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SIMULATION MODELING IN THE SOCIAL CARE SECTOR: A LITERATURE REVIEW

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ABSTRACT

Research into the application of simulation modeling in healthcare is thriving. This is not the case for its step sister, social care, although it has long been recognized that the interface between healthcare and social care often causes problems that affect the performance at both sides. This paper presents a literature review of simulation modeling for the provision of social care services. It discusses the gap between findings from the literature and challenges in social care policies. Potential areas to which simulation modelers can contribute are highlighted. The literature shows that simulation modeling has contributed in areas such as demand, supply, service delivery methods (including the interface between care services and other services), and cost/financial modeling. However, a gap between the work reported in the literature and the challenges in social care policies exists. Hence, more work needs to be done to close the gap.

1 INTRODUCTION

The changes to demographics and regulations in social care in many countries are expected to alter the social care landscape. The key demographic change is the aging society. This means more people are expected to use social care services (thereafter, care services) and, at the same time, the number of people who provide care services, including those who will finance them, is expected to decrease. This paper takes a view of the social care sector in England, which is under the responsibility of the UK Department of Health. However, some of the discussion could be relevant to the social care sector in other countries. The UK Department of Health, in recent public engagement events from September to December 2011 (see http://caringforourfuture.dh.gov.uk/), has identified six main challenges in the social care sector: (1) the provision of good quality care services, (2) the need for personalized services to meet the needs and circumstances of every care user, (3) the need for better integration with relevant services, such as the National Health Service (NHS) and local government services, (4) supporting greater prevention and early intervention, (5) promoting a more diverse and responsive care market, and (6) the need to encourage the financial services sector to introduce more products to help people pay for their care.

Simulation is one of the Operations Research (OR) techniques that has been used to help people make decisions (Pidd 2003, Chapters 7 and 9). A social care system is a complex system involving a number of stakeholders with different, often conflicting, objectives. It may interact with other complex systems. For example, in England, the social care system interacts with the NHS and some local government services. Hence, OR techniques, such as simulation, can and should play a significant role in helping policymakers understand the dynamics of the care system and deliver better policies. This paper reviews the existing simulation literature to understand how simulation has been used in the social care sector. This literature review is not meant to be a comprehensive one as the main objective is to provide a fairly representative overview of the most recent research into the application of simulation modeling in the provision of care services.

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This paper is organized as follows. Section 2 explains the methodology used in the literature search. Section 3 presents the results organized according to the simulation modeling paradigm used, the key system components being modeled, the data sources and data issues. This is followed by a discussion in Section 4 that highlights the gap between the findings and the types of decisions needed in the social care sector. This section also highlights potential areas in the social care sector where simulation modeling can play an important role. Finally, this paper concludes with a summary and suggestions for future work.

2 METHODOLOGY

The author searched for articles (journals, conference proceedings and book chapters) published from January 2000 to May 2012 and written in English from the Web of Science using 'Topic = (simulat* or micro* or macro* or "system dynamics") and (social or aged or elderly or long-term) and care' as the text query. The first term should find articles that use major simulation modeling paradigms such as discrete-event simulation, agent-based simulation, system dynamics, micro-simulation and macro-simulation. The second term is used to increase the relevance score for articles containing the words 'social', 'elderly', 'aged' and 'long-term'. The last term should find articles containing the word 'care'. The keyword 'care' is used because articles on social care may use the words 'care', 'social care', 'aged-care' or 'long-term care' (the trouble is, it may also find articles on healthcare). The search found 5,460 articles. These articles were further filtered by selecting relevant categories such as 'operations research management science' and 'health care sciences services' and resulted in 1,078 articles. The complete list for the categories is given in the Appendix. The results were then sorted based on their relevance. These articles were checked manually by reading each title and abstract. The author is interested in strategic and operational policies that affect the delivery of care services. Therefore, non-relevant topics, such as those aiming to analyze clinical trials and cost-benefit analyses of treatments as well as those not using computer simulation modeling, were excluded. Topics on healthcare services for the elderly were excluded if they did not include any social care components. Non-accessible articles were also excluded from the analysis. In the end, 14 articles were identified and used in the analysis. These articles are: Chung et al. (2009), Desai et al. (2008), Fernandez and Forder (2010), Heffernan and McDonnell (2007), Hsiao and Huang (2012), Jagger et al. (2009), Kemper et al. (2005), Knickman and Snell (2002), Lagergren (2005a, 2005b), Lubitz et al. (2003), Pickard et al. (2000), Spillman and Lubitz (2000), and Wolstenholme et al. (2007).

