Antibiotic Prescribing Decision-making Processes in Secondary Care: 
a System Dynamics Approach

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For dad and mum.


Declaration

I declare that this thesis for examination of the PhD degree for Imperial College London is solely my own work, other than where I have clearly referenced the work of others.

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Nina Jiayue Zhu
Abstract

Introduction

To tackle antimicrobial resistance, strategies to reduce inappropriate consumption of antibiotics have been implemented in health systems in the UK. In secondary care, behavioural antimicrobial stewardship (AMS) interventions have had limited effect in optimising doctors’ antibiotic prescribing practices as reflected in the observed deviation from prescribing guidelines. A powerful analytical tool is required to capture the determinants of antibiotic prescribing decision-making within the complexity of the health system to inform intervention design and allow subsequent impact evaluation.

Methods

A System Dynamics (SD) model was constructed to enable the simulation of antibiotic prescribing decision-making processes in English hospitals. Literature review, secondary analysis of patient records, healthcare professional interviews and survey responses provided the data from SD model development. A qualitative SD model was formulated and validated through a series of tests to ensure the credibility of the model to simulate doctors’ behaviours under different scenarios. Computer-based simulations were performed to predict doctors’ prescribing outcomes measured by the level of guideline compliance.
Results

Maximal improvement in doctors’ guideline compliance at empiric stage could be achieved if senior doctors’ guideline compliance was increased, combined with the microbiology laboratory turnaround time of blood cultures within 24 hours. At review stage, doctors’ decision-making could be enhanced if more opportunities for specialist microbiology input were provided. Improving guideline compliance in junior doctors alone had limited impact on overall prescribing outcomes.

Conclusions

SD modelling enables capture of causal mechanisms and prediction of prescribing outcomes by transparent qualitative mapping and quantitative simulation of complex, dynamic prescribing decision-making processes. SD acknowledges that doctors’ sub-optimal antibiotic prescribing is a feature of bounded rationality compounded by multiple contextual interacting influences. AMS interventions can be re-designed for maximum effect with minimal additional resources, if the most influential healthcare professionals and the most critical events in the prescribing decision-making processes are targeted.

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Abbreviations

AMR – antimicrobial resistance

AMS – antimicrobial stewardship

WHO -World Health Organisation

NHS – National Health Service

PHE – Public Health England

GDP - Gross Domestic Product

UK – United Kingdom

USA – United States of America

SD – System Dynamics

CLD – causal loop diagram

SFD – stock and flow diagram

DES – discrete-event simulation

ABM – agent-based modelling
Chapter 1 Introduction

The Introduction chapter sets the background and the scope of this study. The chapter provides an overview of the project is provided, including the rationale, the research questions, the methodology employed, and summary of the major findings and contributions. The chapter also lays out the organisation of the thesis.

1.1 Thesis overview

Research into the determinants of antimicrobial prescribing decision-making is required for the design, adoption and implementation of interventions, which can help optimise prescribers’ behaviour (Rycroft-Malone et al., 2012). This study provides new insights to better understand healthcare professionals’ decision-making processes when prescribing antibiotics to treat hospital inpatients in the context of healthcare systems in the UK.

Antimicrobial stewardship (AMS), refers to an organisational approach to promote prudent use of antibiotic drugs, and has been implemented in the UK for over two decades (Dixon & Duncan, 2014). AMS approaches can be broadly described as a) front-end: here influencing and guiding the behaviour of prescribers but relying on prescribers to make the optimal choice; b) back end: whereby structural or systems are altered, limiting choice towards an optimal route (Chapter 2, 2.1.1 Introduction). Examples of AMS interventions
include the development of best practice guidelines, and the availability of such guidelines in different formats to aid adoption among different professional groups (Wyatt et al., 1998; Christ-Crain et al., 2004; Foy et al., 2004; Oosterheert et al., 2005; Ashiru-Oredope et al., 2012).

Understanding prescribing behaviours is instrumental if effective stewardship policies are to be developed and implemented successfully. However, extant research has explored which AMS interventions work, but none have comprehensively analysed what works for whom, in which context and when (Ramsay et al., 2003; Arnold & Straus, 2005; Edeghere, Wilson & Hyde, 2010; Davey et al., 2013; Davey et al., 2017) Hence, approaches to capture interaction between individuals and the policy context are needed and at systems level (rather than just at the individual level), systems which may be defined in terms of a team, a hospital or at the wider health system level. While mixed-method approaches have value in addressing these questions, they are limited in their ability to comprehensively capture the effects of multiple influences or interventions concurrently (Benning et al., 2011). Therefore, a powerful analytical tool is required to investigate prescribers’ behaviours taking into consideration multiple influences and interventions within a structural and cultural context (Ahmad & Holmes, 2018). System Dynamics (SD) modelling was selected for its capability of capturing the dynamic and complex nature of healthcare systems, and the flexibility of incorporating qualitative and quantitative evidence to build a comprehensive view of the system as a whole, which could be then used to test policy
alternatives in simulations. This methodological selection was made after an analysis and comparison with other modelling and simulation methodologies which could be used (Chapter 2, 2.5 Context of the study and the reasons for its selection). An SD model was constructed to simulate prescribing decision-making processes in secondary care and to provide estimates of prescribing behaviour under various scenarios, by incorporating quantitative and qualitative data from multiple sources.

1.1.1 Research context

Antimicrobial resistance (AMR) creates a large burden on healthcare systems and economic systems globally (De Kraker et al., 2010). Antimicrobial resistance is associated with increase in mortality, morbidity, length of hospital stay, and healthcare expenditure in European hospitals (Maragakis, Perencevich, & Cosgrove, 2008; Zarb et al., 2011). A systematic review co-authored by the researcher of this study reported that economic burden caused by AMR ranged from $21,832 per case to over $3 trillion in loss to countries, with adverse consequences for their gross domestic product (GDP) (Naylor et al., 2018). The prevalence and impact of drug resistant infectious individuals are growing worldwide, including bloodstream infections due to Escherichia coli (E. coli) resistant to third-generation cephalosporins are growing (De Kraker, 2010). Inappropriate use of antibiotics, especially broad-spectrum antibiotics, is one of the major drivers for the development of
AMR in bacteria (Harbarth & Samore, 2005; Ashiru-Oredope et al., 2013; Holmes et al., 2016; Laxminarayan et al., 2016; Mendelson et al., 2016). It is a national ambition to reduce United Kingdom (UK) antimicrobial use in humans by 15% by 2024 (The UK’s five-year national action plan: tackling antimicrobial resistance 2019-2024). In England, the government has announced a major focus against resistant bacterial strains in hospitals following an 18% increase in E. coli infection cases from 2012/13 to 2015/16. E. coli infections killed more than 5500 patients in 2015 and are set to cost the National Health Service (NHS) in England £2.3 billion by 2018 (Department of Health Media Centre, 2016). A rise of 33.3% in the proportion of broad spectrum antibiotics/total antibiotics prescribed was observed across NHS Trusts in England since 2010, with marked variations in prescribing between different regions and centres (Buckland, 2016). The English surveillance programme for antimicrobial utilisation and resistance (ESPAUR) report 2017 indicated that there has been a 13% reduction in prescriptions in the past five years. However, in secondary care there has been less progress. It has not had a sustained reduction in total antibiotic prescribing in secondary care. Research focuses on applying behavioural science will help policy makers understand which antimicrobial resistance (AMR) interventions work, where and when. A selection of activities targeted at supporting and equipping professionals have been chosen to improve the professional capacity and capability, including drawing on behavioural and implementation science to ensure guideline adherence. In England, ward-based interventions have been recommended to
improve the operation of infection ward rounds in English hospitals (NHS England: promoting appropriate antimicrobial prescribing in secondary care). These national strategic plan in AMR provided the rationale for this research to apply innovative analytical approach to examine doctors’ prescribing behaviour in secondary care, with focus on the decision-making processes which had direct impact on antibiotic prescribing guideline adherence in medical wards.

A variety of AMS interventions have been developed and adopted with a focus on reducing the consumption of antibiotic drugs in both primary and secondary care (Ramsay et al., 2003; Zarb et al., 2011; Ashiru-Oredope et al., 2012). In the past decade, however, the policy focus has shifted from structural/procedural interventions to behavioural interventions in secondary care in order to optimise antibiotic prescribing and to improve individual patient care, as well as reduce hospital expenditure and halt the development of AMR (Tonkin-Crine, Walker, & Butler, 2015). Behaviour-altering AMS interventions include education programmes and strategies using prescribing guidelines (MacDougall & Polk, 2005). In secondary care, behaviour-altering interventions target prescribers (including infectious disease physicians, physicians of other specialties, clinical pharmacists, clinical microbiologists, nurses, infection control staff, and hospital administrators) mainly and aim to improve prescribing practices by changing prescribers’ decision-making, while the ones in primary care target both prescribers and patients (Davey
Earlier published studies have suggested that existing behaviour-altering AMS interventions had limited effectiveness, reflected by non-adherence with prescribing guidelines. In comparison, restrictive interventions, such as limiting or requiring prior authorization when prescribing selected antibiotics, were found more successful in the short term. The effect of voluntary guideline compliance to reinforce appropriate prescribing habits is poor, compared to restrictive interventions (Grimshaw, 2001). However, behaviour-altering interventions were considered to have long-term sustainability (Tonkin-Crine, Walker, & Butler, 2015). While in earlier published studies the challenges to successful and sustained implementation of behaviour-altering AMS interventions and programmes are documented, analysis of how they arise, how they can be addressed, and the interactions of different programmes is missing. Therefore, such an analysis is needed to inform the selection of policy alternatives and shape an optimal ‘mix’ of interventions. To effectively use limited resources for maximal impact on patient outcomes, it is crucial to identify the key determinants of prescribing behaviour. Hence, further investigation on antibiotic prescribing decision-making processes is required. Different factors are likely to influence prescribing practices in secondary care, and therefore in turn influence health outcomes, motivating the employment of new research methodologies in the research area of AMR/AMS and prescribing management.
1.1.2 Research need & knowledge gap

Extant research, which has studied prescribers’ behaviour change, has compared the effectiveness of different behaviour change strategies. This body of research has suggested that active, personalised interventions are more effective than passive dissemination of information. For example, academic detailing (face-to-face individualised educational outreach) was found to improve guideline compliance level than provision of printed educational materials (MacDougall, 2005). Qualitative studies have described the impact of behavioural determinants and etiquette on prescribing. The cultural determinant of ‘non-interference’ dominates prescribing practice of healthcare professionals and prevent them from interact with their colleagues when prescribing (Charani et al., 2011). Attendance of senior physicians in decision-making was found to have influence on trainees and junior physicians’ prescribing habits (Mol et al., 2004). However, there is still limited knowledge about why certain interventions are more effective than others in influencing prescribing behaviour and how interventions work in synergy or may in fact in opposition to influence prescribing behaviour.

The findings of earlier published studies provided minimal insight into the long-term sustainability and unintended consequences as the methodological approaches employed in these studies lacked ability to predict behaviour in the future. The large gap in extant knowledge has motivated this thesis.
1.1.3 Aim and research question

This study aimed to answer the following over-arching research question:

*How can the multiple and concurrent influences on prescribing decision-making processes in secondary care be captured to provide a model for prediction of intervention effects?*

A systems thinking analytical model was developed to achieve this aim by addressing the following sub questions:

- Which stakeholders are involved in prescribing decisions?
- Which influence factors affect prescribing behaviours?
- From where in the health system do these arise? And when during prescribing decision-making processes?

1.1.4 Methodology

This study was completed using the established protocol for a System Dynamics approach (Sterman, 1992; Martinez-Moyano & Richardson, 2013). Component studies, including a rapid literature review and analysis of data from multiple sources, were carried out concurrently to generate the required empirical data and support the development of the SD model. Overview of the study methods, and the position of the component studies in the thesis are indicated in Figure 1.1.
Figure 1.1 Overview of study methods and chapter arrangement

When describing the modelling process, researchers have organised the main modelling activities using different arrangements, varying from three to seven different stages (Table 1.1). Though the way of grouping the modelling activities varies among the different researchers, the activities considered along the different stages remain fairly constant across them (Luna-Reyes & Andersen, 2003).

In this study, the modelling activities were grouped into six stages: conceptualisation, source data analysis, qualitative mapping, quantitative formulation, validation, and simulation, based on the purpose of each group of activity.
Table 1.1 System Dynamics modelling process described across published literature

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<td>System conceptualisation</td>
<td></td>
<td></td>
<td>Dynamic hypothesis</td>
</tr>
<tr>
<td>Formulation</td>
<td>Model formulation</td>
<td>Model representation</td>
<td>Simulation phase (stage 1)</td>
<td>Formulation</td>
</tr>
<tr>
<td>Testing</td>
<td>Analysis of model behaviour</td>
<td>Model behaviour</td>
<td></td>
<td>Testing</td>
</tr>
<tr>
<td></td>
<td>Model evaluation</td>
<td>Model evaluation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implementation</td>
<td>Policy analysis</td>
<td>Policy analysis and model use</td>
<td>Simulation phase (stage 2)</td>
<td>Policy formulation and evaluation</td>
</tr>
<tr>
<td></td>
<td>Model use</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Through a rapid literature review, factors influencing antibiotic prescribing decision-making were identified. These influence factors were categorised into different levels across healthcare systems using a hierarchical framework. Meanwhile, hospital inpatient data collected for the purpose of this study, as well as secondary data from two other sources in the same broad context was analysed to help enhance understanding of prescribers’ decision-making. Concurrently, a systems thinking analytic tool was built based on the findings from the rapid literature review and data analysis.

Ten steps were employed in the model development. First, a rapid literature was conducted to identify the factors influencing prescribing decision-making processes in the context of secondary care in the UK. The identified influence factors were differentiated as barriers and facilitators to improve prescribing practices, and categorised into individual, organisational, and healthcare system levels based on where they occurred in healthcare
systems and when they affected the prescribing decision-making processes using a hierarchical framework.

