A review of implementation of behavioural aspects in the application of OR in healthcare

Abstract

This paper presents a survey of the literature on the application of Operational Research (OR) in healthcare, with a particular focus on behavioural considerations. In order to explore the extent to which behavioural aspects are included, we perform a search of the most relevant OR journals for articles with content related to the representation of behaviour in models, evidence of behavioural change using models, and the impact on organisations beyond the use of a model. A detailed analysis of 130 articles is presented and shows that the majority are focused on improving service delivery at an organisational level. The most common OR methods depicting behaviour are simulation and qualitative methods, but there is evidence of the use across a range of methods. However, in many cases, authors do not necessarily acknowledge the behavioural aspects in their papers. Given many aspects of healthcare are influenced by human behaviour, it is important that that future work makes more explicit the assumptions used to represent behaviour, test the sensitivity of models to different behavioural assumptions, and offer more information about how users employ models to make decisions.

Keywords: Healthcare, Behavioural Operational Research, Literature review

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1. Introduction

Brailsford and Visser (2011) suggest that OR in healthcare should be applied research with emphasis on implementation resulting from collaboration between practitioners and academics. Brailsford and Harper (2008) remark that a significant proportion of healthcare modelling is concerned with organisational issues and service delivery, aiming to improve the effectiveness and efficiency of patient services and healthcare resources. Therefore, behaviour is at the core of OR models applied in healthcare. Reviews of the use of OR in healthcare are not new and have been performed since the 1970's (Brailsford et al, 2009). Moreover, the number of articles in this broad area likely now exceeds 250,000 if we consider that Brailsford et al (2009) found more than 175,000 in 2009, growing at a rate of around 30 published articles each day. In the field of OR in health, there are also institutional efforts, such as The Center for Healthcare Operations Improvement and Research (CHOIR) at the University of Twente, to maintain an online literature database 'ORchestra' covering the growth in the field (Hulshof et al, 2011). However, there is no evidence of the consideration of one particular aspect of the application of OR in healthcare: the implementation of behavioural aspects. Thus, we adopt a search of the most relevant OR journals for this evidence in order to complement the set of papers that are part of this special issue.

There are two key stakeholders in healthcare systems: patients and staff. However, only recently has the importance of their behaviours been acknowledged and considered in articles relating to the application of OR in healthcare. It is perhaps naïve to consider that patients and staff will behave entirely rationally, as is typically assumed and/or embedded in healthcare models, or that behaviours will not change over time. While there is some evidence of considering human behaviour in models for healthcare issues (for example Brailsford and Schmidt (2003); Brailsford, Harper and Sykes (2012); Brailsford ((2016)) and Kang et al ((2016))), there has not been a systematic review of this practice within the related OR/MS literature.

The need to merge both areas, behaviour and the practice of OR in health, is increasingly acknowledged (Brailsford, (2016)). This should help to develop models that capture behaviour realistically and focus the attention of clinicians and policy makers on managing behavioural aspects of the health system. This paper covers an important gap in this area given the importance of behaviour and the increasing number of papers acknowledging this and demonstrating its affect on decision making within healthcare domains.

2. Literature review

2.1. Taxonomy of OR in health

Hulshof et al (2012) studied the extensive literature related with the application of OR/MS in the field of healthcare. In their study, they presented a two-dimensions taxonomy. The first dimension reflects the hierarchical nature of decision making regarding the planning and control of resources (in essence it reflects four levels: strategic, tactical, operational offline, which involves coordinating activities to deal with short-term/immediate demand, and operational online, which implies mechanisms to react to unplanned events) in the healthcare system. The second dimension identifies the various health care services as a patient pathway: ambulatory care services (e.g. outpatient clinics, primary care), emergency care services (e.g. A&E, trauma centres), surgical care services such as operating theatres, inpatient care services involving intensive care units, home care services (e.g. telemedicine) and residential care services (e.g. nursing homes). There are some interesting observations from their work that influence our approach. Firstly, the focus is on optimising operations (outpatient, emergency, surgical, inpatient, home care and residential services) with a focus on matching capacity (staff, resources) to demand (patients). Secondly, computer simulation is widely used which more readily facilitates the inclusion of behavioural aspects of the main 'actors' (e.g. patients, staff, hospitals) in the healthcare system, say than other common OR methods such as mathematical programming approaches. Thirdly, there is a good spread of work across all the decision making levels (strategic, tactical and operational).

Another taxonomy of OR/MS in healthcare that we consider in this study is provided by Brailsford and Vissers (2011) through a review of OR/MS in healthcare within the European context. They focus on healthcare as a system that depends on the particular characteristics of each country: centralised (government-managed) vs. decentralised (market competition); clinical specialists vs. political stakeholders. They propose a two dimensions' framework to analyse OR/MS in healthcare.

Firstly, the dimensions comprising the stages of developing and managing a health service are:

- identifying needs for health services;
- developing a service for the needs;
- forecasting service demand;
- securing resources for the services;
- allocating resources for the services;
- developing programmes and plans to use those resources in the services;
- developing measures and measuring performance; and
- evaluating the results of healthcare delivery.

Secondly, the level of decision making in which the process and operations take place: National/Regional; Hospital/Unit; and Individual (patient/provider). In terms of distribution of papers in OR/MS in healthcare across decision making levels, we can see a focus on Hospital/Unit followed closely by National/Regional level:

- National/Regional: 33%
- Hospital/Unit: 42%
- Individual: 25%

Thirdly, most of the papers are located in the planning, system/resource allocation functional area followed by finance, policy, governance and regulation and public health or community service planning. This result is similar to Hulshof et al (2012):

- finance, policy, governance and regulation
- public health, community service planning
- patient behaviour/characteristics
- planning, system/resource utilisation
- quality management, performance monitoring or review
- risk management, forecasting

- workforce/staff management
- research

Fourthly, they found that strategic level (policy or regulation) papers consist 20-30% of all papers, tactical level (facilitation or commissioning) papers consist of 10-25% of all papers, and most of the papers are at operation level.

Fifthly, in terms of OR/MS methods, these authors use a different categorisation than Hulshof et al (2012) to evaluate the distribution of papers in OR/MS in healthcare from two databases (figures below from ORAHS / RIGHT respectively):

- qualitative modelling (cognitive modelling, process mapping, causal loop diagram): 10 / 15%
- statistical or regression analysis: 15 / 30%
- statistical modelling (Markov models, structural equation modelling): 8 / 28%
- simulation (discrete event simulation, system dynamics, Monte Carlo simulation): 23 / 17%
- mathematical modelling (mathematical programming): 32 / 8%

The focus of this paper is the consideration of behavioural aspects of OR/MS practice in healthcare. We start explaining what behavioural OR/MS is before discussing our methodology for the review of the usage of behavioural aspects in the practice of OR/MS in healthcare.