Desai et al. (2008) noted that while OR techniques have been used widely in healthcare, the use of OR techniques in social care has not been so extensive. This paper searched articles from the Web of Science only. However, the database includes more than 12,000 journals and 148,000 proceedings covering the sciences, social sciences, arts and humanities. Hence, the limited number of articles found during the literature search is consistent with the comment made by Desai et al. (2008).

3 RESULTS

This section explains the results of the literature search. First, it summarizes the simulation modeling paradigms used in the literature. Next, it discusses key components in the provision of care services. Finally, it highlights the data sources used for the modeling work and related data issues.

3.1 Simulation Modeling Paradigms Used in the Literature

The simulation modeling paradigms used in the literature include micro-simulation (7 articles), macro-simulation (3 articles) and system dynamics (4 articles). A micro-simulation inspects each individual at each simulation time point in which one or more random sampling processes are performed to determine the state of each individual at the next simulation time point. At one extreme, the sampling process requires simple random sampling. At the other, it may require a complex regression model. Depending on data availability, some studies may need to aggregate the micro-units in a micro-simulation model into aggregate units. This form of variation is often called macro-simulation modeling. Unlike micro-simulation, system dynamics does not keep track of changes in the state of each individual but focuses more on the population of individuals and rates of individuals moving from one state to another. System dynamics is commonly used to analyze complex feedback systems and mutual interactions in a system over time. The results also show that none of the articles use a multi-paradigm model.

3.2 Main Components of Care Service Provision Discussed in the Literature

Figure 1 shows the main components that enable the provision of care services. Demand refers to care users. In general, care users need good quality care services that are tailored to meet their health condition and personal preferences. Supply refers to service capacity, which includes care workers and institutions. Care workers need a good working environment where they can focus on delivering good quality service to the people they care for. Delivery methods refer to the use of technologies (such as telecare) and/or processes to improve service delivery. The final component simply says that care service provision incurs costs. These costs have to be paid via a private finance arrangement such as care insurance, a public finance arrangement via a government budget, or both through co-payment schemes. Discussion of the findings is segmented based on the components being modeled, i.e. care demand modeling, care supply/workforce modeling, the performance modeling of care delivery methods and cost/financial modeling. An article may be discussed in more than one section if it includes two or more components in the model.

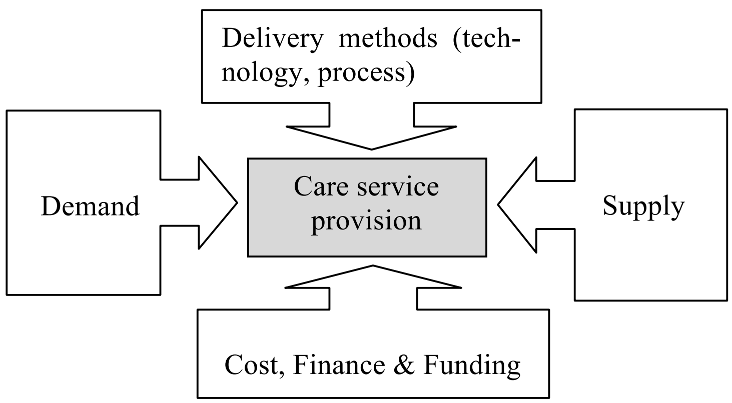

Figure 1: Main components of social care simulation

3.2.1 Demand Modeling

Demand modeling as discussed in the articles is based on work done in developed countries such as the UK (e.g. Jagger et al. 2009; Pickard et al. 2000; Desai et al. 2008), the US (e.g. Kemper et al. 2005) and Sweden (e.g. Lagergren 2005a, 2005b). This perhaps highlights the severity of the aging population situation in the developed countries, especially with the leading edge of the baby boom generation having reached retirement age.