Second, a systems thinking analytical tool, namely System Dynamics (SD) modelling, was selected to analyse the identified influence factors and the interconnections among them and to enable simulation of doctors’ antibiotic decision-making processes with influence factors considered.

Third, in order to formulate the SD model, data collection and processing was conducted in parallel with model construction to analyse data from three different sources, including primary data extracted from the hospital inpatient notes of patients with *E. coli* bloodstream infection, secondary data collected from a survey with Foundation Year doctors and in-depth interviews with specialty registrars and consultants.

Fourth, a schematic map was generated to represent the process of doctors prescribing antibiotics to treat hospital inpatients. The schematic map provided the fundamental structure of the SD model. The results of data analysis were synthesized with the findings from the rapid literature review to provide qualitative and quantitative database for the SD model.

Fifth, the SD model was conceptualised by identifying the research questions that needed to be addressed and defining the purpose of the model, supported by the qualitative findings from the rapid literature review and the analysis of the primary and secondary data.

Sixth, after conceptualisation, qualitative mapping of the SD model was performed using
1) a sub-system diagram to set the scene of the system modelled, 2) a model boundary chart to define the boundaries of the model and categorise key variables into excluded, exogenous, and endogenous variables, and 3) causal loop diagrams to capture the causal relationships between key variables included within the system.

Seventh, the model was parameterised using the quantitative data from the three sources. Estimated values were assigned to each model parameter.

Eighth, a series of validation tests were performed at different stages of model development to verify the SD model structure, parameters, and system behaviour simulated by the model.

Ninth, the model was used to simulate prescribing behaviour, assessed by the level of prescribing guideline compliance among doctors at empiric stage and the level of microbiology review after empiric stage under a series of ‘what if’ scenarios singularly and collectively. The ‘what if’ scenarios included the scenarios with shortened microbiology laboratory turnaround time, the scenarios with increased prescribing guideline compliance level among senior and junior doctors, and scenarios with microbiology laboratory test results available for all patients.

Tenth, the results of ‘what if’ scenario simulations were interpreted using the causal loop diagrams of the SD model to determine the most dominate feedback loops at different stages in antibiotic prescribing decision-making processes to inform future intervention design.
1.1.5 Confidentiality

All persons and hospitals involved in this study are kept anonymous in order to maintain the confidentiality of respondents. Full ethics approval was obtained from the National Health Service (NHS) Research Ethics Committee (REC) (reference number 14/LO/2217) to access the hospital inpatient data. The use of the data was approved by NHS/HSC (Health and Social Care) R&D office and NHS REC. All identifiable information was removed for all patients and healthcare professionals after the analysis of the dataset in this study.

1.1.6 Summary of key findings and contribution

A series of factors influencing prescribing decision-making processes on different levels across healthcare systems were found from the rapid literature review. For example, some influencing factors, such as ‘timeliness of delivery of pathogen information’, could not be solely attributed to one level within the health system as it influenced individual prescriber’s behaviour as well as organisational-level work patterns. Further, the hierarchical framework used in published studies only captured the ‘level’ aspects but ignored the ‘system’ aspects of antibiotic prescribing management. After comparing various modelling and simulation approaches, SD was selected for its capability of capturing the dynamic, complex nature of prescribing management in a systematic manner.
Informed by the evidence in published literature and the analysis of the data extracted from hospital inpatient notes, the microbiology laboratory turnaround time and the influence from senior doctors in medical wards were identified as the two factors that showed the strongest impact on prescribing decision-making processes. Thus, the impact on prescribing decision-making processes from these two influencing factors was assessed by performing simulations to predict prescribing outcome measures under a series of ‘what if’ scenarios associated with these two influence factors in the SD model developed as part of this study. The SD model predicted prescribing behaviour quantitatively for scenarios under which either timely diagnostic information was available when 1) microbiology laboratory turnaround time was shortened, or 2) microbiology tests were performed for all patients, or 3) test results were provided for all patient samples. The SD model also predicted doctors’ decision-making when the guideline compliance level among senior doctors (specialty registrars and consultants) was increased with and without influencing doctors with lower seniority. The guideline compliance level improved significantly when the microbiology laboratory turnaround time was shortened to less than 24 hours for all patients to allow specialty registrars and consultants to make empiric decisions based on pathogen information. Such improvement in guideline compliance could also be achieved alternatively by increasing specialty registrars and consultants’ guideline compliance level at empiric stage before the confirmation of a definitive diagnosis was available. The summarised results of ‘what if’ scenario simulations are presented in the table below (Table
1.2).

Table 1.2 Summarised results of ‘what if’ scenario simulations

<table>
<thead>
<tr>
<th>Policy implication</th>
<th>‘What if’ scenario</th>
<th>Simulation result</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Empiric stage</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shortening microbiology laboratory turnaround time</td>
<td>Scenario 1(a): turnaround time shortened to 2 days or less for all patients</td>
<td>Insignificant</td>
</tr>
<tr>
<td></td>
<td>Scenario 1(b): turnaround time shortened to 1 day or less for all patients</td>
<td>Insignificant</td>
</tr>
<tr>
<td></td>
<td>Scenario 1(c): turnaround time shortened to less than 24 hours for all patients</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 93.3%</td>
</tr>
<tr>
<td></td>
<td>Scenario 2(a): all specialty registrars following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 96.8%</td>
</tr>
<tr>
<td></td>
<td>Scenario 2(b): all consultants following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 95.3%</td>
</tr>
<tr>
<td></td>
<td>Scenario 2(c): all specialty registrars and consultants following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.0%</td>
</tr>
<tr>
<td></td>
<td>Scenario 3(a): all specialty registrars following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 96.9%</td>
</tr>
<tr>
<td></td>
<td>Scenario 3(b): all consultants following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 95.2%</td>
</tr>
<tr>
<td></td>
<td>Scenario 3(c): all specialty registrars and consultants following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.3%</td>
</tr>
<tr>
<td></td>
<td>Scenario 4: combined scenario of shortening turnaround time to less than 24 hours and increasing specialty registrars and consultants’ guideline compliance level</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.4%</td>
</tr>
<tr>
<td><strong>Review stage</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Improving microbiology test practices</td>
<td>Scenario 5(a): performing microbiology tests for the patients who were not tested</td>
<td>Percentage of empiric decisions reviewed by microbiologists increased from 78.1% to 88.3%</td>
</tr>
<tr>
<td></td>
<td>Scenario 5(b): reporting results for the microbiology tests with no result</td>
<td>Percentage of empiric decisions reviewed by microbiologists Increased from 78.1% to 78.7%</td>
</tr>
</tbody>
</table>
This study makes an empirical contribution to the literature on antibiotic prescribing behaviour by demonstrating the ‘system’ aspect of prescribing behaviour and providing quantitative measures of the determinants on prescribing decision-making. It is the first study to develop a fully parameterised SD model in this research area. It is also the first study in the field of prescribing behaviour, which has successfully combined different source data, including qualitative and qualitative data, primary and secondary data collected by various methods, when building the SD model in order to build a comprehensive picture of factors influencing prescribing decisions and their interaction, and to simulate how changes in these factors and their interaction could influence prescribing decisions.

Four important concepts in SD modelling, namely feedback loops, stock-and-flow structures, non-linearity and table function, were translated into practice in this study. The SD model developed as part of this thesis has the potential to be further expanded to include patient-related factors influencing prescribing decision-making processes, and could be adapted to represent prescribing decision-making processes by health professionals at different levels of healthcare settings and in different health systems.

This study also made a theoretical contribution by interpreting doctors’ antibiotic prescribing decision-making processes using the theory of ‘bounded rationality’. Unlike previous research in prescribing behaviour, which assumed that doctors were perfectly
rational when making prescribing decisions, my research evidence in literature and primary and secondary source data to demonstrate that antibiotic prescribing decisions were acceptable, rather than optimal, due to doctors’ bounded rationality. SD modelling was employed as an analytical tool to examine prescribing decision-making processes based on the assumption that decision-makers were not rational.

1.2 Thesis organisation

The thesis is organised in 11 chapters. The chapters that follow Chapter 1 are summarised below. The methods and results of influence factor identification and categorisation are discussed in Chapter 2. The concepts of systems thinking approaches and the principles of SD modelling are discussed in Chapter 3. The methods used to develop the SD model are described in Chapter 3, 4, 5, 6, and Chapter 7. The results of SD model simulation are presented in Chapter 8 and discussed in relation to the literature in Chapter 9. The policy implications of this study are provided in Chapter 10. Chapter 11 concludes this study.

Chapter 2 Factors Influencing Prescribing Behaviour

The rapid literature review conducted to identify the factors which influence prescribing decision-making in secondary care in the UK is described in this chapter. The identified influence factors are classified into either barriers or facilitators, based on whether they
had negative or positive impact on improvement of prescribing practices. A hierarchical framework is adopted for the categorisation of the influence factors. A schematic map is developed to represent the process of doctors treating patients with symptoms of bacterial infections and prescribing antibiotics in the context of English hospitals with identified influence factors incorporated. The limitation of the hierarchical framework leads to the comparison of historically used modelling and simulation approaches in UK healthcare systems and exploration of systems thinking analytical tools. This chapter provides knowledge of the contextual environment in which the SD model is built and helped define the boundaries and identify key variables of the SD model.

Chapter 3 Conceptualisation: Systems Thinking Principles in Health Management

Doctors’ antibiotic decision-making processes occurred within complex, dynamic, and multi-level healthcare systems. To date, many behaviour-altering AMS interventions have failed to improve prescribing practices due to a lack of a powerful analytical tool to analyse, predict and inform doctors’ prescribing decision-making which is influenced by multiple factors across healthcare systems. The advantages of using systems thinking approaches and SD modelling in health management issues have been demonstrated in earlier published research. In this chapter, the concepts of systems thinking, the fundamental principles of SD modelling, and the application of SD in health management and AMR management is discussed in relation to the context of UK healthcare systems (the UK has four healthcare systems, namely England, Northern Ireland, Scotland and Wales).
Chapter 4 Methods

The methods of source data processing and SD modelling are introduced in this chapter. Data from three different sources, including a) secondary data from a survey with Foundation Year doctors, b) secondary data from in-depth interviews with specialty registrars and consultants, and c) primary data from hospital inpatient notes of patients with *E. coli* bacteraemia is analysed to provide both qualitative and quantitative information about doctors’ decision-making processes in English hospitals. The model representing the process of doctors prescribing antibiotics to treat hospital inpatients is built using the established guidance for SD model development.

Chapter 5 System Dynamics Model Description: Qualitative Mapping

In this chapter, the SD model is described qualitatively. The scene is set for the system modelled, and the sub-systems included in the system are presented using a sub-system diagram. The boundaries of the model are defined using a model boundary chart to categorise key variables into excluded, exogenous, and endogenous variables. Causal loop diagrams (CLDs) of the model are presented to capture the causal relationships among key variables included within the system.

Chapter 6 System Dynamics Model Description: Simulation Model

In this chapter, a collection of Stock and Flow Diagrams (SFDs) are drawn to connect all the key variables based on the causal relationships captured by the CLDs in the previous chapter. The estimated values are assigned to all model parameters using the quantitative
data extracted from the source data processed in Chapter 4. The parameterised SD model enables computer-based simulation of doctors’ prescribing decision-making processes.

**Chapter 7 Model Validation and Testing**

The SD model goes through a series of validation tests at different stages of model development to verify the credibility of the model and ensure the confidence in simulation results. Tests to verify a) model structure and b) model parameters are discussed in this chapter. The model is able to replicate system behaviour observed in real life. The percentage of empiric decisions in compliance with guidelines was estimated to be 92.9% by the model, which is a valid reflection of the real-life percentage of 91.9%.

**Chapter 8 Analysis of Scenarios and Simulation Results**

After passing the validation tests for model structure and parameters, the model is used to simulate prescribing behaviour under various ‘what if’ scenarios to provide policy options. The outcome measures of interest are the level of guideline compliance among doctors at empiric stage (when a definitive identification of pathogen is not available) and the level of microbiology review after empiric stage.

The simulation is performed for the following ‘what if’ scenarios:

At empiric stage:

- Scenario 1(a): Shortening microbiology laboratory turnaround time so that the all patient samples are processed in less than 3 days;
- Scenario 1(b): Shortening microbiology laboratory turnaround time so that the all
patient samples are processed in less than 2 days;

- Scenario 1(c): Shortening microbiology laboratory turnaround time so that the all patient samples are processed in less than 24 hours;

- Scenario 2(a): Increasing specialty registrars’ guideline compliance level so that all consultants follow prescribing guidelines, while junior doctors are not influenced;

- Scenario 2(b): Increasing consultants’ guideline compliance level so that all consultants follow prescribing guidelines, while junior doctors are not influenced;

- Scenario 2(c): Increasing specialty registrars and consultants’ guideline compliance level so that all specialty registrars and consultants follow prescribing guidelines, while junior doctors are not influenced;

- Scenario 3(a): Increasing specialty registrars’ guideline compliance level so that all consultants follow prescribing guidelines, while junior doctors are influenced;

- Scenario 3(b): Increasing consultants’ guideline compliance level so that all consultants follow prescribing guidelines, while junior doctors are influenced;

- Scenario 3(c): Increasing specialty registrars and consultants’ guideline compliance level so that all specialty registrars and consultants follow prescribing guidelines, while junior doctors are influenced;

- Scenario 4: Combination of the scenario 1(c) and 3(c) which can improve guideline compliance to the maximal degree.

At review stage:
- Scenario 5(a): Performing microbiology test for all patients (including the patients who did not have microbiology tests performed in real life);

- Scenario 5(b): Providing microbiology laboratory test results for all test performed (including the tests with no result reported by the microbiology laboratory in real life).