2.2. Behavioural Operational Research

There is increasing interest in understanding both human behaviour in practice and how to capture it in OR/MS models. Experiments and theory in fields such as psychology, economics, and finance increasingly recognise aspects of individual behaviour such as decision-making heuristics and biases and adaptations, bounded rationality and misperceptions of feedback affecting the results from quantitative models. Additionally, attributes of human behaviour both shape and are shaped by the physical and institutional systems in which they are embedded (Franco and Hämäläinen, (2016)). Behavioural issues in decision making are widely studied at the individual, group, and organisational levels by judgment and decision making, cognitive psychology, organisation theory, game theory, and economics. Consequently, the rise of behavioural operational research within OR/MS is not surprising but there has not been a review of inclusion of behavioural aspects in OR/MS work in healthcare.

Among many definitions, “behavioural operational research (BOR) is defined as the study of behavioural aspects related to the use of operational research (OR) methods in modelling, problem solving and decision support.” (Hämäläinen, Luoma, and Saarinen, 2013). Franco and Hämäläinen ((2016)) propose a framework for organising the conduct of empirical BOR studies. In this framework, BOR depends on the *type of OR actors*, such as expert modellers, decision analysts, consultants, users, etc., the impact of the *OR methods* (techniques/tools and the routines for using –building, communicating and intervening– the techniques/tools) employed, e.g. mathematical programming, simulation, and the resulting behaviour in the OR actors with the methods during the process, which is called *OR praxis*.

A final important factor is the *context* of the OR praxis such type of organisations, level of decision making, etc. The final aspects of the OR praxis is the BOR-related outcomes, such as changes in cognition, attitudes or interactions. In this paper, we are only focused on the OR method and the selected examples of the behaviour in the OR actors are inferred from the discussions of the authors of academic papers.

In BOR, there are three areas of research (Kunc, Malpass and White, (2016)) that can be associated with the main outcome of OR processes, which are models: *behaviour in models*, *behaviour with models*, and *behaviour beyond models*.

The first area evaluates the representation of behaviour in OR/MS models: behaviour in models. Modelling human behaviour as passive entities, which are predictable or within a range of variation, is different than modelling real people because their behaviour depends on unconscious intuitions, biases, sentiments and traits that are difficult to pin down (Greasly and Owen, (2016)). Human behaviour can be included in models in many different ways depending on the assumptions of the modellers, from fully rational decision makers to boundedly rational decision makers, to non-rational decision makers. In any case, the role of human behaviour in a model can have different impact on the dynamics of the system under study. Some research questions for OR/MS in healthcare are: How are patients portrayed in models? Does the OR/MS technique determine the representation of the patient in the system or vice versa? What kind of behaviour is assumed to drive the work of staff? Greasly and Owen ((2016)) provide a useful table depicting how behaviour is represented, which we adapted for our study, in Table 1.

Approach taken to represent human behaviour	**Description**	**Representation of human behaviour in the model**	**World view of the OR/MS modeller**	**OR/MS technique (examples)**
Simplify by not considering it	Eliminate human behaviour by omission, aggregation and substitution	None or subsumed in one variable	Optimisation	Mathematical programming

Externalise from the model	Incorporate human behaviour outside the model by letting decision makers interact with the model	Behaviour is too complex to codify so it has to be recorded empirically from outside the model	Gaming; Naturalistic decision making	Management flight simulators Experiments using models
Incorporate as a passive flow	Model humans as flows so humans follow similar rules.	Macro level variables inside the model	Continuous process over long term	Continuous simulation System Dynamics Markov models
Incorporate as individual entity	Model human as a machine or material	Meso level variables inside the model	Discrete particles controlled by rules	Discrete Event Simulation
Incorporate through activities	Model human performance in tasks	Meso level variables inside the model	Actions are response to pre-defined sequence of tasks	Discrete Event Simulation
Incorporate as a free individual	Model individual human behaviour	Micro level variables inside the model	Specific attributes of behaviour individually and emergent from interactions with other humans	Agent-Based Simulation

Table 1. Representations of behaviour in OR/MS models

The second area is related with the use of models by decision makers: behaviour with models. In this area, the focus is on how people use models for decision making: what information is used and how it is processed (Katsikopoulos, (2016)). Katsikopoulos ((2016)) propose psychological heuristics where decision making is based on psychological capacities; decision makers do not necessarily use all available information and employ simple computations. Therefore, users may not use the model as an OR modeller expects. Behaviour with model can also be associated with changes in cognitive functions, such as an increase in the number of options considered, evaluation of complexity, occurring during the use of a model in a real setting (Torres, Kunc and O'Brien, 2017; Kazakov and Kunc, (2016)) or through laboratory experiments (Arango, van Ackere and Larsen, (2016); Gonçalves and Villa, (2016)). This is area a well-established stream of research in SD (Gary et al, 2008) . Finally, the use of OR models, e.g. soft models to structure problems, may impact dimensions associated with behaviour such as (affective or cognitive) conflicts (Huh and Kunc, (2016)). A summary is presented in Table 2. Some research questions from this area in OR/MS in healthcare are: How does a healthcare organisation/decision maker use models? What is the role of models in achieving success for allocating patients? When and how do doctors complement their heuristics with a model's insights?

Behavioural change in:	**Description**	**Representation of human behaviour**	**OR/MS technique (examples)**
Heuristics	Adaptive use of heuristics Achievement of success or failure	Elicitation of heuristics and their consequences	Decision analysis
Cognition	Change of mental models Better understanding of complexity	Elements of mental models	System Dynamics
State of mind	Change as a state of mind is usually related with conflict. Conflict can consist of two categories: functional task-related conflict (e.g. cognitive conflict) and dysfunctional emotion-related conflict (e.g. affective conflict)	Level of conflict	Problem structuring methods

Table 2. Behaviour with models: dimensions of behavioural change, representation and OR/MS techniques associated.