One of the main objectives of demand modeling is to project the demand for care services. This is typically linked to population projections. The methods commonly used in population projections include mathematical modeling (Hinde 1998, Chapter 16), cohort components (Hinde 1998, Chapter 17) and individual-based simulation (e.g. Onggo 2008). A set of mathematical equations can be used to project the size of a future population. For many purposes, including projection of the demand for care services, the population structure (i.e. the size of different groups within the population) is more useful than total population size. This can be done using a method called the cohort component method that represents people moving from one population group to another (flow models). This method is very similar to macro-simulation. Individual-based simulation techniques such as micro-simulation and agent-based simulation offer another advantage by allowing individual-specific explanatory variables to be included in the model.

For example, we may include factors such as education level and model its impact on mortality and morbidity. This view is supported by a number of researchers such as Batljan et al. (2009), who argue that simple extrapolation by multiplying the prevalence rate to the projected population could produce misleading projections of the demand for care services. Their argument is based on various research that shows a strong correlation between education level and health condition among the elderly.

Most work in demand modeling has focused on providing more accurate estimations of the future need for care services. One approach is to estimate the number of people with disabilities due to aging. This is what Jagger et al. (2009) did with their macro-simulation model. They used their model to estimate the number of older people with disabilities in England and Wales. They were particularly interested in the impact of dementia on disability among older people. Hence, the model takes into account the prevalence of dementia among older people and the probability of death and disability due to dementia. The model helped them to analyze the impact of various early interventions that might reduce the incidence of dementia, improve the survival rate of older people with dementia, and reduce the disability rate of older people with dementia. Lagergren (2005a, 2005b) argues that a simple projection of the demand for care services that does not take into account health development among older people will overestimate demand. His argument is based on data that show the improvement of health conditions among older people. He shows, using a micro-simulation model, that projecting the demand for care services is very sensitive to assumptions about health development. These examples show that there is a tendency to include more explanatory factors into models to improve the explanatory power of demand projections. If chosen carefully and supported by good quality data, those factors can improve the explanatory power of models. Otherwise, they may produce misleading results.

Another important issue in demand modeling is estimation of the demand for different types of care, such as nursing homes and domiciliary care. This is because each type of care has a different cost structure and requires different resources. Pickard et al. (2000) show an example of modeling work in this area. They use a macro-simulation model to estimate the demand for formal and informal care. In the informal sector, care support is unpaid and mostly undertaken by family, friends, neighbors or volunteers, while in the formal sector, care and support are usually provided by public sector organizations, third sector (voluntary) organizations, and private organizations. To take another example, Desai et al. (2008) used a system dynamics model to estimate the number of people requiring different types of care services in Hampshire (UK). They model the flow of care users in the system from initial contact with the local authority until they leave the system.

Apart from demand level, the duration of time when care or support is needed is also important. This approach is especially useful in calculating the average lifetime cost for individuals. Kemper et al. (2005) used this approach to estimate the distribution of lifetime need for different types of care services using a micro-simulation model.

The demand for care services is partly influenced by the healthcare system. Hence, it is important to understand the interface between the social care system and the healthcare system. Wolstenhome (1993) identified the issue of the interface between healthcare and social care when the UK government passed the responsibility for care services to local government. He developed his argument using a system thinking approach and drew a few conceptual models using system dynamics. His work was developed further in Wolstenholme et al. (2007), in which they show a detailed conceptual model of the interface between primary care, hospitals (medical and surgical sectors) and the social care sector. One of the articles found during the literature search, Heffernan and McDonnell (2007), presents initial modeling work using system dynamics to analyze the interface between social care and healthcare in Australia. There, healthcare is funded by the federal government and social care is funded by local government.