The simulation results predict change in the level of guideline compliance at empiric stage and level of microbiology review after empiric stage under these scenarios. The simulation results suggest that improvement in guideline compliance at empiric stage can be achieved by shortening microbiology laboratory turnaround time to less than 24 hours for all patients with an increase in percentage of empiric decisions in compliance with guideline from 92.9% to 93.3%. Improvement is also achieved under the scenario when all specialty registrars and consultants followed the guidelines and junior doctors were influenced by specialty registrars and consultants at empiric stage and resulted in an increase in percentage empiric decisions in compliance with guidelines from 92.9% to 99.3%. The maximal increase in guideline compliance level is estimated when the scenario of shortening microbiology laboratory turnaround time and specialty registrars and consultants following the guidelines with junior doctors being influenced were simulated together. Under this combined scenario, the percentage of empiric decisions in compliance with guidelines increases from 92.9% to 99.4%.

After empiric stage, the level of microbiology review is significantly improved under the scenario when microbiology laboratory tests were performed for all patients and all test
results were available in 24 hours. The percentage of empiric decisions reviewed by microbiologists increases from 78.1% to 88.3%.

Chapter 9 Discussion

In this chapter, the major findings of the study are discussed in relation to existing evidence for convergence and divergence and then this leads discussion to the contributions made to extant literatures. The comprehensiveness of the SD approach, as implemented here, is a particular strength of the study. Four of the five important concepts of SD modelling were employed in this study, including feedback loops, stock-and-flow structures, non-linearity, and table functions. The fifth concept, time delays, was not quantitatively simulated, but by including it in the qualitative mapping the model provides the potential for this concept to be incorporated (e.g. individualised feedback on guideline compliance levels), and in the thesis future work to include time delays in the SD model is discussed using CLDs of prescribing decision-making processes.

The four main contributions of this study to the empirical knowledge of prescribing behaviour in secondary care and to methods in its analysis are as follows. First, this study demonstrates that the ‘system’ aspects of prescribing behaviour must be considered if effective behaviour-altering interventions are to be implemented. The factors influencing prescribing decision-making processes arise on different levels across healthcare systems with interconnection and interaction among them. Second, by using SD modelling and
simulation, the study captures the impact of behavioural influence factors quantitatively to inform future policy-making. Threshold effects are estimated for various policy alternatives. Third, this study also makes a contribution to literature on public health and health management through the implementation of SD. Fourth, methodologically, the implementation of SD modelling extends the emergent literature on integrating qualitative and quantitative data to address public health issues and specifically to the crucial area of addressing AMR. This is achieved through multiple data analysis methods during the process of SD model development, including regression analysis and mixed-method data triangulation. The full capabilities of SD modelling have been exploited in this study, including the controversial topics and unresolved debates surrounding the use of qualitative and quantitative data.

There are certain limitations in this study, as with all modelling methods from the assumptions and extent of simplification. Also in this study the main outcome indicator is prescribing decision outcomes and we cannot extend this to consequential patient health outcomes. The scope of future work follows from these, with potential to expand the model boundaries, modify the causality maps to incorporate further influence factors; notably the lag time to behaviour adjustments following interventions.

Chapter 10 Translation and potential impact
The simulation results suggest that by improving senior doctors’ prescribing habits, overall guideline compliance level could be increased within a hospital. However, delayed delivery of laboratory results on the pathogens causing the infection, which causes fear of undertreating infections, has negative impact on senior doctors’ practices. Recommendations are made for future education programmes to target senior doctors by providing individual feedback in prescribing practices and changing the cultural environment in medical wards to reduce fear. Timely delivery of microbiology laboratory test results helps doctors to make decisions in line with prescribing guidelines and create opportunities for microbiologists to provide input at empiric stage. However, if shortening microbiology turnaround is not achievable due to limits in resources, management capability and technology, alternative procedural interventions could be implemented to improve blood sampling practices and prevent sample loss and contamination, so that microbiology test results can be provided for all patients to allow microbiology review and appropriate adjustment of empiric decisions.

**Chapter 11 Conclusion**

The conclusion of the study is presented in this chapter. This study demonstrated the ‘system’ aspects of prescribing behaviour management. The system nature of prescribing must be considered if effective behaviour-altering interventions are to be implemented. A fully parameterised SD model is presented in this study to predict doctors’ prescribing
behaviour and test the impact of factors influencing doctors’ decision-making. This study makes contributions to empirical knowledge and methodology in areas related to AMR management, public health and health management, and also to the literature of System Dynamics and operational research.

In sum, in the Introduction chapter, the context and rationale for this research were presented. The main research questions have been presented, as well as the methodology used to answer these questions. Major findings and contribution were summarised. In the second chapter, the rapid literature review to identify factors influencing doctors’ decision-making processes is presented, along with the hierarchical framework employed to categorise the identified influence factors. A schematic map of doctors’ prescribing antibiotic drugs to treat patients admitted in medical wards with symptoms of bacterial infections is also presented in Chapter 2. The findings from the rapid literature review motivates the exploration of the application of a powerful analytical tool to map and analyse prescribing behaviour. The search process for identifying optimal systems thinking approach is discussed also discussed in Chapter 2.
Chapter 2 Factors Influencing Prescribing Behaviour

This study aimed to understand how doctors’ decision-making processes were influenced by different factors in healthcare systems. In the previous chapter, the context and rationale for this study were set. The main research questions have been presented as well as the methodology used to answer these questions. In this chapter, published studies on the factors influencing doctors’ antibiotic prescribing behaviours when treating hospital inpatients in the UK are identified and evaluated through a rapid literature review. A hierarchical framework is employed to investigate where the identified influence factors occurred in healthcare systems.

To identify factors influencing antibiotic prescribing decision-making processes in secondary care, a rapid literature review was performed. A hierarchical framework representing the wider health system was employed to categorise these influence factors based on where they arise within healthcare systems. A schematic map of doctors prescribing antibiotics to treat patients with symptoms with bacterial infections was developed first then expanded to incorporate influence factors identified from the rapid literature review (the schematic map set the structural foundation for the model developed in Chapter 4-7). The categorisation process demonstrated that the hierarchical framework
could not effectively capture the ‘system’ aspects of antibiotic prescribing management, and therefore, an analytic tool that could provide for ‘systems thinking’ was required.

Historically used modelling and simulation approaches were searched to select the appropriate methods to analyse the relationship between antibiotic prescribing behaviour and the factors influencing it. The steps undertaken in this process are discussed in this chapter.

2.1 Literature review

2.1.1 Introduction

AMS interventions were first introduced into health care system in the UK in the 1990s. During the last decade, a series of prescribing guidelines were development to improve prescribing practices in both primary and secondary level. Existing national level prescribing guidelines are listed in Table 2.1.

<table>
<thead>
<tr>
<th>Guideline</th>
<th>Year of publication</th>
<th>Organisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Health and Social Care Act 2008</td>
<td>2008</td>
<td>Department of Health</td>
</tr>
<tr>
<td>Start Smart Then Focus: Antimicrobial Stewardship Toolkit for English Hospitals</td>
<td>2011</td>
<td>Public Health England</td>
</tr>
<tr>
<td>National Antibiotic Management Guidance</td>
<td>2013</td>
<td>Public Health England</td>
</tr>
</tbody>
</table>
A narrative review co-authored by the researcher of this study suggested that despite the implementation of prescribing guidelines and other AMS interventions, policy makers currently do not have necessary evidence to assess whether AMS programmes provide sufficient benefits (Naylor et al., 2017). Extant research has been undertaken to identify a range of factors influencing prescribing decision-making processes and provide evidence base to help policy design. A Cochrane review was conducted by Davey et al to estimate the effectiveness and safety of interventions to improve antibiotic prescribing for hospital inpatients in 2015 (Davey et al., 2013). When assessing AMS interventions, the factors influencing prescribing decision-making processes and utilisation of behaviour-altering interventions were also reported (Davey et al., 2013). However, the mechanism of how these factors affect prescribing decision-making processes, the interaction among these
factors and the interaction between these factors and healthcare systems have not been studied. How to achieve optimal prescribing decisions through interventions in different levels of health systems remains unknown (Harbarth & Samore, 2005; Zarb et al, 2011; Ashiru-Oredope et al, 2016). Identifying the most important influences on the prescribing decision-making process can help address this knowledge gap (Paredes et al., 1996; Hulscher, Grol, & van der Meer, 2010; Rodrigues et al., 2013).

A rapid literature review is a type of knowledge synthesis in which components of the systematic review process are streamlined or accelerated to produce information in a shortened timeframe (Tricco, Langlois, & Straus, 2017). Factors influencing prescribing decision-making processes and implementation of AMS interventions in secondary care in the context of English hospitals specifically were identified through a rapid literature review. The antibiotic prescribing practices provided context within which behaviour-altering AMS interventions were implemented.

2.1.2 Method

The PubMed database was searched for literature published from January 2000 to December 2015 using the search terms listed in Table 2.2.
Additionally, the grey literature was searched using the Institute for Scientific Information (ISI) Web of Knowledge, which identifies journal articles, patents, websites, conference proceedings, and open access material, and reference lists of selected articles were screened.

The factors influencing prescribing decision-making were identified as either ‘barriers’ or ‘facilitators’ to AMS interventions promoting prudent prescribing practices.

Following review of all titles and abstracts, a sample of 25% were reviewed by the second reviewer (RA1) using the following criteria:

**Inclusion criteria:** studies researching influence factors in prescribing decision-making for antimicrobial drugs in hospitals, all types of study design were considered.
Exclusion criteria: studies conducted outside UK, studies conducted in primary care, studies focusing on the administration of medicines based on patients’ request were excluded, as were abstracts, conference proceedings, editorials and letters.

To ensure that the full range of factors could be considered, all studies which met the inclusion criteria were included in the review.

2.1.3 Results: identified influence factors

The initial literature search for studies identifying and describing influence factors in antibiotic prescribing yielded 93 records, of which 12 met the inclusion criteria (Figure 2.1).

Figure 2.1 Rapid literature review attrition diagram

93 records identified through PubMed and grey literature search

88 abstracts for reviewing

5 duplicates removed

Selection criteria applied to abstracts: 36 abstracts excluded

52 eligible abstracts

Selection criteria applied to full text: 40 abstracts excluded

12 eligible articles
36 abstracts were excluded, including 8 studies conducted outside the UK, 21 studies focusing on primary care, and 7 studies focusing on impact on prescribing decision-making processes from patients’ perspective. 40 full-text articles were excluded, including 4 studies on impact on antibiotic prescribing practices from patients’ demand, 11 studies on procedural management to improve infection control (e.g. shortening pre-admission waiting time), 9 studies on antibiotic therapies, and 16 studies on non-behavioural AMS interventions (e.g. campaign to raise public awareness of antibiotic resistance). The included studies were listed in Table 2.3.

**Table 2.3 Included studies and reported influence factors**

<table>
<thead>
<tr>
<th>Study</th>
<th>Author(s)</th>
<th>Year</th>
<th>Reported influence factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>The increasing role of pharmacists in antimicrobial stewardship in</td>
<td>Wickens, et al.</td>
<td>2013</td>
<td>Empirical usage of antimicrobial guidance (facilitator); Sharing antibiotic usage data</td>
</tr>
<tr>
<td>English hospitals</td>
<td></td>
<td></td>
<td>across healthcare systems (facilitator).</td>
</tr>
<tr>
<td>Antimicrobial stewardship: English surveillance programme for</td>
<td>Ashiru-Oredope, et</td>
<td>2013</td>
<td>Following local policies and guidelines (facilitator).</td>
</tr>
<tr>
<td>antimicrobial utilization and resistance (ESPAUR)</td>
<td>al.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Improving the quality of antibiotic prescribing in the NHS by</td>
<td>Ashiru-Oredope, et</td>
<td>2012</td>
<td>Delivery of education and training programmes for all healthcare professionals who issue,</td>
</tr>
<tr>
<td>developing a new Antimicrobial Stewardship Programme: Start Smart—</td>
<td>al.</td>
<td></td>
<td>prescribe and administer antimicrobials (facilitator).</td>
</tr>
<tr>
<td>Then Focus.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Antimicrobial stewardship: an evidence-based, antimicrobial self-</td>
<td>Cooke et al.</td>
<td>2010</td>
<td>Comprehensive education and training, audit and feedback (facilitator).</td>
</tr>
<tr>
<td>assessment toolkit (ASAT) for acute hospitals</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education of healthcare professionals and the public</td>
<td>McNulty, Cookson, &amp;</td>
<td>2012</td>
<td>Electronic production facilitated adherence to common standards and modification of the</td>
</tr>
<tr>
<td></td>
<td>Lewis.</td>
<td></td>
<td>guidance (facilitator).</td>
</tr>
<tr>
<td>Interventions to improve antibiotic prescribing practices for hospital inpatients</td>
<td>Davey, P et al.</td>
<td>2013</td>
<td>Hospital budget adequate to support complex dissemination or implementation strategies (facilitator).</td>
</tr>
<tr>
<td>---</td>
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<td>---</td>
</tr>
<tr>
<td>Understanding the determinants of antimicrobial prescribing within hospitals: the role of “prescribing etiquette”</td>
<td>Charani, et al.</td>
<td>2013</td>
<td>Junior prescribers altered their practices owning to the precedent set by more senior prescribers (barrier); The rule of ‘non-interference with the clinical decisions of others’, despite the existence of local policies (barrier).</td>
</tr>
<tr>
<td>Behaviour change strategies to influence antimicrobial prescribing in acute care: a systematic review</td>
<td>Charani, et al.</td>
<td>2011</td>
<td>Heterogeneous nature of specialist staff as a barrier to behaviour change and the uptake of single-mode interventions (barrier); Increasing prescribers’ involvement in guideline development to improve their confidences in the recommendations (facilitator).</td>
</tr>
<tr>
<td>A quality improvement programme to increase compliance with an anti-infective prescribing policy</td>
<td>Thakkar, et al.</td>
<td>2011</td>
<td>Raising awareness, education and weekly feedback (facilitator).</td>
</tr>
<tr>
<td>An antimicrobial stewardship program initiative: a qualitative study on prescribing practices among hospital doctors</td>
<td>Skodvin et al.</td>
<td>2015</td>
<td>Input from infectious disease specialists, microbiology test results and the newly published national guideline (facilitator); Delayed availability of microbiology test results (barrier); Clinical experience overrides the influence of the national guideline (barrier).</td>
</tr>
<tr>
<td>Antibiotic stewardship: overcoming implementation barriers</td>
<td>Bal &amp; Gould.</td>
<td>2011</td>
<td>Executive level planning, local cooperation, sustained education, emphasis on de-escalation, and use of care bundles could stem the tide of growing resistance (facilitator).</td>
</tr>
<tr>
<td>Antibiotic prescribing in hospitals: a social and behavioural scientific approach</td>
<td>Hulscher, Grol, &amp; van der Meer.</td>
<td>2010</td>
<td>Cultural, socio-cultural, and socio-economic factors (facilitator and barrier).</td>
</tr>
</tbody>
</table>
2.2 Hierarchical framework

2.2.1 Introduction

A framework is defined as ‘schemata of interpretation’ to locate, perceive, identify and label situations (Goffman, 1974). This definition has been expanded through time to include additional factors, such as politics, resources, to help understand character and causation of change when adopting frameworks in research field of policy management (Benford, 2000).