The final area is concerned with the impact on behaviour beyond the use of models: behaviour beyond models. One important consideration of OR methods is that they are not only mathematical or problem structuring techniques but they are also tools for thinking, even (fully or boundedly) rational thinking. When "a model becomes an external and explicit representation of part of reality as seen as people who wish to use it to understand, to change, to manage and to control that part of reality" (Pidd, 2009, p. 12), there is an implicit assertion of the need to do models through a process of discussion and agreement on the design and use of the model underpinned by the social context. Models are created to make impact beyond the mathematical or problem structuring results. Thus, OR methods have a social nature.

This area aims to understand the impact of models through the lens of the socially situated nature of OR practice (White, (2016)). Most models do not prescribe action because they are a guide to action and action is a collective activity aiming at system-level improvement. Therefore, behaviour beyond models intends to evaluate the externalisation of the inclination to act on and modify the environment in problem-solving effort using models (White, (2016)). When the model is used to represent a problem with a group of decision makers, then the behaviour beyond the model observed is “collective efficacy” (White, (2016)). The collective efficacy can be associated with process of interpretation and integration in organisational learning (Crossan, Lane and While, 1999). From an organisational learning perspective, the model can help to institutionalise routines, rules or procedures (Crossan et al, 1999). Table 3 provides a summary of this area. Some research questions for OR/MS in healthcare are: How behaviour is changed in a hospital after the implementation of a staff scheduling system? How ambulance crew improves their effectiveness with a model indicating optimal locations?

Organisational behaviour change expected	**Description**	**Representation of collective behaviour**
Interpreting / Integrating	Interpreting is a process of explaining an insight or idea to others Integrating is a process of developing shared understanding and taking coordinated action through mutual adjustment.	Language Dialogue Storytelling Shared observations
Institutionalising	A process of routinisation where tasks are defined, actions specified, and organisational mechanisms implemented in order to embed the learning that has occurred.	Systems Procedures Structures.

Table 3. Behaviour beyond models: dimensions of behavioural change, representation and OR/MS techniques associated.

3. Review methodology

In order to evaluate the penetration of BOR into the practice of OR in healthcare, we performed a survey of the literature in OR/MS using the academic electronic database SCOPUS (www.scopus.com). The literature survey methodology consisted of three stages.

- In stage 1, a very broad set of search terms was used to produce an initial set of articles in the area of OR in healthcare. The search string was (operational research) AND (health*), appearing in the title, abstract or keywords. Given the focus of the special issue in OR, we did not consider other definitions of the field such as “operations research” or “management science” as well as specific methods such as “system dynamics” or “linear programming”. This focus left out of our sample papers such as Thompson et al (2015). From the initial 1,200 papers, we selected only those papers located in subjects: “Decision Sciences”, “Business, Management and Accounting”, "Computer Science" and "Mathematics" as defined in Scopus, resulting in 427 papers. Initial checks (e.g. authors and journals) on the results indicated that the sample of papers were relevant. For example, the Journal of the Operational Research Society has 221 papers selected and the European Journal of the Operational Research Society has 44 papers in the sample.

- In stage 2, all articles were selected for abstract review by at least one of the authors and a sample was discussed by all authors. After this review, the final selection included 130 unique articles (see appendix for a list of articles) that can be categorised as showing work related with BOR, 43% of the final set of articles. There were 14 papers in two BOR research areas simultaneously. The articles were classified, based on the areas discussed in the literature review, into:
  - Areas of research in BOR: Behaviour in models; Behaviour with models and Behaviour beyond models (see section 2.2)
  - Decision making levels: National; Organisational (hospital/unit) and Individual (see section 2.1)
  - Methods: Qualitative; Decision Analysis; Simulation; Optimisation and Heuristics; Mathematical and Statistical (see section 2.1)
  - Functional area: Finance, Governance and Regulation; Public Health; Service Delivery; Quality management and monitoring; and Risk management (see section 2.1)
- In stage 3, an annotated bibliography was generated to indicate the main characteristics observed in BOR within the context of healthcare. An annotated bibliography is a list of citations where each citation is followed by a brief descriptive and evaluative paragraph to provide insights of this work to the areas of research defined.

It is important to highlight limitations of our study. Firstly, the search tools are limited to the existence of the words in the fields defined, so some academic articles discussing behavioural aspects in healthcare have not been included. Moreover, the use of an academic database left important examples of grey literature outside of our sample especially related with national policy level, e.g. the foresight report from the Government Office for Science (2007). Tacking Obesities: Future Choices. Department of Innovation Universities and Skills, London*. Secondly, the search was across a multi-disciplinary academic database so there are works which are not necessarily OR models. Thirdly, the selection of articles as expression of any of the BOR research areas are affected by the perception of the authors and disagreements, especially in an emergent field as this, could arise.

3.1. Data analysis

The papers are distributed in similar proportion between behaviour in models (52 papers, 36%), behaviour with models (59 papers, 41%) and behaviour beyond models (33 papers, 23%). The distribution of articles in terms of I decision making levels the healthcare system is: national (22%), organisational (57%) and individual (21%) which are similar to Brailsford and Vissers (2011). In terms of OR techniques,qualitative techniques is the largest (34%)

followed by simulation (27%) and decision analysis (17%) with the most quantitative techniques, e.g. hard OR, having on average 7% of the articles.

Figure 1 shows the distribution of the papers presenting behavioural aspects (behaviour in -BiM-, with -BwM- and beyond -BbM-) in terms of decision making level. Most papers are developed at organisational level for all research areas. Behaviour in models is fairly evenly distributed across all levels, although with a slightly higher proportion for national (e.g. behaviour of population in epidemics and chronic diseases) level. The organisational level of the public health system has most of the activity related with behaviour with models (e.g. the use of models in organisational issues such as A&E operations). Interestingly, behaviour beyond models contains a large proportion of papers at individual level (e.g. use of decision making systems to support doctors).