In summary, since demand modeling for care services is often linked to population projections, it is not surprising that the techniques commonly used in population projections, such as micro-simulation (e.g. Kemper et al. 2005; Lagergren 2005a, 2005b), macro-simulation (e.g. Jagger et al. 2009; Pickard et al. 2000) and system dynamics (e.g. Desai et al. 2008; Heffernan and McDonnell 2007), have been reported in the literature. Most work in demand modeling focuses on estimation of the demand for care services. There has been a tendency to include more explanatory factors into models and to estimate the demand for different types of care services (i.e. a finer demand category). Much work has also included scenario analyses, such as the effect of early interventions in reducing demand and changes in assessment criteria to reduce demand.

3.2.2 Supply Modeling

The literature search only found two articles that discuss the supply modeling component (Heffernan and McDonnell 2007; Hsiao and Huang 2012) and both were still at an early stage. This is consistent with Onggo (forthcoming) who notes the lack of simulation modeling work on the supply side of the care sector. This is unfortunate since a good policy in the social care sector should also take into account the dynamics of the facilities and workforce needed to deliver care services.

3.2.3 Performance Modeling of Care Delivery Methods

While demand modeling and supply modeling are important in identifying any potential mismatch between supply and demand in the social care sector, exploring the potential benefits of innovative methods for care service provision is equally important. This is because new methods of service delivery might be able to improve the efficiency of care service provision. To take an example, Wolstenholme et al. (2007) explain how increasing capacity in the social care sector can improve the flow of patients from hospitals to community care more effectively than any other methods. None of the articles presents a model that assesses how new technology can be used to improve the efficiency of care service delivery, despite the recent advances in assistive technologies. This is another area in which simulation modeling could play a more significant role.

3.2.4 Cost and Financial Modeling

Estimates of the lifetime cost of care are a prerequisite to finding the best way to fund the provision of care services. The governments of countries that offer publicly funded care services and private sectors that offer relevant financial products are interested in such estimates. Hence, there has been plenty of work in this area. As in demand modeling, all articles found in the literature search are based on work done in developed countries such as the UK (e.g. Fernandez and Forder 2010; Pickard et al. 2000; Desai et al. 2008), the US (e.g. Kemper et al. 2005; Knickman and Snell 2002; Lubitz et al. 2003; Spillman and Lubitz 2000) and Sweden (e.g. Lagergren 2005a, 2005b). Most analyses take into account both social care and related healthcare cost components. Separating the two cost components is useful because many funding regimes allocate a separate budget for each component.

One of the simplest methods to estimate the future cost of care is to project the demand for care and use that projected demand to calculate discounted cost. Lagergren (2005a), for example, calculated the cost of care by multiplying the demand for various types of care by their respective standard costs that depend on the age, gender, marital status and degree of disability of care users. Lubitz et al. (2003) used a micro-simulation model to show that the expected cumulative health expenditure for healthier people, despite their greater longevity, is similar to those who are less healthy. In earlier work, Spillman and Lubitz (2000) simulated the total national expenditure on care. They separated the healthcare and social care cost components to show that social care costs increase significantly with longevity, while healthcare costs increase with a diminishing effect from longevity. In the context of a city's population, Chung et al. (2009) used a macro-simulation to estimate the cost of care services in Hong Kong. Using sensitivity analysis, they found that demographic changes had a larger impact on the overall cost of care in comparison to the changes in unit costs.

Kemper et al. (2005) used another approach to estimate the cost of care. They developed a micro-simulation model that estimates the lifetime need of various types of care. Based on these estimates, the proportions of costs paid by various payment sources (such as Medicare, Medicaid, private insurance and savings) were calculated.