A hierarchical framework represents multi-level systems by differentiating components of a system as micro, meso and macro level (Rebert, 2011). A hierarchical framework recognises that the system of interest is multi-level, and that smaller scale components are embedded within higher scale components with direct and indirect information exchange across these components (Brailsford, Churilov, & Dangerfield, 2014). Components of the framework operate simultaneously (Brailsford, Churilov, & Dangerfield, 2014).

A hierarchical framework has been employed by public health researchers in the UK to analyse how influence factors arise and how stakeholders at each level framed their understanding of health policy alternatives and determine the degree of congruence within and among the levels (Caldwell & Mays, 2012).

In order to systematically study the factors influencing prescribers’ decision-making processes identified from the rapid literature review, the hierarchical framework was used
to categorise these factors based on \textit{where} in the health system the influences arise. Micro or individual level, referring to factors pertaining to individual patients and healthcare professionals; meso or organisational level, referring to factors arising at the level of healthcare organisations and facilities such as hospitals; macro or system level, referring to the wider healthcare system itself (Robert \textit{et al.}, 2011).

\subsection*{2.2.2 Method}

Influence factors were differentiated as barriers and facilitators to uptake of AMS interventions to improve antibiotic prescribing practices. Categorisation was accomplished using empirical knowledge followed by input from front-line staff from three NHS Trust teaching hospitals in West London, including one junior doctor, one consultant, one medical microbiologist, two nurses, and three pharmacists independent of the study, through a structured feedback meeting.

\subsection*{2.2.3 Results: influence factors on multiple levels}

The categorisation of identified influence factors according the hierarchical framework is presented in Table 2.4. It is acknowledged that some influence factors cannot be solely attributed to one level.
Table 2.4 Influence factors in antibiotic prescribing in UK hospitals

<table>
<thead>
<tr>
<th>Facilitators</th>
<th>Organisational level</th>
<th>Health system level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adapting education programmes and obtaining prescribers’ feedback for future intervention design</td>
<td>Introducing new technology for testing or changes to laboratory turnaround time by substantively changing work patterns</td>
<td>Sharing antibiotic prescribing and patient outcome data nationally</td>
</tr>
<tr>
<td>Low guideline accessibility; low hospital budget for AMS implementation; unregulated de-escalation practices</td>
<td>Low prescribers’ participation in guideline making; national level guideline not suitable for local institutes</td>
<td></td>
</tr>
<tr>
<td>Delayed delivery of pathogen information due to prolonged laboratory turnaround time; senior prescribers’ instruction overriding guidelines</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.2.4 Results: schematic map of prescribing pathway

While studying the influence factors identified from the rapid literature review, data extraction and analysis was performed by reviewing routinely collected hospital data for a group of hospital inpatients with *E. coli* bacteraemia in parallel. The details of the data source, and the methods used to analyse the data will be discussed in Chapter 4 (Chapter 4, 4.5.1 Documentary analysis: hospital inpatient notes review). A schematic map was constructed representing the simplified processes of doctors treating patients with symptoms of bacterial infections admitted to medical wards (Figure 2.2).
The processes presented in the schematic map started with patient admission to a hospital. When patients with symptoms of bacterial infections arrived in the hospital, they were either admitted to medical wards directly, or admitted to the Accident and Emergency (A&E) Department first, then transferred to medical wards.

After patients were admitted to medical wards, blood samples were taken and delivered to microbiology laboratory for tests to identify the pathogen. Meanwhile, prescribers made empiric decisions considering patients’ clinical status and medical history. Prescribers in medical wards included consultants, specialty registrars, core trainees, Foundation Year doctors, and nurses. These doctors were divided into two groups because of the difference in their decision-making processes. Senior doctors, including specialty registrars and consultants, made prescribing decisions either following prescribing guidelines, or relying on their own experience gained from years of practicing, or using diagnostic information.
if microbiology laboratory test results were delivered back to medical wards rapidly. Junior doctors, including Foundation Year 1 and 2 doctors, core trainees and nurses, made prescribing decisions either following prescribing guidelines, or following senior doctors’ instruction. The classification of doctors was performed sorely based on doctors’ prescribing habits according to the main focus of this study. Nurses were included in the group of junior doctors as their prescribing behavioural pattern was identical to Foundation Year doctors and core trainees.

After receiving microbiology laboratory test results, the empiric decisions were adjusted with microbiologists, who were acting as decision makers. For patients who had microbiology laboratory test result, microbiologists reviewed the empiric decisions made by doctors in medical wards. However, a proportion of patients did not have test results. This group of patients either did not have microbiology laboratory test performed or had a blood sample taken and microbiology test performed but did not receive results for the test. The microbiology laboratory failed to provide result due to missing or contaminated blood samples.

The end points of the chronological pathway were patient finished antibiotic courses, discharged from the ward or deceased. Prescribing outcomes were measured at the final stage of the pathway. The level of prescribing guideline compliance among doctors was selected as the outcome measure at empiric stage, while the level of microbiology review was selected as the outcome measure at review stage.
The identified influence factors across the healthcare system overlaid on the prescribing decision-making pathway. These factors influenced doctors’ prescribing decision-making processes collectively, while having interconnection among themselves. The influence factors at different levels of the healthcare system were incorporated in the schematic map. The arrows represented the interconnection between influence factors and the processes when doctors prescribed antibiotics and treated patients, as well as between influence factors. The influence factors may have impact on prescribing decision-making processes directly or on other influence factors at a lower level. The exact dynamics of these interconnections remained unknown at this stage of the study. The schematic map with influence factors incorporated is presented below (Figure 2.3).

**Figure 2.3 Schematic map with influence factors overlaid**
Senior doctors’ influence on junior doctors occurred primarily when doctors were making initial treatment decisions at empiric stage. The *timeliness* and *availability* of microbiology laboratory tests both influenced doctors’ decision-making. At empiric stage, microbiology laboratory turnaround time was crucial for specialty registrars and consultants to make prescribing decisions. At review stage, available microbiology laboratory test result created more opportunities for microbiologists to review empiric decisions made by doctors in medical wards. Adopting education programmes was reported as a facilitator to improve prescribing practices by building the awareness of prescribing guidelines and the risks caused by inappropriate prescribing. Therefore, education programmes were assumed to alter prescribing decisions at the empiric stage.

The schematic maps provided the fundamental structure for the model of prescribing decision-making processes constructed later in this study. To simplify the complex processes in real life, microbiology laboratory turnaround time was assumed to only influence senior doctors’ decision-making at empiric stage. In real life, specialty registrars and consultants acted as decision-makers when treating patients in more critical clinical condition and required more support in diagnostic information. Junior doctors treated patients with less severe infections, while prescribing guidelines or senior doctors’ instruction were enough to support decision-making. Thus, the microbiology laboratory turnaround time was considered as being influential in senior doctors’ decision-making processes at empiric stage.
Evidence in the published literature and the hospital inpatient notes suggested that senior doctors tended to prescribe antibiotics with broader spectrum than the recommendations in prescribing guidelines (Srinivasan et al., 2004; Teo et al., 2013). Again, such prescribing habit was associated with the patients in more critical conditions treated by senior doctors. Senior doctors prescribed antibiotics with broader spectrum to cover all possible infections if patients, normally elderly ones, were in severe medical condition. However, senior doctors’ habit of not complying with prescribing guidelines had impact on junior doctors’ prescribing practices due to the existence of ‘prescribing etiquette’ (Charani et al., 2013). Knowing that adopting education programmes was a facilitator to improve doctors’ prescribing practices, in the later stage of this study, the impact from the facilitator of education programmes will be modelled as improving guideline compliance among senior doctors. This modification to simplify the model was verified by an expert panel of healthcare professionals and researchers in the model validation stage. The details of the validation process will be described in Chapter 7 (Chapter 7, 7.2.1.1 Structure-verification test).

2.3 Discussion

2.3.1 Interlinked influence factors

The results indicated that timely delivery of microbiology laboratory test results was a
crucial factor for adjustment of treatment decisions, and it impacted the decision-making processes at the individual and organisational level in combination with guideline compliance among doctors. Procedural factors were found to delay sample processing and result delivery. However, the impact from availability of microbiology laboratory test results and guidelines and guideline compliance need to be taken in the context of the influence of senior doctors on decision-making, based on the fact that senior doctors tended to prescribe antibiotics with broader spectrum than the recommendations made in guidelines revealed by the inpatient notes review.

The factors influencing antibiotic prescribing decision-making can be classified in different ways. For example, the influence factors can be classified into ‘front-end factors’ (electronic/computer-assisted prescribing system that requires pre-authorisation of certain antibiotics) and ‘back-end factors’ (adoption of education and feedback programmes); or structural/procedural factors (adoption of rapid diagnostic tools, implementation of hospital budget to regulate antibiotic de-escalation) and cultural/behavioural factors (‘prescribing etiquette’, culture of ‘non-interference).

In this study, the ‘micro’, ‘meso’, ‘macro’ hierarchical framework was used to categorise the influence factors into individual level, organisational level, and healthcare system level, to allow the analysis of the influence factors themselves as well as the environment they arise from. The categorisation of influence factors using the micro, meso and macro framework helped understand where they arise from, and also when they occur in the
processes of prescribing decision-making.

The hierarchical model employed is one way of organising influences, but is still a reductionist approach as not all influences could be attributed to a single level and there are many indirect influences, which filter down (or up) across levels. For example, timeliness of microbiology laboratory test results can be categorised into either micro (individual) level or meso (organisational) level, as it can be addressed by altering behaviour of individual healthcare professionals (e.g. reducing workload of microbiology laboratories by regulating blood sampling practices) as well as adjusting structural and procedural factors at organisational level (e.g. adopting rapid diagnostic tools). In addition, the hierarchical framework did not capture the interactions among influence factors. Hence, the knowledge gap which remains, is the incomplete understanding of the mechanisms of how the influence factors impact on the final prescribing decision-making. A strong analytical tool is required, therefore, to analyse the impact of multiple influence factors individually and collectively on the doctors’ decision-making processes.

2.3.2 Heterogeneity in prescribing behaviour

The evidence from previous literature and the research conducted in the Health Protection and Research Unit (HPRU) in AMR in Imperial College London has revealed that the prescribing behaviour in medical wards differed from the practices, such as acute care and
surgical theatres (Charani, 2011; Ashiru-Oredope, 2012; Charani, 2013; Charani, 2017). In medical wards, decision-making processes are collectivist, rationalised, and policy-informed. Pharmacists, microbiologists and doctors in wards contribute to prescribing decisions collectively. Though infection markers (C-reactive protein, white cell count, and temperature) are an important part of the process, the team members try to rationalize their decisions, making efforts to align them with local policy and readily involve other healthcare professionals. While in surgery, the diagnosis of infection is reliant on infection markers. The decision-making processes focus more on prevention and prophylaxis than on treatment of infections. In surgery, senior surgeons are often absent from the ward, leaving junior staff to make complex medical decisions. Such decision-making processes often result in defensive prescribing behaviour due to fear of blame, and furthermore, prolonged and inappropriate antibiotic use. Some of the influence factors identified in this thesis, for example, delayed pathogen information (prolonged laboratory turnaround time) and senior prescribers’ instruction overriding guidelines, do not apply to the antibiotic prescribing decision-making processes in surgical theatres. Further investigation needs to be done to identify the determinants in different settings and describe the causal relationships between the determinants and the prescribing decision-making processes.
2.4 The need for a systems thinking approach to explore prescribing behaviour

Policy makers have been aware that fragmented thinking created problems when designing AMS interventions. Interrelationships between parts of a system must be studied rather than narrowly focusing on the parts themselves (Buising, 2015). Multiple perspectives, conditions, connections and capabilities should be incorporated when analysing the system (Tomson & Vlad, 2014). In addition, such analysis must consider the dynamic nature of systems, as systems develop and evolve.

Systems approach involves every professional working on every level across healthcare systems, from senior management to front-line staff. AMS interventions should aim to adjust healthcare professionals’ daily practice considering the time consumption of behaviour change, rather than aiming to solve the problem by taking one-off activity (Buising, 2015).

