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Developing agent-based models of complex health behaviour

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ABSTRACT

Managing non-communicable diseases requires policy makers to adopt a whole systems perspective that adequately represents the complex causal architecture of human behaviour. Agent-based modelling is a computational method to understand the behaviour of complex systems by simulating the actions of entities within the system, including the way these individuals influence and are influenced by their physical and social environment. The potential benefits of this method have led to several calls for greater use in public health research. We discuss three challenges facing potential modellers: model specification, obtaining required data, and developing good practices. We also present steps to assist researchers to meet these challenges and implement their agent-based model.

1. Introduction

Agent-based modelling (ABM) is a computational method that simulates individuals making decisions according to programmable rules. Those rules are set by the modeller to represent key elements of the real world decisions, including the individuals' own characteristics and their social and physical environment (Bonabeau, 2002; Epstein, 2006; Gilbert, 2008; Railsback and Grimm, 2011). This makes it particularly valuable where place is an important factor in behaviour. There have been several calls for greater use of ABM to understand public health issues and to formulate and evaluate plans to address them (including Auchincloss and Diez Roux, 2008; El-Sayed et al., 2012; Chalabi and Lorenc, 2013). These calls are consistent with broader encouragement of a complex systems perspective of public health issues (Luke and Stamatakis, 2012; Academy of Medical Sciences, 2016; Rutter et al., 2017).

This paper is aimed at public health researchers who have been persuaded by these calls to action and are considering their next steps. It is intended to assist potential modellers to assess whether ABM is a viable and useful method for their research question and set them on an appropriate path if the answer is 'yes'.

We start by describing relevant features of ABM, emphasising the particular way of thinking that is embodied in the method and the benefits of that framing. The paper then discusses three challenges that are particularly salient for public health researchers who wish to represent human behaviour in ABMs, such as researchers interested in non-communicable diseases, and how these challenges might be overcome. These challenges are: appropriately representing behaviour mechanisms, obtaining data to calibrate those mechanisms and validate the model, and developing the skills to undertake and report ABM based research.

2. Agent-based modelling: what and why?

Many issues in public health are complex; that is, behaviour of the system arises partly from interactions rather than simply the characteristics of the individuals within the system (Luke and Stamatakis, 2012; Rutter et al., 2017). Complex interactions can be conceptualised as social processes such as social influence and social support (Berkman et al., 2000), and as place effects such as air quality and transport availability (Macintyre et al., 2002). Complex systems also involve interactions through time, where actions in the past affect the future decision making context; for example the feedback cycle (presented in Rutter et al., 2017) where a smoking ban in public areas reduces the visibility of smoking, which reduces uptake and hence future visibility.

Models are used to help understand, interpret and forecast system

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behaviour. However, traditional modelling methods focus on individuals rather than their interactions and are therefore not well suited to understanding complex systems or characterising their future behaviour (Smith and Conrey, 2007; Resnicow and Page, 2008; Luke and Stamatakis, 2012; Rutter et al., 2017). Even systems with simple entities and interactions can lead to behaviour that cannot be understood and analysed from the assumption of independent individuals. Instead, complex systems methods such as system dynamics, social network analysis and agent-based modelling explicitly model interactions, directly representing some theoretical understanding of their real world existence and effects (Gilbert and Troitzsch, 2005; Luke and Stamatakis, 2012; Badham, 2014; Sayama, 2015).

In an ABM, simulated individuals make decisions according to programmed rules. What is distinctive about ABM is that the representation is agent-centric (to use the terminology of Wilensky and Rand, 2015): the rules represent the process or mechanism by which the simulated individuals make their decisions, including their personal characteristics and the social and physical environment. That is, causation is expressed directly in model rules as 'I, the agent, have certain characteristics and beliefs of my own as well as information about the world around me, and therefore will do some action' (see examples below). Those actions may affect the agent's characteristics (such as adopting some behaviour) and may also influence the agent's environment, for example by consuming resources.

