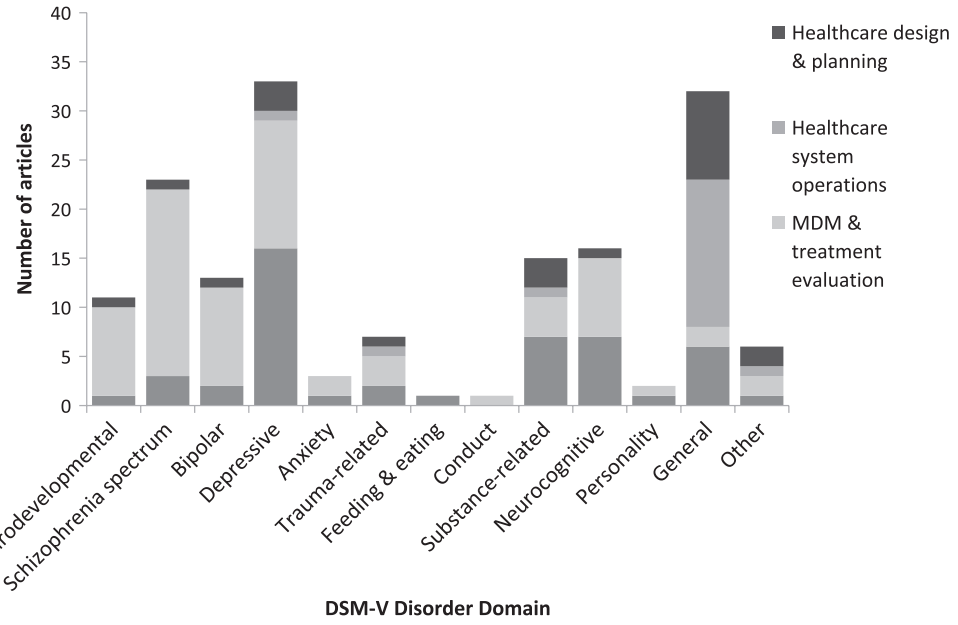

Figure 3. Count of articles by area and DSM-V domain.
Notes: MDM: Medical decision making. The count exceeds 160 due to the inclusion of multiple illnesses in individual articles.

(n = 7); population screening (n = 9), especially in military contexts; and service demand and access (n = 3). Abdelhamid, Kuhlman, Marathe, Ravi, and Reid (2016) and Hoffer, Bobashev, and Morris (2009) provided novel applications, modelling depression contagion and a local heroin market, respectively.

While the most frequent method was Markov, all methods were represented in this area, with four articles using DES, three articles applying ABM, Monte Carlo or SD, and 2 articles using microsimulation (see Table 4). Model validation was reported by two-thirds of articles, with a preference for data fit validation (n = 11). One article reported implementation.

4. Discussion

This paper aimed to systematically review the application of simulation modelling in mental healthcare. From the literature emerged a range of key findings, novel applications, challenges and opportunities for the field of mental healthcare simulation.

4.1. Key findings

A reader of earlier healthcare simulation reviews may be forgiven for believing that simulation modelling was absent in the area of mental health; however we found a well-developed literature dating back to 1955. Early authors provided critical contributions to the deinstitutionalisation of care for people with mental health problems in America, through work on the design of new services and their insertion into existing systems and infrastructure.

Since this early work, mental health modelling has been most active in MDM and treatment evaluation, cost-effectiveness analysis and epidemiology, with a focus on: depression, schizophrenia, bipolar disorder, dementia and substance abuse/addiction. While previous reviews have found different priority areas (e.g. hospital scheduling and organisation (Fone et al., 2003), planning and system resource utilisation (Brailsford et al., 2009)), this most likely reflects shifting priorities over time and between specialty areas. In particular, the focus on depression and dementia likely reflects increased awareness and reported prevalence in the general community, while the attention on schizophrenia, bipolar disorder and substance abuse/addiction may reflect the greater severity and social impact of these illnesses. Despite shifting research priorities over time, Markov modelling has remained the preferred method across areas and illnesses. This conclusion is different from that of Forsberg et al. (2011) who identified DES as the preferred method in healthcare decisions, despite including Markov modelling in their analysis. While this discrepancy may in part be due to our inclusion of pharmaceutical and treatment cost-effectiveness models, these account for only 55.2% of Markov modelling applications (Table 5). In fact, Markov modelling was used in at least one quarter of articles in all areas, most likely due to the relative simplicity of the approach and software required (e.g. Excel). As technology and modelling literacy has improved, there has been a shift away from Markov modelling, with increasing numbers of articles using other methods since 2005 (Figure 2). Even within the area of MDM and treatment evaluation, Markov modelling is being replaced by DES, possibly in response to arguments regarding the superior clinical validity of DES (Afzali et al., 2012; Heeg et al., 2008).