‘Whole-of-system’ approaches were endorsed when designing AMS interventions during the past decade (Mendel, 2014). Whole-of-system approach was recommended to optimising antibiotic use and making prudent antibiotic management an integral part of the behaviour of all healthcare professionals (Charani, Cooke, & Holmes, 2010). While the ‘system’ aspects of antibiotic prescribing and AMS management were recognised, and the requirement of a whole-of-system approach to analyse prescribing behaviour was
acknowledged, existing research did not provide methodological approaches that were strong enough meet the requirement (Buising, 2015).

The limitations in earlier research motivated the adoption of a systems thinking approach and a simulation methodology to demonstrate not only the components (levels) of health system, but also the relationships among these components and the relationship between the components and the broader context (system), thus providing a platform to test the impact of influences (and interventions acting upon them) in a dynamic fashion.

2.5 Context of the study and the reasons for its selection

2.5.1 Antibiotic prescribing in secondary care

This study focused on the antibiotic prescribing behaviour in secondary care, based on following reasons. First, reducing total antibiotic use and inappropriate antibiotic prescribing in secondary care is the government’s policy focus (NHS England: Promoting Appropriate Antimicrobial Prescribing in Secondary Care). It is a national ambition to reduce UK antimicrobial use in humans by 15% by 2024 (The UK’s five-year national action plan: tackling antimicrobial resistance 2019-2024). The English surveillance programme for antimicrobial utilisation and resistance (ESPAUR) report 2017 indicated that there has been a 13% reduction in prescriptions in the past five years. However, in secondary care there has been less progress. It has not had a sustained reduction in total
Second, the nature of the problem and issues is more prevalent in terms of antibiotic use and infection management of vulnerable patients. The emergency, selection and spread of resistant bacteria is a threat to hospital inpatients because infections with resistant bacteria result in increased patient morbidity, mortality, and hospital length of stay. AMR is also associated with more severe patient outcomes and sometimes deaths (European Antibiotic Awareness Day: Key Messages for Hospital Prescribers).

Third, the consequences behavioural changes (antibiotic prescribing behaviour) are demonstrable in a shorter timeframe in secondary care than in primary or community care. This thesis used a systems thinking modelling method to simulate antibiotic prescribing decision-making processes. The model was constructed using measurable behaviour indicators (guideline compliance) among hospital doctors. And the model was simulated in order to provide quantitative evidence to guide the design of behaviour-altering interventions. When examine behaviour changes in health, the outcomes must be measurable, achievable, and relevant for the patients (Heath, 2015). Within secondary care, measuring the impact of positive changes is more realistic than in primary care and community settings.

At last, the antibiotic prescribing decisions-making processes involve multidisciplinary workforce in secondary care. While in primary care, general practitioners (GPs) are often making prescribing decisions without support from other health professionals. The
diversity in prescribing behaviour was examined in this thesis with the focus on secondary care. The evidence from previous literature and the research conducted in the Health Protection and Research Unit (HPRU) in AMR in Imperial College London has revealed that the prescribing behaviour in medical wards differed from the practices, such as acute care and surgical theatres (Charani, 2011; Ashiru-Oredope, 2012; Charani, 2013; Charani, 2017). A systems thinking model will be built in the later stage of this study to simulate doctors’ prescribing decision-making processes within a system which was equivalent to medical wards in an English hospital. The source data employed to formulate the model was collected from medical wards across different specialties. The model will be validated by various health professionals working in medical wards (senior and junior doctors, nurses, pharmacists), as well as hospital managers and other healthcare researchers who had comprehensive understanding of the heterogeneity in prescribing decision-making processes in different environments (i.e. communities/primary care, ambulance/Accident and Emergency(A&E), medical wards, surgical theatres, and long-term care facilities) to ensure that the model is a valid representation of real-life phenomena in medical wards.

2.5.2 The selection of modelling method

In order to find the appropriate method to provide quantitative estimation of the prescribing outcome measure considering all factors influencing the processes, the simulation and
modelling methods used in earlier published studies to support policy design and evaluation in healthcare systems in the UK have been reviewed.

The NHS in England and all the UK healthcare systems (in England, Northern Ireland, Scotland and Wales respectively) are under significant pressure to respond to rising demand without immediate prospect of additional funding (Kirwan et al., 2017). Modelling and simulation have always been considered beneficial tools to help operational management compared to the traditional ‘try it and see’ experimental approaches (Kirwan et al., 2017). By employing modelling and simulation, NHS personnel can be engaged across the care pathway in service redesign exercises, promoting ‘buy in’ from everyone on the need for change and acceptance of new service models or ways of working (The UK Modelling and Simulation in Healthcare Network, 2014). With the aid of computer-based software platforms, qualitative systems thinking models can be translated into operational, quantitative, ‘simulatable’ models to test system behaviour over time (dynamics). Dynamic simulation modelling methods are used to design and develop mathematical representations (i.e. formal models) of the operation of processes and systems to experiment with and test interventions and scenarios and their consequences over time to enhance the understanding of the system or process, communicate findings, and inform policy and intervention design (Banks 1998; Harrison et al., 2007; Sokolowski & Banks, 2011; Marshall et al., 2015).

Modelling and simulation methods used by researchers analysing UK healthcare systems
to support policy design and evaluation are listed in Table 2.5. The methods incorporating elements of dynamic systems thinking are highlighted (marked by *).

**Table 2.5 Modelling and simulation methods used in published studies analysing UK healthcare systems**

<table>
<thead>
<tr>
<th>Methods</th>
<th>Use in UK healthcare systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qualitative modelling:</td>
<td></td>
</tr>
<tr>
<td>Cognitive mapping*</td>
<td>Construct a system of concepts linked to form chains of action-oriented argumentation. Used to integrate experts’ opinion on public health policy issues (Eden &amp; Ackermann, 2004)</td>
</tr>
<tr>
<td>Process mapping*</td>
<td>Create a visual picture of how the pathway currently works, exposing areas of duplication, waste, unhelping variation and unnecessary steps. Used to map patients’ journey in walk-in clinics to reduce waiting time (NHS improvement: Online library of Quality, Service Improvement and Redesign tools: Conventional process mapping)</td>
</tr>
<tr>
<td>Soft Systems Methods (SSM) Strategic Options and Decision Analysis (SODA)*</td>
<td>Cognitive mapping using computer software to support decision-making and channel the cooperation of a variety of stakeholders into addressing complex, unstructured management problems. Used by NHS to help tele-health system design (Jacobs, 2004)</td>
</tr>
<tr>
<td>Causal Loop Diagrams (CLDs)*</td>
<td>Visualise variables in a system interrelated with causal relationships. Used to investigate compromises with the NHS Balanced Scorecard (Patel, Chaussalet, &amp; Millard, 2008). Construction of a CLD is part of SD model development.</td>
</tr>
<tr>
<td>Mathematical modelling:</td>
<td></td>
</tr>
<tr>
<td>Regression</td>
<td>Estimate the relationships among variables using a set of statistical processes. Used to analyse health expenditure of the OECD countries (Gerdtham et al., 1992).</td>
</tr>
<tr>
<td>Forecasting</td>
<td>Make prediction using past and present data to analyse trends. Used to predict the healthcare system performance during heatwaves (Kovats &amp; Kristie, 2006).</td>
</tr>
<tr>
<td>Optimisation</td>
<td>Select best element from some set of available alternatives using mathematical software. Used to design diabetic retinopathy screening programme (Scanlon et al., 2015).</td>
</tr>
<tr>
<td>Queueing Theory</td>
<td>Construct a queuing model to predict queue length and waiting time. Used to analyse the 4-hour completion time in accident and emergency departments of NHS hospitals (Mayhew &amp; Smith, 2008).</td>
</tr>
<tr>
<td>Markov models*</td>
<td>Model randomly changing systems and predict future system behaviour based on current states. Used to evaluate the length of stay of elderly patients in long-term care facilities (Xie, Chaussalet, &amp; Millard, 2005).</td>
</tr>
<tr>
<td>Analytic models*</td>
<td>Use mathematical expression constructed using well-known operations that lend themselves readily to calculation. Used to evaluate the cost-effectiveness of long-acting reversible contraceptive methods in the UK (Mavranezouli, 2008).</td>
</tr>
</tbody>
</table>
Simulation: to test ‘what-if’ scenarios for service design; to determine levels of uncertainty; to provide visualisations and inform clear understanding and dialogue amongst stakeholders; to develop forecasts/projections of future performance.

**Discrete-event simulation**
Model the operation of a system as a discrete sequence of events in time with each event occurring at a time point and changing the state of the system. Used to model the operations of emergency departments in NHS hospitals (Komashie & Mousavi, 2005).

**System dynamics**
Discuss in later chapters (Chapter 3, 3.2 System Dynamics methodology principles; Chapter 4, 4.6 System Dynamics modelling)

**Monte Carlo simulation**
Model the probability of different outcomes in a process that cannot easily be predicted due to the intervention of random variables. Used to assess the impact from healthcare worker hand hygiene behaviour on transmission of MRSA (Beggs, Shepherd, & Kerr 2009).

**Agent-based simulation**
Model the action and interaction of autonomous agents with a view to evaluate their impact on system status. Used to help guideline development for preventing healthcare-associated infections in NHS hospitals (Meng et al., 2014)

**Behavioural simulation**
Simulate autonomous entities with support from psychological studies on human behaviour. Used to synthesize self-administered questionnaire, experimental designs, role-playing and scenarios for data collection (Andersen, 2008).

System Dynamics (SD), discrete-event simulation (DES), and agent-based modelling (ABM) are the three highlighted modelling methods in operational research methodologies in the recent years as they are well suited for decision-making and management problems in sociology, economics and public health (Harrison et al., 2007).

In this particular study, a dynamic analytic modelling method is required to assess the factors influencing prescribing decision-making processes and examine policy alternatives. SD modelling was selected based on its capability of 1) capturing the ‘system’ aspects of prescribing decision-making, 2) providing estimates of healthcare professionals’ behaviour under various policy scenarios based on causal relationships between influence factors and decision-making, and 3) incorporating both quantifiable and non-quantifiable variables. In addition, due to the unique development process of SD models, statistical significance and sample size of source data have little relevance to the validity of SD models.
The method of SD has minimal requirement of sample size to support model parameterisation as an SD model operates on established causal mechanism. Hence, the source data collection will not require extra financial input to recruit participants to build a large study group. The discussion of the principles of SD modelling is expanded in the next chapter (Chapter 3, 3.2.1 System Dynamics modelling). The rationale of selecting SD modelling in this study is described in Chapter 4 (Chapter 4, 4.1 Rationale for selecting System Dynamics in this research).

In this chapter, the factors influencing doctors’ antibiotic prescribing decision-making processes in the context of English hospitals were identified and categorised. A schematic map was constructed to simplify and visualise the processes of how doctors with different seniority making decisions to treat patients with symptoms of bacterial infections with influence factors on different levels across healthcare systems incorporated. An SD model will be constructed based on the schematic map in the later stage of the study. Chapter 3 to Chapter 8 cover the steps undertaken to develop and simulate the SD model. In Chapter 3, the SD model is conceptualised by describing the research questions that needed to be answered and the purpose of the model. The concepts of systems thinking and the fundamental principles of SD modelling are also discussion in relation the nature health systems, and health management. In Chapter 4, the methods taken to process source data and construct the SD model are described. A well-established guideline is followed to build the model. In Chapter 5, the modelled system is described qualitatively using sub-system
diagram, model boundary chart, and causal loop diagrams. In Chapter 6, stock and flow diagrams are constructed to translate the qualitative maps of the model into simulatable model. A series of key variables are identified through such process for the SD model. The findings from the analysis of the primary and secondary data in Chapter 4 are synthesized to provide estimates of the key variables included in the SD model. In Chapter 7, the process to validate the structure, the parameters, and the ability to reproduce the system existing in real life by performing a series of model validation tests is described. In Chapter 8, the prediction of prescribing outcome measures is provided through SD model simulation under different scenarios to understand doctors’ decision-making processes when facing changes in influence factors.

Key points in Chapter 2:

- The factors influencing prescribing decision-making processes were identified through a rapid literature review and categorised into individual, organisational, and health systems level, using a hierarchical framework.

- The literature evidence suggested that the influence factors on individual level had the strongest impact on doctors’ prescribing decisions.

- A systems thinking analytical tool is required to examine complex antibiotic prescribing decision-making processes influenced by multiple interlinked factors.
Chapter 3 Conceptualisation: Systems Thinking Principles in Health Management

The previous chapter presented the application of a hierarchical framework to categorise influence factors influencing prescriber behaviours and a discussion on its usefulness for mapping where interventions might be usefully employed to modify prescribing behaviour. The analysis revealed that a hierarchical framework approach was not capable of capturing the ‘system’ aspects of antibiotic prescribing.

A complete understanding of the interconnections among the influence factors and between the influence factors and the environment where these factors arise, and the impact on doctors’ decision-making processes from the influence factors requires a systems thinking analytical tool. Modelling and simulating methods previously used in managing NHS and healthcare systems in the UK were therefore reviewed. SD modelling was selected for its capability of simulating complex and dynamic system behaviour.

In this chapter, the concepts of systems thinking and the principles of SD modelling are discussed in relation to the nature of health systems and health management. The SD model built in the later stage of this study is conceptualised by defining the purpose of the model. The SD model aims to address the following research questions: which stakeholders are involved in prescribing decisions; which influence factors affect prescribing behaviours; from where in the health system do these influence factors arise; and when during
prescribing decision-making processes.

3.1 Definition of systems thinking

3.1.1 Systems and systems thinking

Commonly understood meanings of “system” generally refer to a “complex whole of related parts”—whether it is biological (e.g. an ecosystem), structural (e.g. a electricity system), organised ideas (e.g. the democratic system), or any other assemblage of components comprising a whole (Cabrera, Colosi, & Lobdell, 2008).