Agent-centric representation allows ABM to deal with interaction and change because the behaviour of the system is generated by (or emerges from) the actions of the simulated individuals and is measured from the simulation output (Gilbert, 2008; Chalabi and Lorenc, 2013; Spruijt-Metz et al., 2015). The model is 'run' by stepping through simulated time with agents remaking their decisions. Both agent-agent and agent-environment interactions are expressed in the rules. Agents adapt over time by changing their decisions as the situation around them changes. Heterogeneity is also accommodated, as the same agent in different situations can make different decisions, and different agents in the same situation can make different decisions.

ABMs therefore allow potentially greater fidelity between the complex system being modelled and the model. In turn, this fidelity supports extrapolation from model behaviour to real world system behaviour, which allows insights from the model to be used to understand the system and compare policy options.

In public health, ABM is particularly suited to infectious disease epidemiology, where interactions between individuals are a key driver of system behaviour and the transmission mechanisms are relatively well understood. There are several large, established ABM epidemic models to project epidemic impact under hypothetical outbreak control options (Eubank et al., 2004; Van den Broeck et al., 2011; Grefenstette et al., 2013). There are also detailed models of specific diseases in specific locations (Hunter et al., 2017).

In contrast, there is limited use of ABM in non-communicable disease research. A recent review (Nianogo and Arah, 2015) identified only 22 studies. Furthermore, six of these studies simply use the language and tools of ABM to conduct simulations of independent, individual-based processes (such as disease progression) over a heterogeneous population, but do not include interactions. Such use of ABM is outside the scope of this paper as the systems being modelled are not complex and other methods are available, such as microsimulation or Markov models (Weinstein et al., 2003).

This difference in activity raises the question as to why ABM is not more popular in non-communicable disease research, particularly since the social and physical environments are known to influence many health behaviours (Macintyre et al., 2002). In this paper, we argue that there are three salient challenges in ABM for the potential modeller of non-communicable diseases.

We first describe two public health ABMs, to clarify the benefits of the perspective provided by this method and to assist with the discussion of challenges. These examples were selected primarily because of the published level of detail about agents' decision rules and source data. Both models focus on human behaviour, but in different public health contexts (active travel and protective behaviour). Both also explicitly model place, and the spatial factors influence the behaviour of the agents. In addition, the models have different purposes and hence level of detail in their representation of real-world behaviour.

2.1. Two example agent-based models

The ABM by Yang and Diez-Roux (2013) simulates decisions about whether children will walk to school based on perceived safety and the distance to be walked (see Box 1 for summary). The model objective is to generate hypotheses for later research. Consistent with the objective of plausibility rather than realism, much of the model design has an

Box 1
Key features of the walking to school ABM by Yang and Diez-Roux (2013).

Example ABM: Walking to school

Modelled process: Households making decisions about whether their child should walk to school.

Purpose: To generate hypotheses for later research, particularly concerning safety interventions and school placement.

Reference: Yang and Diez-Roux (2013)

Process specification: Agents take into account the household's attitude toward walking to school and two barriers of known importance: perceived safety and distance to school. This is expressed in two conditions (adapted from Eqs. 1–4 of Yang and Diez-Roux, 2013). Whether the child is willing to walk (Eq. (1)) combines the child's attitude (A) and the distance to be travelled (d, with a decay parameter β). Whether the child's household allows the child to walk (Eq. (2)) assesses whether there are sufficient walkers (W) on the path that the child would take to satisfy the concern (C) of the child's household about safety. If both conditions are met, the child walks.

$$A + e^{-\beta d} > 1 \tag{1}$$

$$\text{mean over route}(1 - W^{-0.6}) > C \tag{2}$$

Agent characteristics: Attitude and concern level are personal attributes of the agents. Concern is fixed over time. Attitude changes in response to changes in the total number of children walking, which provides a 'safety in numbers' feedback cycle over time; more walkers increases attitudes and safety, which both tend to increase the number of walkers. The physical environment influence is expressed through the distance element. The social environment is represented through the number of walkers on the specific route to be taken by the child.

Calibration: Attitude and concern level are randomly drawn from an arbitrary uniform distribution for each household. Some parameters were set from theory; $W^{-0.6}$ is the probability of a pedestrian-car collision from prior research. Other parameter values were assigned to give the best fit between model estimates of the proportion of children walking different distances and travel survey data.

Validation: Quality of the fit concerning proportion of children walking by distance and travel survey data.