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Nine challenges in incorporating the dynamics of behaviour in infectious diseases models

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ABSTRACT

Traditionally, the spread of infectious diseases in human populations has been modelled with static parameters. These parameters, however, can change when individuals change their behaviour. If these changes are themselves influenced by the disease dynamics, there is scope for mechanistic models of behaviour to improve our understanding of this interaction. Here, we present challenges in modelling changes in behaviour relating to disease dynamics, specifically: how to incorporate behavioural changes in models of infectious disease dynamics, how to inform measurement of relevant behaviour to parameterise such models, and how to determine the impact of behavioural changes on observed disease dynamics.

Introduction

Human behaviour may be influenced by a myriad of factors ranging from media to person-to-person communication. The behavioural response towards an infectious disease (e.g., whether to get vaccinated, or whether to stay at home during an epidemic) is shaped by a combination of these influences, and how people evaluate them with respect to the alternatives. Additionally, behavioural responses are influenced by various factors, such as religious or cultural beliefs and norms, that can be clustered both spatially and socially. Even within social groups, there is individual-level variability, and responses are constrained by our personal circumstances. For example, people may be asked or feel obliged to turn up for work irrespective of whether they feel at risk of infection.

The interrelationship between the spread of an infectious disease and the behaviour towards it is subject to a number of dynamic feedbacks. Specifically, an outbreak of an infectious disease can trigger behavioural responses, which in turn can affect the course of the epidemic. Mathematical models provide an invaluable tool to study such feedbacks. Yet, behavioural dynamics have, until recently, rarely been incorporated in models of infectious disease dynamics. Taking into account individual behavioural heterogeneities and shifts in such models can be important because (1) predictions may be unreliable if they fail to take into account behavioural dynamics and (2) most policies target individual-level behaviour and not macro-scale dynamics.

To formulate models in which infectious disease dynamics and behaviour are interdependent, we need to understand the mechanisms behind any mutual influence. To what extent do people themselves, their social "networks", media opinion leaders, or health care providers affect individual behaviour? And how are the perceptions that determine behaviour influenced by properties of an infection, such as its prevalence or severity? There are often several ways of interpreting the same influence; in the case of disease prevalence, for example, people could respond to current prevalence, recent prevalence, or historical prevalence. Disease severity also affects behaviour (Sadique et al., 2013), but the relationship is not necessarily straight-forward: different responses will be prompted by a disease that infects 50% of a population and kills 1% of those infected versus an infection that infects only 0.5% but kills

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them all. Lastly, knowing that "No man is an island, . . .any man's death diminishes me, because I am involved in mankind," people might be aware of external risks, but are not necessarily good at estimating their chance of occurring.

The following challenges relate to the overarching questions of how to incorporate behavioural changes in models of infectious disease dynamics. We do not aim to provide a new perspective or comprehensive review on these topics, which can be found in numerous recent works (Ferguson, 2007; Funk et al., 2010; Bauch and Galvani, 2013; Manfredi and d'Onofrio, 2013). Instead, our goal is to summarise some open questions and challenges in the field that are an important focus of immediate research, and that we hope will serve as an entry point for those interested in getting involved.

1. Set the baseline and determine the effect of departing from it

A key challenge underlying many of the points addressed in this paper is to set an appropriate baseline of behaviour. Two important "baseline" behaviours stand out, one related to mixing, that is how people go about activities of daily life that involve some risk of infection (e.g., going to school, or having sex) and the other related to disease prevention and control. The contact baseline, or the "normal mixing" behaviour, can be disrupted by an epidemic through a number of mechanisms. For example, individuals can choose to change their behaviour in an attempt to reduce their risk (Auld, 2003), or their behaviour can be influenced by the nature of being ill (Lloyd-Smith et al., 2004; Van Kerckhove et al., 2013), both of which affect contact patterns. The other relevant "baseline" refers to people's inherent willingness to partake in preventative behaviours; most people, for example, follow official recommendations and have their children vaccinated.