Systems thinking is a formal, abstract, and structured cognitive endeavour (Fuenmayor, 1991). Systems thinking looks at the inter-relationships among different components and between components and context of a system, rather than narrowly focusing on the individual components themselves (Cabrera, Colosi, & Lobdell, 2008). Systems thinking helps to better prepare for emerging challenges and anticipate rather than react to events. It takes into account that systems develop and evolve with understanding of renewal, change and transformation. In systems thinking, structures, patterns of interaction, events and organizational dynamics are considered as components of larger structures (Atun, 2012). In practice, systems thinking means careful consideration of possible consequences of policies and actions, generating scenarios through group working and joint thinking (Atun, 2012).
3.1.2 Health systems

The history of health systems framework development and employment can be tracked back to 1960s. In 2012, Hoffman *et al.* identified 41 health systems frameworks developed since 1972, 19 of these encompassed the whole health system while the remainder focused on components of health systems and the interaction among the components (Hoffman *et al.*, 2012). Different health system frameworks were developed to offer a better understanding of health systems, to offer a way of comparing health systems, or help with informing managerial decisions to change health systems, or to outline a method to evaluate their performance or changes in performance (Hoffman *et al.*, 2012). Despite ambiguity in the exact definition and conceptualisation of health systems, there is arguably now a global consensus that the research on health systems is essential for gaining greater attention in the issues in health systems and strengthening health systems to achieve better global health (Travis *et al.*, 2004). The trend of the use of the term “health systems research” in MEDLINE records was plotted using the knowledge-based search engine for biomedical texts GoPubMed which reports the frequency of publications in different research areas (*Figure 3.1*). In addition, a study in scientific writing on health systems published between 1990 and 2014 globally using bibliometric procedure produced the plot of number of publications in health systems (Phillips, Sheff, & Boyer, 2015) (*Figure 3.2*). Overall, an increase in the amount of publications and relative research interest in health systems research was observed.
Figure 3.1 Number of use of ‘health systems research’ in publications in Medline records

Health systems are extraordinarily complex social structures. Like all complex systems, they are multi-level, nonlinear and highly sophisticated. Despite embracing rapid technological innovation and constant reorganization, health systems are strongly resistant
to planned change (*i.e.* interventions and policies). Inadequately designed interventions often upset the equilibrium within complex systems to resist such interventions, leading to ‘policy resistance’ (Atun, 2012). The complexity in health systems and issues in health systems management is a consequence of “the sheer number of independent players, established policies, zealously guarded interests, entrenched professional silos and divergent cultures” (Hoffman *et al.*, 2012).

The methodological reader published by the WHO Alliance for Health Policy & Systems Research (HPSR) identified a broad range of study designs featured in health policy research, including both qualitative and quantitative methods, and both fixed (study design established before data collection) and flexible (study design evolving during the study process) strategies (Gilson, 2012). Despite the variety of study designs, the common barriers associated with the complexity of health systems are experienced by researchers using different types of methods, approaches, and strategies (Gilson, 2012). Problems in health system research are caused by a web of elements and the unpredictable interactions among the elements, for example, the interlinked structural and cultural factors influencing doctors’ prescribing behaviour in hospitals. The complexity in health systems often limits the usefulness of mechanistic “cause-and-effect” approaches typically applied in earlier research in health systems and evaluation of changes to them. Research questions cannot be answered with methods like randomisation and control groups, which are commonly used in biomedical and clinical medicine research. Additionally, health systems researchers
often conduct their work in difficult political environments and in contexts that are constantly evolving (Janovsky & World Health Organisation, 1996; Gilson, 2012).

In 2007, the concept of ‘whole of system’ was firstly mentioned by World Health Organisation (WHO) to promote understanding and research in health systems and has become ubiquitous in health system research (World Health Organization Maximizing Positive Synergies Collaborative Group, 2009). It is recognised that all components of a health system are interrelated and interacting dynamically. Both anticipated and unanticipated are to be expected when predicting performance of health systems. The ‘whole-of-system’ concept emphasized that policy alternatives must be evaluated for potential effects on the functioning of the entire health system and ultimately health outcomes; analysis of health care management issues must encompass the entire health system to the extent possible (Forrester, 1994; Ritchie-Dunham & Galván, 1999).

3.2 System Dynamics methodology principles

3.2.1 System Dynamics modelling

Systems thinking analytical tools, such as SD modelling, help researchers gain insights in the underlying structure of a complex situation (Department of Health, 2014). They demonstrate how elements inside the modelled system interrelate and where the opportunities are to intervene within the system and influence its behaviour.
The principles of SD were developed in 1956 at the Massachusetts Institute of Technology (MIT) by Forrester (Forrester, 1997). He introduced his ideas in ‘Industrial Dynamics’, and launched his thoughts as a ‘major breakthrough for decision makers’ (Forrester, 1958). Applications of the method spread into the social sciences area later, and as a consequence Forrester re-named the technique ‘system dynamics’. (Forrester, 1997). Before moving on to the discussion of the principles of SD and SD modelling, the definition of the important concepts and frequently used terminology in SD is provided in the table below (Table 3.1). In the later sections in this chapter and later chapters, detailed description of these concepts and terminology is included with examples.

Table 3.1 Concepts and terminology in System Dynamics (Luenberger, 1964; Hamilton, 1980; Barlas, 1989; Sterman, 1992; Wolstenholme 1993; Baines & Harrison, 1999)

<table>
<thead>
<tr>
<th>Terminology</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation</td>
<td>Simulation is the actual running of the programme that contains the algorithms and equations of a model.</td>
</tr>
<tr>
<td>‘White-box’ approaches</td>
<td>‘White-box’ approaches aim to capture how systems actually operate in real life. The internal causal structure is more crucial to ensure the validity of the ‘white-box’ models than the accuracy of simulation results.</td>
</tr>
<tr>
<td>‘Black-box’ approaches</td>
<td>‘Black-box’ approaches are applied when there is no sufficient evidence to support the understanding the exact interconnection mechanism among modelled variables. They are useful when the primary interest is in fitting data regardless of a particular mathematical structure of the model.</td>
</tr>
<tr>
<td>Cause-effect/cause relationships</td>
<td>Cause-effect/causal relationships between two or more variables means that one event (effect) is the result of the occurrence of the other event (cause).</td>
</tr>
<tr>
<td>‘Hard’ variables</td>
<td>‘Hard’ variables are quantifiable variables. The quantification process of a ‘hard’ variable can be validated.</td>
</tr>
<tr>
<td>‘Soft’ variables</td>
<td>‘Soft’ variables, sometimes referred as ‘intangibles’, are used to describe attributes of human behaviour or effects that variations in such behaviour produce. Numerical data are often unavailable or non-existent when estimating values for ‘soft’ variables.</td>
</tr>
<tr>
<td>Feedback loops</td>
<td>When the outputs of a system are routed back as inputs as part of a chain of cause-and-effect, a feedback loop is formed</td>
</tr>
<tr>
<td>Causal loop diagrams (CLDs)</td>
<td>CLDs are drawn to represent the system structure by connecting the key variables within the system modelled to form feedback loops based on the cause-effect relationships between the variables.</td>
</tr>
<tr>
<td>Resource</td>
<td>A system operates to change the accumulation of resource within the system. Resource may be physical (e.g. material), or non-physical (e.g. information, knowledge, emotion).</td>
</tr>
<tr>
<td>Stock</td>
<td>Stocks/stock variables are accumulations of resources which is relevant to the concern. A stock is a measurable quantity of any resource in a system at any point in any time.</td>
</tr>
<tr>
<td>Flow</td>
<td>Flows/flow variables are movements and transition of resource between stocks in the system.</td>
</tr>
<tr>
<td>Rate</td>
<td>The resources flow through stocks in certain speed, the speed of system activities increasing or depleting resource level in stock are represented by ‘rate’ variables and measured by the unit of resource divided by time unit.</td>
</tr>
<tr>
<td>Stock and flow diagrams (SFDs)</td>
<td>SFDs are drawn to connect the stock and flow variables based on the causal relationships between them. SFDs are the quantitative form of SD modelling.</td>
</tr>
<tr>
<td>Non-linearity</td>
<td>Relationships between variables in complex systems existing in real life normally do not obey the principle of superposition. These relationships, and the systems these relationships occurred, are considered as non-linear relationships (systems).</td>
</tr>
<tr>
<td>Time delays</td>
<td>Time delays occur when consequences of actions are not immediately visible. Time delays may be caused by transition of materials, completion of tasks, or lag time associated with behaviour change.</td>
</tr>
</tbody>
</table>

SD conceptualises systems as being constructed of complex networks of feedback loops. Non-linear relationships and time delays within the systems are drivers of dynamic and complex system behaviour, and the sources of policy resistance (Forrester, 1994; Sterman,
2002; Lebcir, 2006). SD relies on a combination of qualitative and quantitative analysis. 

The modelling process includes qualitative mapping of systems using feedback loops and translating the qualitative maps into rigorous quantitative simulation models (Lebcir, 2006). SD modelling, which is the modelling and simulation activity employing the concepts of SD, exists in both qualitative and quantitative form (Wolstenholme, 1990).

Qualitative SD modelling uses causal loop diagrams (CLDs) to represent the system by connecting the key variables within the system modelled based on the cause-effect relationships between the variables. When the outputs of a system are routed back as inputs as part of a chain of cause-and-effect, a feedback loop is formed. CLDs and feedback loops of antibiotic prescribing decision-making processes are described in detail in Chapter 5 (Chapter 5, 5.2.1 System behaviour and causality, 5.2.2 Causal loop diagrams) when qualitative maps of the SD model built in this study are described.

The ‘resource variables’ in SD modelling represent the various ‘resources’ which flow through a variety of ‘states’ according to ‘rates’ (Baines & Harrison, 1999). The resource may be physical (e.g. material), or non-physical (e.g. information, knowledge, emotion). The ‘state’, commonly known as ‘stock’, may be accumulation of resources, which is relevant to the concern. A stock is a measurable quantity of any resource in a system at any point in any time. The measurement of a stock is the unit of the resource. Even all activities cease within the system, stocks, or states, continue to exist. The resources flow through
states/stocks at a certain speed, the speed of system activities increasing or depleting 
resource level in stock are represented by ‘rate’ variables and measured by the unit of 
resource divided by time unit. Stock-and-flow structures, which connect the stock and flow 
variables based on the causal relationships between them, are the quantitative form of SD 
modelling. The concept of stocks and flows is discussed again in Chapter 6 when 
constructing the stock and flow diagrams (SFDs) of the model built in this study (Chapter 
6, 6.2 Structure of the simulation model).

Apart from feedback loops and stock-and-flow structures, SD modelling also has three 
other important concepts, which are non-linearity, table functions, and time delays 
(Sterman, 1994).

Mathematically, a linear system obeys the principle of superposition (Luenberger, 1964). 
The linearity of a system can be tested using homogeneity and additivity (Mohapatra, 1980). 
When the magnitude of the input variable is doubled in a system, if it can be predicted that 
the output function will also be doubled, homogeneity is obeyed. When there are more than 
one input variables, if the overall output of the system is the sum of the outputs for each 
input variable, additivity is obeyed. The rules of homogeneity and additivity are together 
referred as the principle of superposition. Systems that satisfy both homogeneity and 
additivity are considered to be linear systems (Mohapatra, 1980) Relationships between 
variables in complex systems existing in real life normally do not obey the principle of 
superposition. These relationships, and the systems in which these relationships occurred,
are considered as non-linear relationships (systems). When building an SD model, researchers may be faced with a situation where there is a relationship between two variables but no simple algebraic equation to define the non-linear relationship (Wang & Boyd, 2010). In this case, a table function can be generated to connect independent and dependent variables and represent the relationship. The discussion of non-linearity and table functions will be expanded in Chapter 6 using the system modelled in this study as an example (Chapter 6, 6.3.4.3 Estimation of senior doctors’ influence: table function).

Time delays are a critical source of dynamics in nearly all systems (Hamilton, 1980). Time delays in general fall into two categories, material delay, which is caused by transferring materials or completing a task within the system, and information delay, which is associated with behaviour change of the intelligent agents (human beings) in response to information. In the real world, it takes time to collect and report information, to make decisions, to implement decisions, and for decisions to affect the state of the system. The discussion of time delays is expanded in Chapter 8 (Chapter 8, 8.5.2 The missing piece: time element).

3.2.2 ‘Bounded rationality’

Decisions made in real-world systems are mostly characterised by complexity and uncertainty. Complexity can be described as consisting of three dimensions: 1) quantity,
the number of relevant elements; 2) connectivity: number of connections between the relevant elements; and 3) functionality: functional intricacy of the connections between the relevant elements (Größler, 2004). The complex nature of the systems causes the uncertainty in results of managerial decisions, meaning that the results cannot be calculated with certainty because influences between connected elements are not fully known, and system states in the future are difficult to predict. Due to the presence of complexity and uncertainty in real-world systems, classical economic theory and its assumption of perfect rationality holds only partially. In classical economic theory, decision makers know about future consequences of any chosen alternative and are assumed to make optimal decisions based on such information. Humans have limitations of capability, even in those of higher intelligence, to make a rational choice, or formulate an optimal solution for a complex problem. Hence, the term ‘bounded rationality’ is used to designate rational choice that takes into account the cognitive limitations of decision-makers in both knowledge and computational capacity, as well as the limitation in the time available to make a decision (Simon, 1990). Decision-makers act somewhere in the continuum between perfect rationality and mindless behaviour (Sterman, 2000).