Once the cost of care has been estimated, it is possible to develop a model that explores a viable funding strategy to meet that cost. For example, Fernandez and Forder (2010) used a micro-simulation model to explore possible funding strategies for care services in England. They specifically compared the existing means-tested model with a universal model called the National Care System. Knickman and Snell (2002) developed a micro-simulation model to estimate the future income and asset patterns of the Baby Boom generation (i.e. the future financial viability of older people) in the US. The simulation model is based on two sub-models that simulate future demographic characteristics (including labor force participation, income and assets) and the demand for care (including disability, use of different types of care and methods of payment), respectively.

3.2.5 Summary on Modeling Work

A summary of the modeling work of the main components of care service provision discussed in the literature is shown in Table 1, below. The table shows that the three modeling paradigms have been applied to demand modeling. The choice between micro-simulation and macro-simulation is influenced by the availability of the required longitudinal micro-data. This is mentioned in the two articles on macro-simulation. The two articles on system dynamics deal with the demand from the interface between care services and other services (healthcare and local government). This is not surprising because system dynamics has been used extensively to analyze feedback in various systems including social systems.

Table 1: Summary of the literature review

Category	**Micro-simulation**	**Macro-simulation**	**System Dynamics**
Demand (projection, analysis, types, preferences)	Kemper et al. (2005); Lagergren (2005a, 2005b);	Jagger et al. (2009); Pickard et al. (2000);	Desai et al. (2008); Heffernan and McDonnell (2007);
Supply (projection, analysis, knowledge, skills)			Hsiao and Huang (2012); Heffernan and McDonnell (2007);
Delivery Methods (performance, quality)			Hsiao and Huang (2012); Wolstenholme et al. (2007);
Cost/Finance/Funding	Fernandez and Forder (2010); Kemper et al. (2005); Lagergren (2005a, 2005b); Lubitz et al. (2003); Knickman and Snell (2002); Spillman and Lubitz (2000);	Chung et al. (2009)	

The lack of work using micro-simulation and macro-simulation to model supply and delivery methods is likely due to the general lack of simulation modeling work in these two areas. The author does not see any reason why micro-simulation and macro-simulation cannot be used in the supply modeling area. Both modeling paradigms have been used in manpower planning. Similarly, both modeling paradigms have been used to model delivery methods in various areas, e.g. in the maintenance of distributed physical infrastructure. Hence, the two modeling paradigms could be applied to model the delivery of care services (such as home visits and telecare). The dominance of micro-simulation in cost modeling is perhaps not too surprising, because the cost of care may vary significantly between individuals. Micro-simulation provides a natural choice provided that the required longitudinal micro-data are available.

3.3 Data Sources

Micro-simulation models require detailed longitudinal data to parameterize the micro-units (in this case, individuals or households). This type of data is expensive to collect. Hence, the data are often obtained from various national longitudinal surveys (usually funded by the public sector and accessible to researchers and policy-makers).

An example of such data in the UK is the British Household Panel Survey (BHPS). This survey follows the same representative sample(s) (households and individuals) over a number of years. Since the survey started in 1991, it has collected detailed data on social and economic changes at the individual and household level. These were the data source used in Fernandez and Forder (2010) to assess the viability of the National Care System.

In the US, Duke University has carried out a longitudinal survey called the National Long-term Care Survey (NLTCS). This survey follows individuals from the age of 65 until they die (or can no longer be contacted). The survey began in 1982 and was designed to collect data that could be used to improve social care need policies. Knickman and Snell (2002) and Kemper et al. (2005) used the data from this survey to estimate various prevalence rates. Another example of a relevant longitudinal survey in the US is the Medicare Current Beneficiary Survey (MCBS), which is mainly used to determine expenditures and sources of payment for all services used by Medicare beneficiaries. Lubitz et al. (2003), Spillman and Lubitz (2000) and Kemper et al. (2005) used the data obtained from MCBS in their micro-simulation model.