A "baseline" or equilibrium might be attained through game theoretic analysis (Gersovitz, 2013; Geoffard and Philipson, 1997) under the assumption that people make rational decisions by weighing up the private benefits and costs of different options, yielding a certain fraction of the population seeking vaccination, or adopting safe sex. In the absence of data on such "baseline" behaviour, the theoretical equilibrium can provide a useful starting point. This can then be disrupted by some event, such as the Measles–mumps–rubella (MMR) scandal in the United Kingdom. How exactly and under which circumstances such disruptions manifest themselves is an open research question, and one that can only be answered by relating game-theoretical or other modelling approaches more closely with independent observations of behaviour.

2. Assess how and to what extent behaviour should be modelled explicitly

During model development, an investigator must decide whether to treat a given quantity as a dynamic one which evolves in response to other quantities (a model "variable"), or as a fixed value that is exogenously imposed by the modeller (a model "parameter"). Traditional epidemic models account for behaviour implicitly through parameters such as the basic reproduction number. In contrast, modelling the dynamics of behaviour towards infectious diseases requires endogenising behaviour by making it a model variable. However, this leaves questions about which aspects of behaviour should be endogenised, and which should remain as model parameters. This is more than just a technical decision, because it has implications for how we understand and interpret behavioural dynamics. A relevant question is: To what extent is vaccination behaviour determined by response to disease dynamics, and to what extent is it determined by vaccine availability and social norms? In other words, to what extent are vaccine scares historical accidents (exogenous treatment), and to what extent are they enabled by the inherent instability of high vaccine coverage caused by vaccine-generated herd immunity (endogenous treatment)?

Intuitively, if behaviour depends on quantities that change rapidly, such as disease dynamics in a fast-expanding outbreak, then behaviour should probably be represented endogenously. If behaviour depends on quantities that change more slowly, such as social norms or vaccine supply, then it might be possible to represent behaviour through a model parameter. Which of the two scenarios applies, however, also depends on the timescales considered, as social norms and vaccine supply do evolve, yet over long periods. The question of whichever approach is most appropriate in a given scenario can be addressed more rigorously by formulating a collection of variant models where different aspects of behaviour are treated as variables or parameters, and then using model selection methods to determine which variant model best explains the data.

3. Determine the minimal level of detail required to model differences in behaviour

How much psychological detail is required for models to be able to capture the dynamics of population-level behaviour? There are many different models of health-related behaviour in psychology, but for epidemiological purposes a crude understanding of the major drivers and their relative strength is probably sufficient. In the same way that thermodynamic laws are not formulated to depend on the details of molecular-level dynamics, can we model population-level behaviour in a simple, aggregate way without explicit reference to individual-level dynamics?

The key challenge then becomes heterogeneity. How well does the simple model work for everybody? Are there identifiable groups whose response is predictably different, and how important are they epidemiologically? Is there a "landscape" of predispositions to certain behaviours (i.e., will some people be more inclined to follow official guidelines than others)? If yes, do people fall into discrete groups or is that landscape continuous? For example, are risk-averse versus risk-seeking tendencies bimodal, or distributed across a more continuous distribution? How do individuals perceive risks of both infection and adverse effects from control measures and how does the perception of risk change with disease prevalence in the population?

Many of these questions have been studied in econometrics (Gersovitz, 2013), but it remains an open challenge to translate these insights into mechanistic models of infectious disease dynamics. Exploring these questions in mechanistic models and testing different scenarios could yield the limits as well as strengths of "simpler" models, as well as suggest appropriate studies (e.g., through population surveys) that would directly inform model parameters.

4. Quantify changes in reporting behaviour

Data used to track an epidemic typically rely on reporting by individual doctors or hospitals, and therefore depend on how many people seek medical care, how likely doctors are to identify a case correctly, and how likely they are to report it. How does people's health-seeking behaviour change during the course of an outbreak? The propensity to visit a doctor is likely to depend on levels of concern and on public health messages, both of which are subject to change as an outbreak progresses. Evidence from the 2009 flu pandemic in the UK suggested that individuals' likelihood of