Historically, the idea of bounded rationality and SD modelling have common backgrounds and appeared around the same time (mid 1950s). When studying a system, diagramming the causal relationships within the system help infer system behaviour to a limited extent only when the system structure is relatively simple. The limitations of qualitative mapping
are discussed in Chapter 5 (Chapter 5, 5.2.3 Limitations of causal loop diagrams). If a feedback structure includes more than 3 to 4 feedback loops, it becomes extremely difficult to infer its behaviour. This is due to the ‘bounded rationality’ principle of human brains, which reflects the limitations of the human brain in front of the sheer complexity present in real-world systems (Selten, 1990). In 1952, Herbert A. Simon proposed bounded rationality as an alternative basis for the traditional mathematical modelling of decision-making and recommended simulation to deal with complexity in managerial decisions (Simon, 1952; Simon, 1972). The principle of bounded rationality was described as “the capacity of the human brain for formulating and solving complex problems is very small compared with the size of the problem whose solution is required for objectively rational behaviour in the real world - or even for a reasonable approximation to such objective rationality’ when he proposed ‘the models of man” (Simon, 1957). The intended rationality of a person requires him or her to construct a simplified model of the real situation in order to deal with it. He or she behaves rationally with respect to this model he or she constructed. However, such behaviour might not be optimal with respect to the real world. To predict this person’s behaviour, one must understand the way in which the simplified model was constructed, and this construction process will certainly be related to his or her psychological properties as a perceiving, thinking, and learning animal.

The principle of SD was developed in 1956 at the Massachusetts Institute of Technology (MIT) by Jay W. Forrester, a pioneering computer engineer and systems scientist, to help
managers make better decisions in organisations. Forrester wrote about the advances in decision-making as one of the foundations of SD, and later made an explicit reference to bounded rationality in 1989 (Forrester, 1961; Forrester, 1989). In 1983, the two sets of ideas merged in the article ‘System dynamics: portraying bounded rationality’ by John Morecroft (Morecroft, 1983). Morecroft is a leading expert in strategic modelling and system dynamics and the recipient of the 2019 Outstanding Contribution Award of the UK System Dynamics Society for his work on decision-making and information feedback in models of the firm. Morecroft is convinced that bounded rationality is a basic concept in every social and economic system, thus, it is helpful to describe the reality of systems. Morecroft demonstrated bounded rationality using Forrester’s market growth model, within which the sub-systems tried to act rationally (intended rationality) but the system as a whole did not show optimal behaviour when the sub-systems operated collectively.

Bounded rationality is embedded in all SD model at least implicitly, if not explicitly. Following Morecroft, John Sterman, who is mostly considered as the current leader of the SD school of thought, also engaged the analysis of bounded rationality in SD. Sterman described forecasts into the future as they are (prescriptive) but not as they should be (prescriptive) (Sterman, 1987; Sterman, 1990). He concluded that human decision-makers are not able to think in feedback loops, especially in the presence of multiple interlinked feedback loops, as they do not realise that their own behaviour has an impact on the whole system and the feedback on itself due to the limited nature of human information-
processing capabilities. To reflect real-world situations, models need to include boundedly rational agents (human decision-makers), feedback loops, and time delays involved in capacity adjustment, which are the most essential concepts in SD modelling.

During recent years, bounded rationality and SD modelling became inseparable concepts. There are two major perspectives on bounded rationality in SD, which are the content perspective (bounded rationality must be represented in SD models) and the process perspective (the modelling process itself is affected by bounded rationality).

First, bounded rational decision-making should be represented in SD models because of the need to increase external validity. Boundedly rational behaviour must be replicated in model structure and in policies within the model in order to represent reality validly. In an SD model of stocks and flows, physical structure of the model and the material flow might be not affected by bounded rationality. However, how policies control the flow does depend on the rationality of the decision-makers in the system. Artefacts of bounded rationality can mostly be found in information links within SD models: “functional dependencies are simplified, delayed and distorted information is used, or information is simply ignored” (Größler, 2004). Morecroft developed a list of ‘information filters’ to help interpret how cognitive characteristics of individual decision-makers are influenced by organisational and environmental determinants (i.e. how bounded rationality emerges). The information filters include human’s cognitive limitations; operating goals, rewards and incentives; information, measurement and communication systems; organisational and geographical
structure; and culture, tradition, folklore and leadership (Morecroft, 1994). These information filters can be used to validate decision rules and cause-effect relations in a SD model.

The second perspective considers the influence of bounded rationality in the model development process, as the modellers are prone to possess only limited capabilities to perceive and understand real-world systems (Sterman, 2000). SD modellers often pursue a similar development pattern, which is referred as the ‘standard method’. Such method was proposed by Randers (Randers, 1980), Richardson and Pugh (Richardson & Pugh, 1981), and Roberts et al (Robert et al., 1983) to ensure the quality and reliability of the model development process. The ‘standard method’ suggests four phases when developing an SD model: conceptualisation, formulation, testing and implementation. However, numerous modellers have discussed the issues they experienced when following this method publicly for the suppose of refining the SD methodology framework (Keating, 1999). These modellers stated two major issues. First, they often over simplified the situation they intended to model during the conceptualisation phase due to the limited knowledge they had. Second, the ‘standard method’ suggests model implementation as a final phase as would be found in a system development life cycle model. The modellers have questioned this view, describing their insights and contributions to organisations as ‘interventions’, ‘modelling for learning’, or ‘changing mental models’ (Senge, 1990; Graham, 1994; Morecroft, 1994). These modellers acknowledged that the limitations in their calculation
capability (‘bounded rationality’) resulted in the difficulties in implementing the model (which was over-simplified at the conceptualisation stage). To overcome the bounded rationality of the modellers, the ‘standard method’ has been expended and refined. The conceptualisation phase was decomposed into two phases: problem identification and system conceptualisation. And the implementation phase has been depicted as a parallel activity, overlapping the other model development stages (Keating, 1999).

The focus of this research, which is doctors’ prescribing behaviour, is the outcome of bounded rationality. The factors influencing individual doctors’ antibiotic prescribing behaviour are the timeliness and availability of microbiology laboratory test results, and senior doctors’ decision-making. Using the idea of bounded rationality, the doctors’ prescribing decision-making is bounded by the cognitive limitations in both knowledge (knowledge in pathogens that caused the infections, patient’s co-morbidities and infection history, etc) and computational capacity (to calculate an optimal solution to treat potential infections, cause minimal adverse clinical outcomes and/or the development of AMR, and consider other factors such as stocking, financial incentives, etc), and the limitation in the time available to make a decision (an empiric prescription must be made as soon as possible even without diagnostic information). The existence of ‘prescribing etiquette’, the principle of non-interference, and the situation when senior doctors’ decision-making overriding prescribing guidelines and influencing junior doctors’ guideline compliance, all suggest that decision-makers act like ‘satisficers’, searching through available alternatives until an
acceptability threshold is met. Doctors were seeking a satisfactory solution rather than an optimal one when prescribing antibiotics.

Bounded rationality and its resulting poor performances are due to two basic and related deficiencies of humans’ mental models. First, humans’ cognitive maps of the causal structure of systems are vastly simplified compared to the complexity of systems themselves. Second, the dynamics of causal maps cannot be inferred correctly by humans. In this case, systems’ behaviour over time cannot be inferred. No mental model can assess adequately the impact of externally imposed changes or allocate responsibility for delay and disruption occurring in complex real-world systems (Sterman, 1992). Learning about the system is only possible through simulation. Model and simulation are two inseparable concepts in operational research. A model is an approach combining diagrams, algorithms, and equations used to capture the behaviour of the system modelled. By contrast, simulation is the imitation of the operation of a real-world process or system, often with the help of computer-based software programmes. Simulation is the actual running of the programme that contains the algorithms and equations of a model. A researcher would first build a model, then simulate the model. SD met criticism in its early days of development. A major problem with SD was identified in the early years, in that the mathematical equations used in SD were too complex to be interpreted by managers (Pidd, 1992). However, Forrester foresaw this problem and predicted that the application of SD modelling would be popularised with the development of computer science (Forrester,
By performing computer-based simulation, complex equations can be solved rapidly whilst being hidden behind a graphical interface (Peterson & Richmond, 1994). With the aid of computer-based simulation, SD models can predict possible responses of complex systems to different decisions so that their leverage points are identified, so that the opportunities are created for external interference to re-design the system structures enhance desired behaviour or to eliminate undesirable behaviour (Lane & Oliva, 1998). Using computer-based software programmes, logical consequences of the ‘what if’ assumptions can be computed infallibly under controlled conditions, allowing conduction of experiments of policy alternatives which are not feasible or ethical in the real system.

### 3.3 Why System Dynamics modelling is appropriate in health management

Evidence-informed guidance and policies are needed to strengthen health systems and improves their receptiveness to interventions and innovations (Atun, 2012). Despite the huge investment in health care sector in most countries, health systems have not yet delivered the expected improvements (Ferlie & Shortell, 2001). Even in organisations with the necessary ingredients for success, failure of policies or strategies is becoming the rule rather than the exception (Sterman 1994). Additionally, the understanding of why many well-intentioned policies and interventions aimed at improving health systems did not
achieve desired outcomes but led to unexpected or unintended consequences is very limited (Atun & Menabde, 2008; Atun, 2012). An important factor, which explains the chronic failure in health system management, is the lack of adequate tools and methods to analyse, design, implement, and evaluate actions and policies (Lebcir, 2006). The analytical tools used for analysing health systems and the heuristics used to generate policy decisions are too simplistic for health systems that are complex (Lane, Monefeldt, & Rosenhead, 2000; Lebcir, 2006). Fragmented thinking created problems when designing health interventions (Buising, 2015).

In order to solve the problems in complex health care systems management, the way of framing, formulating, and analysing these problems must be changed (Lebcir, 2006). Interrelationships between parts of a system must be studied rather than narrowly focusing on the parts themselves (Buising, 2015). Multiple perspectives, conditions, connections and capabilities should be incorporated when analysing the system (Tomson & Vlad, 2014). Policy alternatives must be evaluated for potential effects on the functioning of the entire health system and ultimately health outcomes (Ritchie-Dunham & Galván, 1999). Holistic approaches that focus on not only part of the system but incorporate all the sub-systems and their interconnections are required to perform analysis, design, implementation, and evaluation in systemic manner (Trochim et al., 2006; Adam & de Savigny, 2012). The most suitable tools and techniques to satisfy the requirements are systems thinking and particularly SD modelling. SD modelling can be an effective tool to address many of these
concerns and contribute towards improved health system performance or better health care provision (Sterman 1994; Lebcir, 2006; Atun & Menabde, 2008; Atun, 2012). This contribution can be significant as SD modelling is able to effectively solve strategic and tactical problems involving aggregate flows of patients and resources (Dangerfield, 1999). SD modelling also provides opportunity to improve decision-makers’ understanding of the sources of undesired system behaviour through both qualitative and quantitative analysis of the system performance (Wolstenholme, 1990; Wolstenholme, 2004).

The four major reasons that make SD modelling a suitable tool for public health and health system management are as follows. First, health care management and health systems involve many cause-effect relationships and feedback loops. For example, increased incidence of childhood obesity resulted in the taxation on sugar-sweetened beverages, which caused the decrease in consumption and therefore the incidence (Brownell et al., 2009). Second, health systems decisions involve many delays, which means consequences of actions are not immediately visible. For example, time delay occurred between the time at which a doctor was introduced to a guideline and the time at which the doctor adjusted his or her behaviour to comply the guideline (Maue et al., 2004). Third, health care management requires understanding of non-linear relationships, which means the prediction of future system behaviour in response to an action might be completely wrong if the current conditions of the system were not considered. For example, the time spent in hospital for a disease was non-linearly linked to the time spent waiting before admission,
as the patient’s condition may worsen during the time spent on the waiting list (Coyle, 1984). Fourth, both ‘soft’ and ‘hard’ variables exist in health care management. ‘Hard’ variables are quantifiable, and the quantification processes can be validated. In contrast, ‘soft’ variables, sometimes referred as ‘intangibles’, are used to describe attributes of human behaviour or effects that variations in such behaviour produce. Numerical data are often unavailable or non-existent when estimating values for ‘soft’ variables. ‘Soft’ variables are involved in almost all health systems and health decision-making processes. Because of these four reasons, health management issues are highly dynamic and complex. Hence, SD modelling is an appropriate methodology to be applied in health management. SD modelling can be used in health systems for hypothesis testing and generation of scenarios, as well as enhanced joint thinking, group learning and shared understanding of problems (Wolstenholme 1993; Dangerfield, Fang, & Roberts, 2001; Atun et al., 2005; Atun et al., 2010; Lebcir, Atun, & Coker, 2010).

The selection of SD modelling can be also discussed in a theoretical perspective. It is widely acknowledged that drug prescribing by doctors, not only antibiotic drug prescribing, is a complex phenomenon influenced by various factors. However, to date, research on the prescribing decisions of physician lacks sound theoretical foundations. Most of the existing studies in the area of drug prescription explain doctors’ decision-making processes using the exploratory approach rather than a theoretical one (Manchanda & Honka, 2005; Vancelik, 2007; Theodorou, 2009; Murshid & Mohaidin, 2017). A few theoretical models
have been employed in the prescription research, including reasoned action theory and planned behaviour theory (Gallan, 2004; Rashidian, 2006; Godin, 2008). Recently, researchers used the Theoretical Domain Framework (TDF) for the first time to explore antibiotic prescribing behaviour in primary care in the UK. The fundamental proposition of these theories is similar to the assumption of rationality in classic economic models. These theories assumed that individuals are rational in decision-making, and therefore cognitive approach can be utilised to explain behaviour. However, it is also reported in these studies that the employed model did not incorporate emotional variables. Moreover, both literature evidence and the primary information collected from survey and interviews suggested that doctors’ prescribing decisions were influenced by multiple cultural and emotional factors and far away from being perfectly rational. A different theoretical model is required to develop better understanding and design better interventions to change doctors’ behaviour. A theoretical model that does not assume perfect rationality, a model that acknowledge the limitation in information and time available for decision-making and the limitation in doctors’ cognitive capacity. This theoretical model indeed is ‘bounded rationality’. In this thesis, the theory of ‘bounded rationality’ was chosen to interpret doctors’ antibiotic prescribing behaviours in the hospitals. SD modelling was applied because of its technical strengths and its fundamental axiom that the method itself was built upon (Chapter 3, 3.3.3 ‘Bounded rationality’).
3.4 Summary of System Dynamics applications in health management and antimicrobial resistance

Previous applications of SD modelling in health management and AMR management are discussed in this section. As shown in Table 3.2, the reviews conducted to identify the application of simulation modelling methods and SD modelling at different times suggested that the popularisation of SD modelling methods started in 1990s and experienced exponential growth in 2000s. In the last decade, SD modelling has been used in a variety of substantive areas in the context of health management.