Another key feature of the literature was a strong emphasis on build-for-purpose, where modellers used

the most appropriate method for the research question. Thus SD was used for issues of patient flows and resource optimisation; ABM was used for service access; and DES and Markov modelling were used for epidemiology and cost-utility analyses. There was also a rise in multi-method modelling, which recognises that different segments of the health system have different profiles requiring different modelling methods. For example, while emergency departments may be treated as closed systems with clear stocks and flows (i.e. a SD model), community mental health services are more likely shaped by patient-centred features such as geographic access, and the cognitive and social aspects of choice (i.e. an ABM).

Model validation was reported by a large number of articles, but varied significantly by area, and model implementation was still very rare. Again, it seemed that model purpose was driving these decisions. The reporting of model validation methods was strongest in MDM and treatment evaluation, where the likely requirements of health technology assessment organisations have created a higher level of standardisation and transparency in model reporting. This area also focussed on comparative modelling, presumably driven by the need to prove the superiority of a drug or treatment option over a major competitor. In this environment, interactivity with the model and implementation of the findings were secondary concerns. The opposite was the case for health system operations and design and planning. The function of models in these settings is to provide critical learning incidents for the users, rather than providing highly reliable cost estimates (Gogi et al., 2016), hence our observed pattern of higher levels of implementation and greater interactivity at the cost of model validation.

4.2. Novel applications

The major challenge in modelling mental healthcare is capturing the complex biopsychosocial interactions that shape mental illness, but as computing technology and the quality of epidemiological and service use data have improved, so has the complexity of simulation models. In the area of MDM and treatment evaluation, this is best captured by Heeg et al. (2005), who presented a DES of the lifetime treatment course of schizophrenia, accounting for: individual (e.g. sex, age), illness (e.g. severity, symptom profile), treatment (e.g. type, side effects, compliance), social (e.g. employment, marital status) and environmental (e.g. care setting) factors. Rather than simulating the efficacy of two antipsychotics in a vacuum, Heeg *et al* placed the analysis of pharmaceuticals within a real-world context, in order to understand the effect of social and environmental factors on their efficacy.

This is mirrored in epidemiology, where descriptive models of prevalence and incidence have moved to more complex models of disease progression (e.g. Lopez, 2009) and a greater emphasis on the physical environment. Morrissey, Hynes, Clarke, and O'Donoghue (2010), Morrissey, Clarke, Williamson, Daly, and O'Donoghue (2015) applied spatial microsimulation to explore depression in Ireland, using a national dataset of psychiatric service use and small area estimates of prevalence to explore the factors that shape service use in at-risk populations. At the other extreme, Abdelhamid et al. (2016) combined an ABM of depressive symptoms with a social network ABM to identify the key factors in the spread of depression in an American college population.

There is also an increased focus on proactive and holistic applications of simulation. Musdal (2013), and Wang, Glover, Rhodes, and Nightingale (2013), for example, both address the rise in demand for PTSD services in military veterans by evaluating the screening and referral processes of the American Veterans Health Administration. But while Musdal considers the scheduling and optimisation of existing screening, diagnosis and treatment procedures, Wang *et al*. take a wider view, including organisational factors and individual factors from pre-enlistment to post-discharge in their analysis of PTSD prevention and treatment. In a very different application, Rabiul Alam and colleagues' combined Markov modelling with real-time sensor data to predict suicide risk (Rabiul Alam, Cho, Huh, & Hong, 2014) and psychiatric emergencies in real patients (Rabiul Alam, Abedin, Ameen, & Hong, 2016), highlighting the strength of using epidemiological simulations to underpin the interpretation of individual-level data.

4.3. Limitations

This review took a purposefully broader approach than previous reviews, expanding the general search term of "simulation model*" to include all specific modelling methods (e.g. "markov model*") and using "mental health*" and "psychiatr*" over a more narrow "healthcare OR health care". Despite this, it is likely that this review excludes a significant body of work, primarily in the form of unpublished models created as part of organisational or government consultancies.