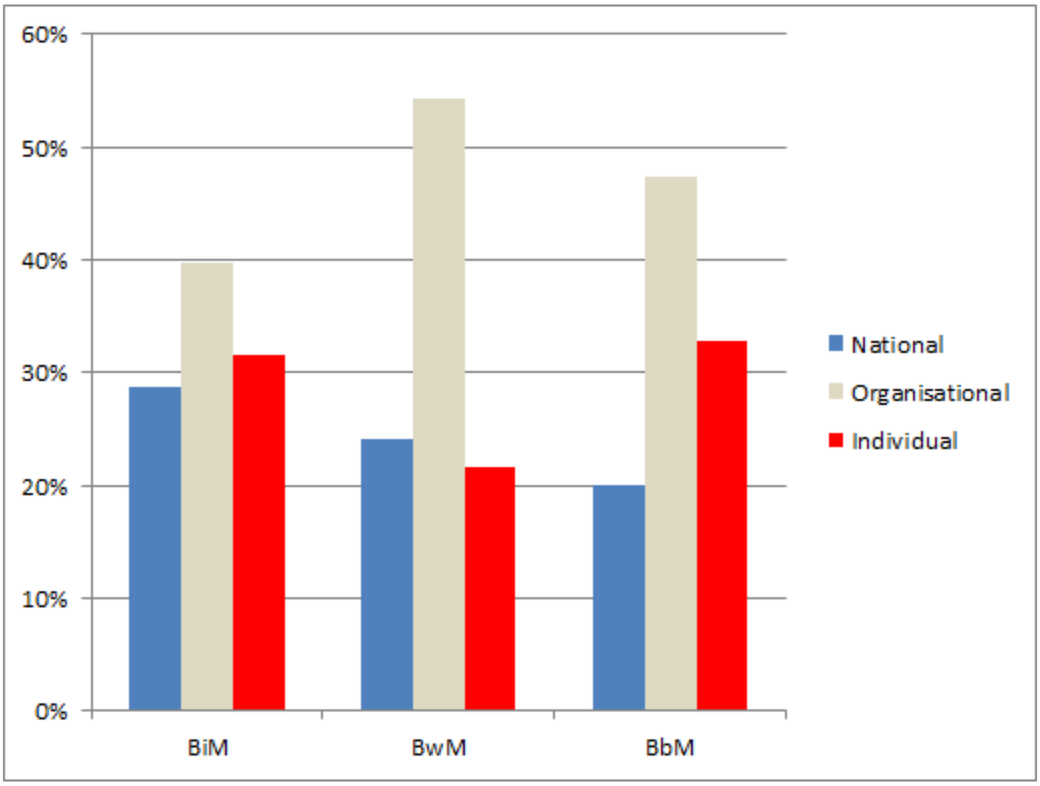

Figure 1. Distribution of papers for decision making level within each BOR research area

Figure 2 shows the distribution of papers in terms of methods identified in the papers. Not surprisingly, behaviour in models is mostly reflected in papers using simulation followed by statistical and qualitative methods. Since a paper could be associated with more than one method, the existence of statistical methods in behaviour in models is due to its complementarity with simulation methods. In terms of behaviour with models, the most important OR techniques are related with qualitative methods. This result is also not surprising given the traditional concern from OR scholars on the use of Soft OR tools by users. Finally, behaviour beyond models also contains a large proportion of papers associated with qualitative OR. The data illustrates that the penetration of BOR is mostly confined to qualitative, decision analysis and simulation techniques, which is aligned to traditional OR practice that considers human behaviour relevant in problem solving.

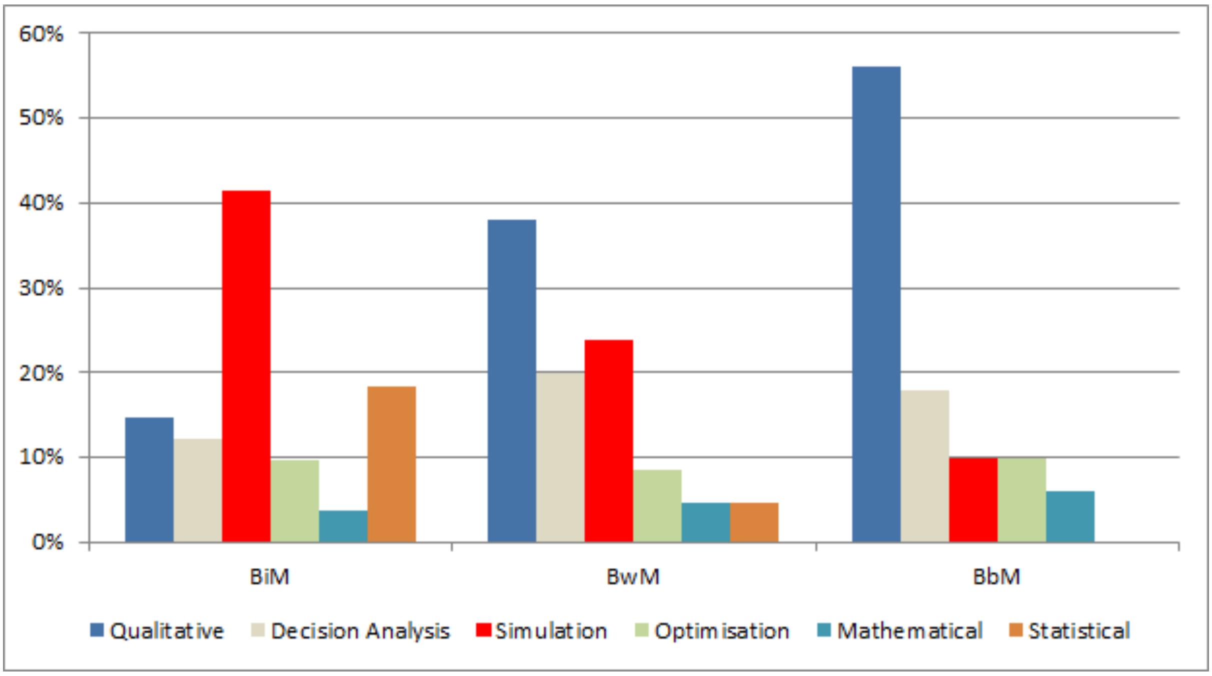

Figure 2. Distribution of papers according to methods in each BOR research area

Figure 3 shows the distribution of papers based on the functional area of the healthcare system. The proportion of papers confirms the focus on the most important issue at organisational level, service delivery, for all areas of BOR. Then, public health (typically a national level issue) is also equally represented in all BOR areas. Other functional areas, except finance and governance, are marginal areas of activity for BOR.