In Sweden, the Swedish Ministry for Social Affairs started a project called the Swedish National study on Aging and Care (SNAC). One of its sub-projects, SNAC-Kungsholmen (SNAC-K), aims to understand the aging process and to identify early interventions to improve health and social care for the elderly. As part of the SNAC-K project, they have carried out a longitudinal survey that follows individuals aged 60 or above living at home and in institutions since 2001. Lagergren (2005a 2005b) used the main data from this project to set the parameters for his micro-simulation model.

The detailed longitudinal data required for a micro-simulation model may not always be available. In some cases however, aggregate data collected from cross-sectional surveys may be available. In these cases, macro-simulation model could be an option. This is one of the reasons why Chung et al. (2009) chose macro-simulation for their study. They used readily available aggregate data from official demographic projections (i.e. the Hong Kong Annual Digest of Statistics and Hong Kong Population Projections 2007-2036) and thematic household survey data on topics proposed by various government departments. They also used various sources to parameterize the health status of the population. Their data sources included Hong Kong's Domestic Health Accounts and other routine data from relevant government departments, Hospital Authority and care service providers. In a similar vein, Pickard et al. (2000) used the population projection data produced by the Personal Social Services Research Unit (PSSRU). They also used the General Household Survey (GHS) to estimate the number of elderly people who received some informal help.

One of the main tenets of system dynamics modeling is that the structure of a system determines its behavior. Hence, analysis of the structure of a system can provide insights and improve our understanding of the behavior of an existing system or be used to estimate the behavior of a new system, as shown in Wolstenhome (2007). Structural analysis is commonly done by drawing a conceptual model that represents the relationships between key factors in the system. A conceptual model cannot be simulated without specifying the mathematical equations that quantify the relationships between all factors in the model. To specify those equations we need relevant data. Since simulation of a system dynamics model allows us to quantify the effect of one factor on another factor, it should offer more insights than structural analysis alone. This is shown in Desai et al. (2008). They used data collected from the recording system of Hampshire County Council to specify the required mathematical equations. As a result, they could quantify the effect of two policies on performance.

3.4 Data Issues

It is widely known that one of the factors that affect the quality of a simulation model is the quality of the data. There has been research into data collection methodology to improve the effectiveness of the data collection process in simulation modeling projects (e.g. Hill and Onggo 2012; Skoogh and Johansson 2008). Most work found from the literature review reported data issues that had to be resolved before they could produce useful output from simulation. The data problems reported are as follows.

The required data do not exist: This is probably the most common data issue. Any research into the data collection methodology used in simulation modeling should address this issue (e.g. Hill and Onggo 2012; Skoogh and Johansson 2008). This is usually solved by collecting data, estimating data, or making assumptions in the absence of data. For example, the upper age limit in the Swedish National Survey of Living Conditions means that data for people older than the upper limit were not recorded (Batljan et al. 2009; Lagergren 2000a; Lagergren 2000b). Consequently, the authors had to estimate the parameters for the missing age groups. Kemper et al. (2005) had to use non-Medicare data because relevant Medicare data were lacking. Thus data had to be estimated from other sources such as the National Assisted Living Survey. Spillman and Lubitz (2000) noted that the earliest data in the Continuous Medicare History Sample were from 1974, so data on payments were not available for persons older than 87 years when they died. They had to use regression analysis to estimate those payments. Lagergren (2000a) stated that even an answer to the basic question: "Who gets what care?" could not be obtained from the official statistics. These examples show the prevalence of the data problem.

Lack of samples/observations in the data: Even if available, data may not have enough samples in one or more data subsets. This was apparent when Lagergren (2000a) needed to make some calculations that involved a large number of data subsets. He reported that the number of samples in some subsets was too small, which could lead to misleading results due to the influence of random errors. Spillman and Lubitz (2000) also found the same issue with their data source, i.e. the samples they obtained from the National Medical Expenditure Survey were too small.