There are also weaknesses in our data screening and extraction. There were many articles that were excluded as subclinical, including the large body of work from Levy and colleagues modelling public smoking policy (see Mielczarek & Uziałko-Mydlikowska, 2012, p. 200 for a description of this research). Hence, our focus on ICD-10 and DSM-V illnesses meant that proactive interventions for mental health (versus illness) were often overlooked. We also used an exclusive classification scheme, relying on the article's aim to identify a primary area or function when multiple were suggested. Hence we did not capture the complexity of models that addressed multiple areas or functions. However, in both cases, given the lack of coverage of this literature in the past, we chose to sacrifice depth for synthesis.

4.4. Challenges and opportunities

4.4.1. Implementation

Reporting on model implementation is still largely absent, despite being identified as an area for improvement as early as England & Roberts, 1978 review. Subsequent authors have recommended different solutions, including the application of soft systems methodology (Lehaney & Hlupic, 1995) and the PDSA cycle (Forsberg et al., 2011) to the implementation of future simulations. Other authors have questioned whether implementation is important in simulation modelling, commenting that implementation failure is ubiquitous in operational research (Tunnicliffe-Wilson, 1981).

Perhaps a significant barrier in healthcare simulation is the lack of focus on *healthcare* implementation. The healthcare context is fundamentally different to other simulation environments, with highly permeable boundaries between organisations and multiple levels of funding and compliance demands. The movement of individuals through this system and between disease states is not linear, nor is it simply rule-based. In other words, the system is complex (Plsek & Greenhalgh, 2001). Hence perhaps the field should consider exploring models of implementation and stakeholder engagement designed specifically for this complex environment (see Nilsen, 2015 for a review of clinical implementation models).

4.4.2. Coherence

We echo concerns raised by many previous reviewers about the lack of a coherent literature, without shared terminology (van Sambeek et al., 2010), shared standards (Lehaney & Hlupic, 1995; Smith-Daniels et al., 1988), or a "natural home" for publication (Fone et al., 2003, p. 333). While early reviews described a literature with a series of large, shared models (see England & Roberts, 1978), this is no longer the case. The focus on local models for local stakeholders increases the risk of unnecessary duplication and prevents the development of a coherent research direction. It also ensures that attempts such as this review to synthesise the literature will continue to exclude a vast body of unpublished models created as part of organisational or government consultancies (van Sambeek et al., 2010). One solution to this problem is the sharing of existing epidemiological models. Patten and colleagues have already demonstrated this possibility, with national epidemiological models of depression, reused and refined across national boundaries (Patten, 2005, 2006, 2010; Patten, Gordon-Brown, & Meadows, 2010; Patten et al., 2012; Patten & Lee, 2004a; 2004b, 2004c, Patten & Lee, 2005; Patten & Meadows, 2009). Generalised epidemiological models not only provide a shared framework for international research, but may also reduce the financial and time costs involved in initial simulation development.

Another solution lies in the use of open source software for research collaboration and model review. Rather than a novel proposition, this would be a return to the shared model development of the 1970s, when open source software was the technological norm (von Hippel & von Krogh, 2003). This may already be occurring, with Mielczarek and Uziałko-Mydlikowska's (2012) review identifying a trend towards multi-method platforms and a preference for generic coding languages for creating simulations. However, even here there is a problem, as multiple open source software options exist, and there is no consensus on exactly how, or where, modellers should congregate. There are also commercial considerations which may prevent such transparency.

In these situations Günal and Pidd (2010) suggested a minimal reporting standard of model description, to allow others to replicate the approach. We found this standard already in place in the reporting of MDM and treatment evaluation models. There was clear and systematic reporting of model structure, assumptions, data sources, validation and results, across journal articles. While the requirements of health technology assessment organisations have likely facilitated this higher level of standardisation and transparency, it is an approach that can be applied across the literature.

5. Conclusion

Despite the lack of representation in previous healthcare simulation reviews, we found a strong body of literature applying simulation modelling to mental healthcare, especially in the areas of cost-effectiveness analysis and epidemiology. However, the literature is challenged by a tension between implementation and collaboration. Built-for-purpose models increase the chance of implementation success, but reduce collaboration by reducing model transparency and generalisability. Despite these challenges, widespread and innovative applications of simulation in mental healthcare highlight continued academic and stakeholder interest. To ensure the future success of mental healthcare simulation, researchers and practitioners must find ways to collaborate across silos using open source software to share existing epidemiological models as the foundations for higher-level models of treatment effectiveness, system operations and healthcare design and planning.

Disclosure statement

No potential conflict of interest was reported by the authors.

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