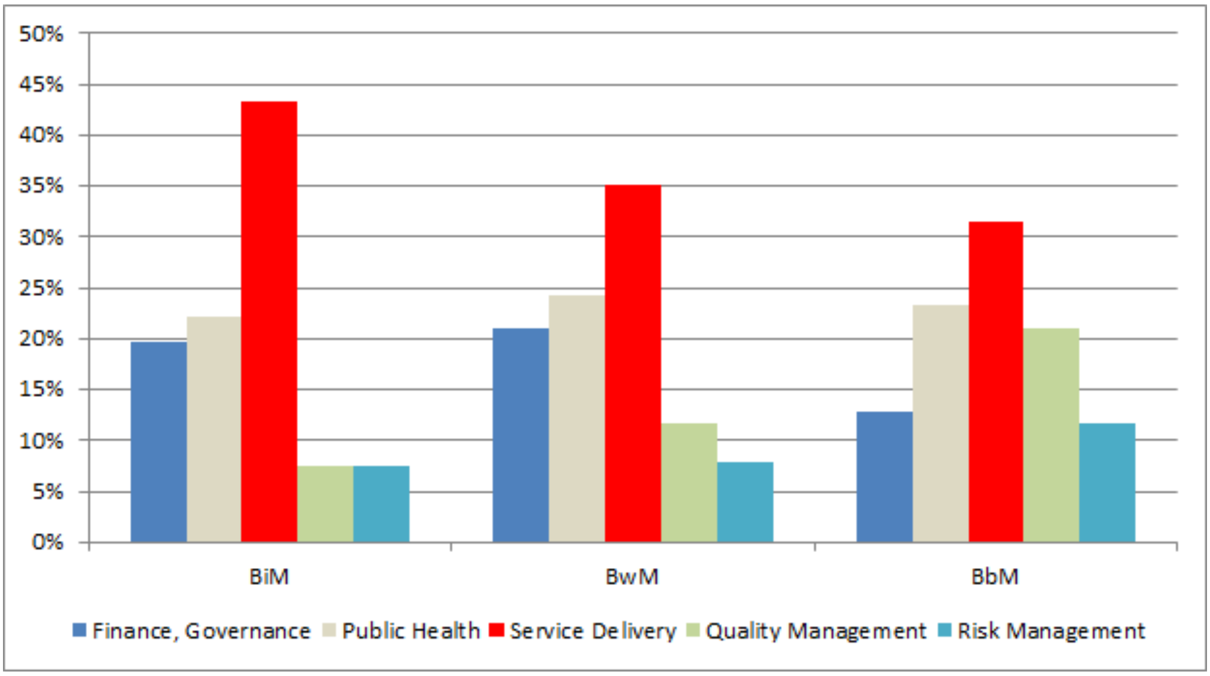

Figure 3. Distribution of papers according to functional area in each BOR research area

4. Qualitative insights from the selected papers

In this section, we present some more specific insights related to behavioural aspects of the application of OR/MS in healthcare. The insights are obtained from the review of selected papers that reflect emerging themes from each area of BOR. In the case of behaviour in models, the focus is on the OR/MS methods following the focus of Table 1. Behaviour with models reflects on the issues faced by users with the use of different OR/MS methods, e.g. soft and hard OR, as we address some of the behavioural changes in decision making suggested in Table 2. Behaviour beyond models represent accounts of behavioural changes in organisations or policy makers generated by the use of OR/MS methods suggested in Table 3.

4.1. Behaviour in models

An analysis of those papers incorporating behaviour in models reveals a wide coverage of OR/MS methods and approaches that have been utilised to achieve the desired behavioural functionality. These range from capturing patient and staff decision making at an individual level, through to emerging system-wide behaviours and their impact on the dynamics of the health system under study. Papers in this category also span the breadth of decision making levels and functional areas, indicating their appropriateness and usefulness for a wide consideration of healthcare modelling projects, although by far the most common theme in this category were behaviors captured using simulation for service delivery problems. This is not so surprising given simulation is arguably more conducive for capturing behaviour (such as agent based and discrete event for individuals, and system dynamics for feedback and system-wide behaviours) and given a strong focus of OR/MS healthcare modelling literature exploring service delivery problems (Brailsford et al, 2009, Hulshof et al, 2012). Some examples of papers, primarily selected with the intention to highlight different methods, are described below.

DES has a long tradition on representing operations in healthcare models with a particular consideration of human behaviours (paper 81). In our selection of papers, DES has been employed for the patient journey (paper 17) and use of hospital units (paper 31, 115). In more detail, paper (25) considers DES for identifying service locations and their impact on healthcare quality. Taking as a case study musculoskeletal physiotherapy services, the authors develop a discrete event simulation (DES) with embedded heuristics to model patient behaviour. The combined DES-heuristic approach provides an effective mechanism for incorporating the individuality of the patients in the flows along the patient pathways, subject to the varying availabilities of key resources. In particular, it captures the feedback that is critical in system performance, especially where waiting times are important. The authors demonstrate that the behaviour of a relatively small proportion of patients can affect the experience of all, and thus highlights the need for behavioural considerations when planning healthcare service locations and delivery of care.

Screening is an area where OR/MS has paid a lot of attention since representing the behaviour of patients is critical for national policies (papers 28, 72, 81, 86, 87, 91). In most cases, the OR/MS methods were either simulation or mathematical models. For example, mammography is known to be the most effective way of breast cancer detection. Paper (28) evaluates the efficacy of mammography screening guidelines against compliance through the use of a partially observable Markov chain model. The model is able to evaluate a wide range of screening policies based on patients' estimated adherence behaviour, in turn based on age, race, perceptions of breast cancer risk etc. incorporate the risk behaviour of the decision maker and explore how different risk attitudes (risk averse, risk seeking) along with adherence behaviour may affect a policy's efficiency. Markov models were also employed to represent risk behaviour related with hip replacement in paper (101).

Agent-based simulation (ABS) is also used to represent behaviour in OR/MS, e.g. papers (8) and (41), from physicians and patients. Paper (8) evaluates alternative co-payment scenarios for contributing to health systems financing. To meet growing healthcare needs with declining resources, the authors note that decision-makers must identify new ways to avoid reducing the quality of services offered to citizens. A co-payment is when an individual seeking service may be required to contribute towards the costs. The developed ABS can be used by decision-makers as a decision support tool to compare different co-payment rules and evaluate their impact on the public budget and the health expense of different groups of citizens. The authors capture both physician and patient behaviours using data from Italy on prescription requests including suasion effects by Government policy. Model experimentations are used to provide national policy insights and guidelines on co-payment schemes. In the case of paper (41), the authors used ABS to support their study of patient behaviour in terms of selecting hospitals.