Inconsistent data definitions: The same data source that has been used for a long period may experience changes in its data definitions. For example, between 1975 and 1979, the upper age limit in the Swedish National Survey of Living Conditions was 75 years (Batljan et al. 2009). However, between 1980 and 1999, the upper limit was raised to 85 years. This inconsistency forced the authors to make careful translations of the data during the affected collection periods.

Data separated among several sources: This requires a process that combines data from various sources. This process may face issues such as different data formats, different units and different data definitions. To take one example, Lagergren (2000a, 2000b) explains that there was a fundamental difference between the data on health status from two of the data sources he used. The health status in one data source was self-rated by the respondents while the health status in the other data source was entered by an outside observer. For this reason, he had to omit the data on dementia which was one of the key factors in his work. In another case, Kemper et al. (2005) noticed that there were at least two definitions of disability: (1) limitations on the activities of daily living (ADL) such as eating, bathing and dressing, (2) limitations on the instrumental activities of daily living (IADL) such as getting around outside the home and preparing meals. Hence, it is important to know the semantic meaning of data collected from multiple sources.

Bias in data: There are various reasons why data may be biased, such as incorrect data collection, changes in data collection methods, wrong samples, etc. One of the examples found in the literature is reported by Lagergren (2000a). He notes that there were strong reasons to believe that the data in one of his data sources were skewed for a certain age group.

Data are not in the right format: Data are often available in a format that is not ready for use. This is a very common problem because data collection might not have been designed for use in simulation modeling. Desai et al. (2008), for example, mention certain issues encountered in obtaining the required data in the right format for their simulation model and that the transformation process took a considerable amount of time.

Data need cleansing due to missing data, duplications, etc.: Desai et al. (2008) also mention that they needed to cleanse data due to missing data, duplication, etc. This is another common data issue. The author has been involved in a number of simulation projects and all of them required data cleansing.

4 DISCUSSION

The six main challenges in the social care sector identified during the recent public engagement discussion are listed in Section 1. This discussion involved key stakeholders and gathered opinions from the public from more than 300 engagement events and other communication channels. Hence, some of these challenges may also be relevant to the social care sector in other countries. This section analyzes whether the articles discussed in Section 3 have addressed these challenges.

The first two challenges, i.e. *the provision of good quality care services* and *the need for personalized services to meet the needs and circumstances of every care user*, require good projections of the demand for care services at a finer level to accommodate personalized services. They also require good projections of the supply capacity for care services. Projections are difficult, even at a more aggregated level (as shown in Section 3.2.1), let alone at a finer level. One of the key challenges in demand projections is that the demand for care services depends on various factors, such as health, culture, socio-demography, etc. To include these factors into demand models, we need significant investment in data collection processes. The personalization agenda makes data requirements even more demanding. Hence, it is not surprising that not all the articles found in the literature review adequately address the personalization agenda. To make projecting even more difficult, future care demands may not follow demographic projections. In fact, researchers do not seem to agree on which of three hypotheses – compression, expansion or postponement of morbidity and disability – are likely to happen (Thorslund and Parker 2007). Simulation modeling allows us to include more explanatory factors and thus project a finer level of demand under different hypotheses for morbidity and disability projections.

Section 3.2.2 shows that the simulation modeling work on the supply side of care services is limited. This is rather unfortunate because simulation modeling has been used with considerable success in manpower planning in other sectors, as shown in the survey carried out by Edwards (1983). Wang (2005) identified that simulation is one of the four main approaches to modeling and analysis in manpower planning. Hence, simulation modeling could and should play an important role in modeling and analyzing the social care workforce. The personalization agenda makes the role of simulation modeling even more important, due to the need to include the more detailed skills of care workers.