System Dynamics (SD) models have been widely used in healthcare to model population level behaviour in chronic diseases (papers 2, 13, 23, 28, 35), epidemics (paper 97, 107, 111) and patient pathways through services (papers 24, 30, 92). For example, paper (29) develops a SD model to analyse potential innovative approaches and interventions for improving health outcomes in a low-income, urban community. This SD model contributes to the literature by simulating relative intervention effects on community-level chronic disease prevalence. The authors consider feedback and behaviour effects relating to the constructs of income and employment, neighbourhood attractiveness, and social. The study confirms the persistence of rising chronic disease trends in a low-income, urban community, and points to potentially effective 'triple bottom line' interventions, in the social/environmental and economic realms, towards reversing these trends. Their findings support hypotheses that addressing the societal and environmental determinants of health disparities may have a greater impact on population health than attempting to improve health-related behaviours or to increase access to health-care services. The simulated intervention effects can inform public health and urban planners in resource allocation decisions.

Trust in a service provided by any health facility is of vital importance to its sustainability. With a case study on community health centres in North India, as a means of delivering highly accessible, low-cost health service in the developing world, Paper (21) considers the expected level of uptake of services throughout a region and its effect on sustainability of any facility to adi regional healthcare planners. A Monte Carlo simulation is used in modelling the spatio-temporal spread of usage of the service. The behavioural focus is on capturing patient trust in the provider , which is built both through word-of-mouth contacts and previous development activities. The authors demonstrate the use of OR modelling for the dynamic growth of trust and usage in a community clinic as news travels throughout a geographical area, and is used to provide insights and guidelines on designing and implementing sustainable community services.

A usual issue faced by OR/MS modellers is how to capture experts' decision making. One of the methods is fuzzy logic. Paper (16) studies the important life-saving issue of transplantations, focussing on lung transplant allocations in the US. Under the current waiting list strategy in which lungs are allocated to transplant candidates based on their waiting time, the number of deaths on the waiting list has increased dramatically. In order to overcome the drawbacks they observe in the literature, and to develop an effective and efficient expert system to mimic and efficiently replicate the transplant experts' decision making process, their study proposes fuzzy lung allocation system (FLAS). FLAS uses fuzzy logic approaches to capture doctor's behaviours and decision making. The model was shown to mimic the current lung allocation process with a reasonable degree of accuracy and demonstrate that fuzzy rules allows for better human understanding. Another paper that aims to capture experts' decision making processes is multi-criteria decision analysis. Paper (20) discusses the use of multi-criteria decision analysis for the selection of a MRI system through identifying preferences and building consensus on the correct choice.

Mathematical programming is less commonly associated with representing behaviour. However, we found a set of papers representing behaviour in different ways (papers 5, 27 and 34). For example, paper (34) uses integer programming to match patient and physician preferences in designing a primary care facility network, which accounts for the interests of different stakeholders while maximising access to healthcare. The novel feature of the discrete location-allocation model is that it accounts for physicians' and patients' preferences, akin to their behaviours and trade-offs. Using a case study based in Turkey, the authors for example evaluate the trade-off between patients' access-related measures and physician satisfaction. Given the relative importance of these two objectives, the authors suggest the tool could be used by planner to achieve the desired balance between them in planning network services.

In paper (7), the authors note that hospital capacity planning is often studied and optimised in isolation, ignoring the interactions between hospitals. For the case of critical care units (CCUs), where timely access is vital and resources very expensive, they capture the behaviours between two neighbouring CCUs through the development of a generic game theoretical model that accounts for the rational actions of the two units. The game theoretic model is underpinned by a queueing model that takes into account the stochastic nature of queueing systems. The authors conclude that rational behaviour can have a damaging effect on overall patient throughput, thus advocating the need to consider behaviours and interactions between hospitals and decision makers within the wider healthcare system. One of the authors also developed a game theoretic model to represent patient behaviour related with the choice of hospital for treatment (paper 41).

Finally, Social Network Analysis (SNA) is employed in paper 36 for a very different health setting: that of modelling the emerging coordination and knowledge transfer process during a disease outbreak. When multiple agencies respond to a disease outbreak (i.e., H1N1 and SARS), the coordination of actions is complex and evolves over time. Using a case study of an H1N1 outbreak in Australia, the authors reveal that profound understanding of social network behaviour and emerging coordination concepts are pivotal to the optimisation of knowledge transfer process which is a prerequisite for successful outbreak intervention. This paper provides a good example of behavioural modelling for a public health at a national level, and contrasts with the predominant focus in the literature on local service delivery problems.

4.2. Behaviour with models

As can be seen in Figure 2, there are three OR/MS methods, qualitative methods, decision analysis and simulation, which jointly capture more than 80% of all studies related with behaviour with models. This is an intuitive result since most behavioural work addressing the psychological aspects of model implementation related to hard OR modeling has taken place in decision analysis and simulation (Franco and Hamalainen, (2016)), and, of course, qualitative modelling, e.g. soft OR. On the one hand, the distribution across healthcare levels is also quite skewed with almost 60% of the studies referring to the organisational level. On the other hand, the distribution of behavioural studies across functional areas is more uniform with service delivery being an area with relatively high frequency and risk management being one area with low frequency. In this section, we survey a few papers on behaviour with models to highlight how different methods have impacted users decision making as they engaged with OR/MS models. We identified two key themes in this literature.

First, researchers seem to have realised that healthcare practitioners and administrators are suspicious of silver bullets. The users of an OR/MS method are much more likely to accept to models if they are provided not with just a single tool but rather with a toolkit (papers 1, 4, 9, 15, 19, 33, 38, 49, 52, 59, 67, 73). For example, paper (67) discusses the mixing of OR methodologies. More specifically, the authors mixed models for studying patient flow in a pediatric intensive care unit. In the hard OR part of the study a simulation model was built by following the flow of 397 consecutive patients. Outcomes of the patient observation, such as the mean and variance of delays, were then discussed in interviews with nursing staff and subsequently cognitive maps were built (which can also be fed back into the simulation model). This mixed approach resulted in a better understanding of the complexity in the operations so delays would not be reduced by simply increasing beds but rather employing better staffing strategies. Two further studies, papers (1) and (59), corroborated this conclusion in broader contexts. Both studies use system dynamics as a base and integrate soft(er) components into it. Paper (59) had an empirical focus like paper (67) and in fact studied the same problem of understanding and improving patient flow. In a comprehensive project initiated by the UK Department of Health's Services Division, the project in paper (59) started with hospital site visits and interviews with NHS staff. They built dynamics maps at the core and system level. The map development also involved five senior staff and it involved a rigorous iterative process: the initial maps served as input to workshops with NHS staff which led to the revision of the maps and finally to the design of intervention themes through a better understanding of the complexity in patient flows. Paper (1) had a conceptual focus, performed a literature review and made recommendations for healthcare research. They argued the introduction of soft systems methodology into the system dynamics approach during the problem formulation stage to facilitate the interaction with stakeholders. Papers (4, 9, 33, 49) also promoted the use of soft systems methodology with discrete event modelling as a way of facilitating problem formulation. Papers (38, 51 and 73) discuss the usage of mostly soft OR methods.

Papers (6) and (18) perform a set of field studies to evaluate the issues related with stakeholder engagement in simulation projects that lead the lack of use of simulation models. In paper (18), the authors found that communication gaps between project modellers and stakeholder groups is the top primary factor contributing the most to the poor stakeholder engagement in healthcare simulation projects, followed by poor management support, clinician's high workload and failure in producing tangible and quick results. In paper (6), the author propose 15 key performance indicators to represent the level of successful delivery of a simulation project. The authors of this paper performed an interesting review of the literature on evaluating challenges, success and failure factors in simulation projects and they suggested most studies only present qualitative evidence so their proposal for using key performance indicators. However, simulation projects may not be simple to measure given the extensive implications in the broad organisation or over long periods.

Second, some studies consider the ways in which OR models can provide insight to their users. One direction of this work emphasises the benefits of simple models (Katsikopoulos, Durbach and Stewart, 2017). It is noteworthy that both themes are also central in the approach of psychological heuristics to the study of behaviour with models (Katsikopoulos, (2016)). Paper (73) also highlight how simple models can help clarify the reasons for stakeholder conflict. Among ways of fostering user insight through OR modeling, simplicity is a second main theme of this section, which was observed in papers (69, 98). We next discuss two studies that explore the role of simplicity in behaviour with models. Paper (98) worked with the outpatients department of an NHS hospital. The goal was to reduce unexpected patient no-shows. The authors put premium on the fact that the practitioners group wanted models that were transparent, easy to use (and yet realistic).The authors delivered what they call ‘simple rules’, as for example a flowchart expressing logically the steps governing a patient’s arrival, processing, and departure. It should be noted that such simple rules have similar form to that of some of the psychological heuristics discussed previously. Of course eventually these simple rules morphed and were combined into more complicated visual models. Paper (69) present an engaging and informed view of the reasons why NHS staff are often interested in simple messages and rules. Starting from a previous simulation analysis of bed occupancy, they built a convincing case for the use of simple mathematical models. For example, they discussed how a very simple moving-average model for forecasting bed occupancy could enable anticipatory planning in hospitals.

The studies we have reviewed in this section investigated the use of models through qualitative research methods. We end the section by discussing a study which used the quantitative methods of controlled experimentation in the lab and inferential statistics for data analysis to understand how users engage with models. Paper (77) tested if providing simulation output would lead to insight for why the NHS 111 telephone service for non-emergency healthcare is not achieving its targets. The experimental participants were undergraduate students and some of them were presented with the animation of a simulation model, others with the statistical results of the same model, whereas the control group of the participants was provided with no simulation output. There was a small (statistically significant) effect of presenting the statistical results from the model but not of presenting the animation.

4.3. Behaviour beyond models

Similarly to the two previous areas, most of the work concentrates in organisational level, usually the impact of OR/MS methods and outputs on organisational changes associated with the delivery of health services. It is clear there is a strong use of qualitative methods in this area given the strong engagement with stakeholders during the development of the models that generate organisational learning. In this section, we discuss the main aspects identified in the set of papers categorised as “behaviour beyond models”.

Most evidence of behaviour beyond models come from longitudinal accounts of the use of OR/MS methods in specific organisations. One of the examples is paper (94). In this article, members of an OR group inside the Department of Health in England described their work spanning five years using System Dynamics modelling. The impact of models were observed mostly in the development of government policies to achieve political targets. Models offered confidence to policymakers in the achievement of targets through the evaluation of alternative values. One interesting insight is the context for the use of this type of model. The authors claimed they had political support and it seemed to have been an important factor impacting the behaviour of policymakers. Although it was not measured directly, the authors claimed that users made changes on the policy based on the results obtained from the model and they categorised the models as ‘useful tools’ for learning. Some interesting dimensions of models affecting their usefulness for policymakers discussed were: model size and complexity could affect the dynamics of the discussion with users and subsequent behaviour; and the software interface could preclude working directly with the decision maker affecting their trust on the results. Similar dimensions were highlighted by (104). Another example is paper (129). This article was written by a practitioner working in a health authority and provided an inside perspective on the impact of models on behaviour. The author suggest most impact beyond the model is observed when models are not sophisticated and produced as needed. Another important dimension impacting behaviour is by building confidence at a personal level between the OR/MS analyst and the users. Paper (76) provided a similar comment on how modelling was perceived as a scientific practice rather than helping the decision makers commit to a course of action before there is sufficient evidence.

The OR field has not adopted theories and approaches to explain how the interaction between modellers and decision makers in organisations leads to changes in their behaviour but the knowledge management literature provides some useful examples. For example, (47) used collaboration literature to understand the challenges and shortcomings of the interactions between researchers and decision makers and propose a set of indicators based on critical dimensions of the collaboration such as communication, collaborative process, and dissemination of the results. For example, communication indicators should include: clarity, relevance and timeliness of the communication in a project; collaborative process indicators should consider: joint meetings at every stage and discussion on dissemination plans during projects; and indicators related with the dissemination of the results should encompass: multiple type of reporting formats, diverse languages according to audience, inclusion of recommendations for actions, simplicity and conciseness of the reports. These measures can be included as part of OR projects to achieve impact beyond the development of a model and the results obtained.

In many OR models, there is an implicit consideration that the design of the solutions originated from an OR model should involve standardisation of processes and decision rules. However, standardisation can substantially affect the implementation of the solution and reducing the change of behaviour beyond the model due to the resistance originated from the users of the solution. Information systems literature provides useful examples of research on the impact on behaviour of Information technology solutions, which a common way of generating change in many organisations. (53) discussed the behavioural responses to standardisation that would require a process of stabilisation and closure through negotiations with users. In (53), the process of negotiation for the implementation of a standard template for health data capture was associated to the production of a boundary object. (53) defined boundary object as a stable structure subject to interpretation and different meanings depending on the context. Another important insight from this work was the longitudinal approach to data collection that involved workshops, observations of practices and interviews during the implementation of the solution. (55) employed Actor-Network Theory (ANT) to explore issues of implementation of IT systems. (58) evaluated the impact of institutional factors on process of standardising. (54) applied Adaptive structuration theory (AST) to identify the *spirit,* which is related to how people act when using a system and interpreting its features, in information technology applications to help HIV prevention. In conclusion, OR practitioners need to understand the impact of the solutions on the working environment, e.g. the standardisation processes, to be able to generate change beyond the model. There are a plethora of theories applied in Information systems that can be suitable.