Another issue relevant to the provision of care services is the use of better processes and/or better assistive technologies. There has been a number of significant advances in the field of medical informatics and ubiquitous computing that could improve the provision of future care services. These include technologies such as telecare/telemonitoring, smart houses, wearable devices and bio-sensors. Bharucha et al. (2009) describe a survey of assistive technology for care delivery. New technologies may need new processes. For example, telemonitoring technology allows care users to live in their home while being monitored remotely. This will require new processes that take into account the health, safety and privacy of care users before the technology can be used in practice. Simulation modeling (such as discrete-event simulation) has been used extensively to evaluate various processes. Hence, there is no reason why simulation modeling cannot be used to assess the new assistive technologies and the new processes that may be made available making use of these new technologies.

The next challenge on the list is *the need for better integration with relevant services*, such as the National Health Service (NHS) in the UK and local government services. The literature contains a few good examples of simulation modeling work that helps policymakers tackle this challenge. Wolstenhome (1993, 2007) shows how a system dynamics conceptual model can identify the problem at the interface between healthcare and social care. In other work, Desai et al. (2008) developed a system dynamics simulation model of the interface between local government and care service providers. This model allowed them to run scenario analyses to demonstrate potential problems or improvements. They tested two scenarios: (1) using tighter means-tested criteria and (2) using different staff skills mixes.

The next challenge is *the need to support greater prevention and early intervention*. This is another area in which simulation modeling has made useful contributions. Jagger et al. (2009) used a macro-simulation model to analyze the impact of various early interventions that could reduce the incidence of dementia, improve the survival rate of older people with dementia, and reduce the disability rate of older people with dementia. Lubitz (2003) shows that health promotion efforts aimed at young people may improve their health and longevity without increasing health expenditure using their simulation model. Lagergren (2005b) discusses intervention in generic form, i.e. representing it with reduced demand without specifying what the intervention is. Although prevention and intervention usually target care users, the author believes they should also target care providers to avoid potential issues in the future provision of care services. For example, Pickard et al. (2000) discuss the effects of an intervention on the supply of care, i.e. increasing support for informal carers.

The final two challenges are closely related, i.e. to promote a more diverse and responsive care market and to encourage more financial products to be offered by the private financial sector to help people pay for their care. First, we need to understand how the care market might work, i.e. how care users and care providers interact to trade care services for money. The interactions can be direct or through intermediaries. Simulation modeling (such as agent-based simulation) is a suitable modeling technique for market analysis. The analysis can be extended to cover the market for financial products for care, such as care insurance, reverse mortgages and equity-release schemes. The literature shows that there has been some initial work in this area. For example, Knickman and Snell (2002) built a simulation model to understand how individuals accumulate their assets to assess the viability of certain financial products. Fernandez and Forder (2010) show how a National Care System might perform using their simulation model. However, more work needs to be done to analyze possible sustainable financial/funding schemes to pay for good quality care services.

5 SUMMARY

The potential areas to which simulation modeling could be applied can be divided into four categories: demand, supply, delivery method and cost/finance. This paper shows that the number of research articles on the application of simulation modeling to the provision of care services is limited, especially in the areas of care supply and care delivery methods. Hence, there are good opportunities for simulation researchers who are interested in contributing to improving the provision of social care services.

This paper has listed key data sources from longitudinal studies that have been used by researchers of social care services. This paper has also discussed related data issues. Hence, simulation researchers who are interested in developing simulation models for the provision of social care services may find this information useful. Finally, this paper has discussed the gap between findings from the literature and the challenges in social care policies. Potential areas in which simulation modeling work can make a real impact (based on the public engagement discussion organized by the UK Department of Health) have been identified. These include the provision of good quality personalized care services (especially the supply side and the use of assistive technologies), the interface between care services and relevant services, intervention and early prevention, and the sustainable financing of care services.

A LIST OF WEB OF SCIENCE CATEGORIES

operations research management science, social sciences biomedical, health care sciences services, primary health care, demography, health policy services, computer science information systems, medical informatics, computer science interdisciplinary applications, economics, telecommunications, social sciences interdisciplinary, computer science artificial intelligence, behavioral sciences, nursing, sociology, management, geriatrics gerontology, computer science theory methods, social issues, social work, computer science software engineering, gerontology

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