Another aspect affecting behaviour beyond the model is the implementation of easy-to-use versions of sophisticated models. (102) described the process of transforming a model from a communication tool into a tool to set and achieve targets while it was implemented in a spreadsheet. (35) provided a description of transforming a model into a management flight simulator and its use in a workshop with policy makers to define policies for changing prescription reimbursement. The literature does not have many explanation of these activities in healthcare.

One of the main areas in OR that explore the behaviour beyond the model is soft OR. In paper (84), the author reflected on issues that affected the implementation of a Soft Systems Methodology project and defined four different quadrants to evaluate the impact on behaviour beyond a model. The author concluded the project failed due to a failure on the translation and transmission of ideas from the representatives of the stakeholders in the project to their respective groups due to communication issues, level of engagement and cultural dissimilarities in reaching consensus. In paper (59), there is an account on how a model was used in three workshops to elicit ideas for improvement which were employed by the Department of Health for defining the work of a modernisation programme. Among the drivers of favouring the impact of the model in the organisation, the authors suggested: interest in the client of experimenting with the modelling method and the need for modernisation in the organisation together with a balance between content and process aspects of the project such as language employed, format of the graphics, clear structure of the workshops with enough communication to the participants.

5. Discussion: Key insights for the application of BOR in healthcare

It was a nice surprise to find out a good number of papers accounting for behavioural aspects in models within a widespread set of OR methods, although in many cases the author(s) did not make formal reference to BOR. However, there is a strong preference for OR methods that have enough of a flexible and rich structure to incorporate behaviour, such as simulation and problem structuring methods, and are also naturally interactive with stakeholders, such as again simulation and problem structuring methods. It is important that some of the more mathematical methods, e.g. linear programming or queuing models, also consider behavioural issues and explicitly account for them in their projects and papers. This is an area where behaviour in operations management has been working for a while. For example, Boudreau et al. (2003) offered a list of behavioral assumptions considered in OR models such as people do not influence the performance observed, are predictable in their actions, independent and observable.

Our findings suggest that users of OR methods are much more likely to accept to use models if they are provided not with just a single tool, but rather with a toolkit that facilitate their understanding of complexity. Sachdeva, Williams and Quigley (2007) note that acceptance of OR results has not been as forthcoming in the US since the application of OR in the US typically involves hard OR modeling and the mathematical language used, as well as a perceived over-precision, seems to lead to a lack of acceptance by stakeholders such as physicians. They argue thus that combining hard OR with soft OR might increase acceptance in the US, and one can also make similar arguments for worldwide adoption of models.

Another possible aspect to explore in terms of improvement of user behaviour with models is how simple models, such as moving average for forecasting bed occupancy, can enable better decision making. These ideas resonate with recent trends in the use of simple mathematical models for different strands of decision making--inference and classification, multi-attribute and multi-criteria choice, as well as forecasting (Katsikopoulos, Durbach and Stewart, 2017).

Most studies investigated human behaviour by using qualitative research methods. Experimentation with models is not a new field (for a summary on SD see Gary et al, 2008) but it is not widely document in articles in the field OR in health. However, there is evidence of large scale experimentation with models, management gaming, such as the Kings Fund activity called “Windmill 2007” (Liddell and McMahon, 2006)*. The work of Gogi, Tako and Robinson (2016) offers a glimpse into this area but these findings need replication, ideally with non-students as participants. Still, in our opinion, such experimental studies are a promising dimension of behavioural OR work and we hope to see more of them in the future.

In many cases, there is no direct measurements of users making changes on their behaviours based on the results obtained from a model nor surveys with their opinions about the models, e.g. do they find models as 'useful tools' for learning? It is clear that some dimensions of OR models can be affecting their usefulness for users which can be further investigated within the context of healthcare, e.g. model size and complexity and the software interface. Some measures of the impact on behaviour were observed in terms of the adoption of language and symbols, accounts of positive feedback from participants to their managers who were part of the steering committee, additional projects using the same modelling method, usage of the improvement ideas on future actions such as changes in layout and capital investment. However, more systematic collection of data and accounting of it in the papers is necessary.

From these observations, it emerges that models can impact on behaviour when they are understood and developed within an expected time while the modellers have established confidence by interacting with decision makers during the process. In other words, it is not the precision in technical terms of model as the main factor affecting the behaviour beyond the model, but the timeliness of its results. The OR field has not adopted theories and approaches to explain how the interaction between modellers and decision makers in organisations leads to changes in their behaviour, but the knowledge management literature provides some useful examples.

This paper has two main limitations. Firstly, the selection of papers through the use of keywords did not capture other relevant papers. Secondly, the field of BOR is still emergent without strong established theoretical frameworks to define the three areas of study so the authors may have associated certain papers incorrectly. For example, behaviour with models imply behavioural changes that are mostly at individual level, such as changes in heuristics or cognition, but these changes can definitively influence the behaviour of the organisation, e.g. institutionalising some approaches to decision making, so behaviour with models may become behaviour beyond models.

6. Conclusions

This paper presents a review of the literature describing application of OR/MS in healthcare that contains behavioural aspects related with the use of models, their impact on organisations, and the representation of patients and physicians. Even though it is still an emerging area in OR/MS, we observed that more than a third of the papers in our search contained some behavioural aspect, even if in many cases the author(s) did not acknowledge as such. However, one might advocate that almost all applications of OR/MS should consider behavioural aspects given the core of practice is still determined or influenced by human behaviour. Therefore, it is important that future work makes more explicit the assumptions used to represent behaviour, test the sensitivity of models to different behavioural assumptions, and offer more information about how users employ models to make decisions. Finally, the relevance of OR/MS in healthcare is associated with the impact on healthcare organisations, the area of behaviour beyond models, but collecting data to understand the impact and evaluating it will imply adopting new theories, e.g. organisational learning, and considering studies, e.g. longitudinal studies, beyond the simple development of a model.

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8. Appendix - 3611 words

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