Table 3.2 Literature in modelling methods in health management

<table>
<thead>
<tr>
<th>Study</th>
<th>Aim</th>
<th>Method</th>
<th>Main findings related to SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation modelling and health-care decision making. (Klein et al.,</td>
<td>To develop an annotated bibliography to provide the access to the</td>
<td>Review</td>
<td>SD modelling was not included in the bibliography. Deterministic or Monte Carlo simulation, and stochastic and discrete-event simulations were applied to support healthcare decision-making.</td>
</tr>
<tr>
<td>1993)</td>
<td>literature of simulation modelling and its application in healthcare decision-making</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Systematic review of the use and value of computer simulation</td>
<td>To identify studies in the use of computer simulation modelling in</td>
<td>Systematic</td>
<td>At the time when the study was complete, no study using SD modelling in public health and care delivery was identified.</td>
</tr>
<tr>
<td>modelling in population health and health care delivery. (Fone et al,</td>
<td>population health and health care delivery</td>
<td>review</td>
<td></td>
</tr>
<tr>
<td>2003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Applications of System Dynamics modelling to support health policy.</td>
<td>To identify articles published up to April 2015 that described the</td>
<td>Systematic</td>
<td>6 papers were identified, comprising 8 case studies of the application of SD modelling to support health policy design in smoking cessation in New Zealand; alcohol-related harm reduction in the UK; cardiovascular disease prevention in the US; cervical cancer screening, chlamydia screening, and</td>
</tr>
</tbody>
</table>
emergency health and social care in England; forensic mental health in England; pharmacotherapy maintenance in Australia (Tobias, Cavana, & Bloomfield, 2010; McKelvie et al., 2010; Loyo et al., 2010; Smith et al., 2004; Chalmers et al., 2009). The result of the systematic review suggested that SD modelling provided policy makers with powerful tools to support the design of targeted, effective and equitable policy response for complex problems.

Apart from the studies identified through the systematic review conducted in 2015, SD modelling has been applied to explore policy options for improving neonatal health in Uganda (Semwanga, Nakubulwa, & Adam, 2016); model the impact of educational interventions on the abuse of pharmaceutical opioids in the US (Wakeland et al., 2013); managing waiting time for patients with coronary heart diseases in the UK (Taylor, 1998). The researcher of this study has previously applied SD modelling in the research area of maternal health in health systems by developing a simulatable SD model to simulate pregnant women’s care-seeking behaviour in Pakistan and provide estimates of neonatal mortality to demonstrate that patients’ care-seeking behaviour was influenced by socio-economic and social networking factors. An article reporting the development process and simulation results of the maternal health SD model has been submitted for publication to *The Lancet Global Health* and is currently under review.

Additionally, SD modelling has demonstrated its capability in solving problems in public health management when it was employed to simulate population flows, predict health
seeking behaviour, support health decision-making, test health policy alternatives, and evaluate effectiveness of health interventions in earlier research (Klein et al., 1993; Royston et al., 1999; Barton, Bryan, & Robinson, 2004; Lane & Husemann, 2008; Günal & Pidd, 2010).

Specifically, in relation to this study, search for application of SD modelling in the research field of AMR management was also conducted (Table 3.3). SD modelling had not been utilised to investigate antibiotic prescribing behaviour and decision-making processes at the time when this study was conducted.

**Table 3.3 Recent literature in System Dynamics modelling in antimicrobial resistance**

<table>
<thead>
<tr>
<th>Study</th>
<th>Site/context</th>
<th>Application of SD modelling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Toward a dynamic theory of antibiotic resistance. (Homer et al., 2001)</td>
<td>USA</td>
<td>A non-simulatable SD model was developed to qualitatively represent the process of AMR development in relation to antibiotic prescribing</td>
</tr>
<tr>
<td>Impact of an effective multidrug-resistant tuberculosis control programme in the setting of an immature HIV epidemic: System Dynamics simulation model. (Atun et al., 2005)</td>
<td>Russia</td>
<td>A simulatable SD model was developed to manage the treatment policies to address colliding epidemics of tuberculosis, drug-resistant tuberculosis and injecting drug users driven HIV.</td>
</tr>
<tr>
<td>High coverage with HAART is required to substantially reduce the number of deaths from tuberculosis: System Dynamics simulation. (Atun et al., 2007)</td>
<td>Russia</td>
<td>A simulatable SD model was developed to simulate the transmission dynamics of drug-resistant tuberculosis, multidrug-resistant tuberculosis and HIV to estimate the impact of coverage with highly active antiretroviral therapy.</td>
</tr>
<tr>
<td>Sustainable antimicrobial use in bovine practice: a System Dynamics approach. (Lhermie et al., 2017)</td>
<td>Western European public policies</td>
<td>A simulatable SD model was constructed to assess the impact of AMR development from antimicrobial use in bovine.</td>
</tr>
</tbody>
</table>
Antibiotic prescribing decision-making processes are complex and dynamic, cause-effect and feedback loops exist between doctors’ prescribing behaviour and the factors arise from multiple levels across healthcare systems. Time delays occur in the process of doctors improving their practices in response to the changes in intervention and policy environment. Non-linear relationships, and ‘hard’ and ‘soft’ variables are involved in prescribing decision-making processes. The requirement of a ‘systems thinking’ analytical tool to analyse and map doctors’ prescribing behaviour, and the successful application of system thinking approaches and SD modelling in other areas in health management have provided the rationale to employ SD modelling in this study.

The SD model that is to be built in the later stage of the study is conceptualised by defining the purpose of the model (Randers, 1980). The SD model aims to address the following research questions: which stakeholders are involved in prescribing decisions; which influence factors affect prescribing behaviours; from where in the health system do these influence factors arise; and when during prescribing decision-making processes, by capturing causal relationships between prescribing decision-making processes and factors influencing the processes; and predicting prescribing outcomes in response to changes in the influence factors.

In the next chapter, the methods employed to construct the model and process the source data are described.
An article was drafted to report the findings from the rapid literature review and describe the process of employing the hierarchical framework, searching for the dynamic analytical tool to analyse prescribing decision-making processes, and conceptualising the model when SD modelling was selected by the researcher of this study. The article has been submitted for publication to *BMC Health Services Research* and is currently under review.

Key points in Chapter 3:

- SD modelling is a systems thinking modelling methods which recognises decision-makers’ ‘bounded rationality’.
- SD has been applied in various health management issues and demonstrated its capability in help develop understanding and predict complex system behaviour.
Chapter 4 Methods

In the previous chapter, an SD model was conceptualised by defining the purpose of the model. The SD model aims to predict doctors’ antibiotic prescribing decision-making processes in the context of hospitals in the NHS in England. In this chapter, the screening of modelling and simulation methods is performed and discussed to provide the rationale of selecting SD modelling in this research. The methods used to build the SD model and analyse the source data are described.

4.1 Rationale for selecting System Dynamics in this research

A powerful analytical tool is required to study prescribing decision-making processes within complex health systems. This analytical tool must be simulatable, and meet the requirements in capturing both ‘system’ and ‘dynamic’ aspect of prescribing decision-making, allowing simulation, and being efficient and effective considering the limit in research resources.
4.1.1 Capturing ‘System’

As discussed in the previous chapters, factors influencing doctors’ decision-making processes occurred on multiple levels across healthcare systems. These factors influence doctors’ prescribing individually and collectively while interacting with each other and with the system environment of which these factors arise.

‘Whole-of-system’ approaches were endorsed when designing AMS interventions during the past decade (Mendel, 2014). While the ‘system’ aspects of antibiotic prescribing and AMS management were recognised, and the requirement of a whole-of-system approach to analyse prescribing behaviour was acknowledged, existing research did not provide methodological approaches that were strong enough meet the requirement (Buising, 2015).

Antibiotic prescribing decision-making processes are complex and dynamic. These processes involve cause-effect relationships and feedback loops, time delays, and non-linear relationships. The factors influencing prescribing decision-making processes include both ‘hard’ and ‘soft’ variables. A powerful systems thinking analytical tool is required to analyse antibiotic prescribing behaviour in a systemic manner. Modelling and simulation methods previously used in NHS England and healthcare systems in the UK were reviewed in the earlier chapter (Chapter 2, 2.5 Context of the study and the reasons for its selection, Table 2.5). Among these methods, qualitative methods such as cognitive mapping, process mapping, soft systems methods (SSM), causal loop diagrams (CLDs), mathematical
modelling methods such as Markov models and analytic models, and simulation methods such as discrete-event simulation (DES), System Dynamics (SD) modelling, are considered systems thinking methods (Smith et al., 2001; The UK Modelling and Simulation in Healthcare Network, 2014).

4.1.2 Capturing ‘Dynamics’

In this study, the analytical tool required must be simulatable so that the dynamic aspect of antibiotic prescribing decision-making processes can be captured so that the change over time in prescribing outcomes of the modelled system can be predicted, considering the evolutionary nature of health systems. Among different modelling approaches, dynamic simulation modelling methods are favoured by policy makers and researchers for their ability to test system behaviour over time. They experiment with and test interventions and scenarios and their consequences over time by simulating the operation of processes and systems to enhance the understanding of the system or process, communicate findings, and inform policy and intervention design (Banks 1998; Harrison et al., 2007; Sokolowski & Banks, 2011; Marshall et al., 2015).

Modelling and simulation methods previously used in NHS England and healthcare systems in the UK were reviewed in the earlier chapter (Chapter 2, 2.5 Context of the study and the reasons for its selection, Table 2.5). Among these previously used models, the
simulatable ones incorporated the elements of systems (Markov models and analytic models) are compared with dynamic simulation models, which include SD modelling, discrete-event simulation (DES) (Smith et al., 2001; Marshall et al., 2015) (Table 4.1). Notice that agent-based modelling (ABM) is also one type of dynamic modelling method, however, ABM focuses on the behaviour of each individual inside a system instead of the system behaviour, hence, it is considered not suitable for this study (Grimm et al., 2006).

Through comparison, one can decide that dynamic simulation models are suitable to model non-linear behaviour in complex systems. In comparison to Markov models and analytic models, dynamic simulation models deal with complex systems within which the relationships were non-linear.

| Table 4.1 Comparison between dynamic simulation models and other types of models |
|--------------------------------|-----------|-----|--------------------------------|------------------|---------------------|
|                               | Mode of description | Indexing | Linearity | Procedure to provide solution | Population character |
| Dynamic simulation models     | Implicitly via rules or equations | Time and space | Non-linear | Simulation | Open population |
| Markov models                | Implicitly via transition matrices of probabilities | Time | Linear | Closed-form solution (for simple systems) or simulation | Cohorts |
| Analytic models              | Closed-form expressions (explicit functions of time) | Varies | Linear | Direct evaluation | Varies |

In addition, an 8-point checklist can be used to determine whether dynamic simulation was suitable for the problem of interest before building models and performing simulations.
The 8-point checklist, referred as the SIMULATE checklist, is developed to assist health researchers and decision makers in deciding whether dynamic simulation modelling methods were appropriate to address specific health care delivery issues (Marshall et al., 2015). The 8 points included in the SIMULATE checklist are System, Interactions, Multi-level, Understanding, Loops, Agents, Time, and Emergence (Marshall et al., 2015) (Table 4.2).

Antibiotic prescribing in hospitals, considered health care delivered in secondary care, can be assessed using the 8-point checklist (Goldmann et al., 1996; Cooke & Holmes, 2007). The findings from the rapid literature review were analysed using the SIMULATE checklist to decide whether dynamic simulation modelling methods are suitable to analyse prescribing decision-making processes.

Table 4.2 Using the SIMULATE checklist in this study (adapted from Marshall, 2015)

<table>
<thead>
<tr>
<th>Checklist</th>
<th>Does your problem require?</th>
<th>Using in this Study</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>System</strong></td>
<td>Modelling multiple events, relationships, and stakeholders representing health care delivery processes?</td>
<td>Yes, multiple events (making empiric decisions, reviewing, de-escalating, escalating, blood sampling), relationships (relationships between junior and senior doctors, between doctors and patients, between doctors and microbiologists), multiple stakeholders (doctors, microbiologists, other healthcare professionals) present in prescribing decision-making processes.</td>
</tr>
<tr>
<td><strong>Interaction</strong></td>
<td>Including nonlinear or spatial relationships among stakeholders and their context that influence behaviours and make outcomes in the system difficult to anticipate?</td>
<td>Yes, non-linear relationships are involved in the complex antibiotic prescribing decision-making processes. Prescribing behavioural outcomes, patients’ health outcomes, AMR-related outcomes, and health economic outcomes cannot be anticipated based on stakeholders’ behaviour.</td>
</tr>
<tr>
<td><strong>Multi-level</strong></td>
<td>Modelling a health care delivery problem from strategic, tactical, or operational perspectives?</td>
<td>Yes, the categorisation of influence factors using the hierarchical framework demonstrated the multi-level nature of the antibiotic prescribing management. The problem is from strategic (policy formulation at healthcare systems level); tactical (management at organisational level), and operational level (decision-making and prescribing at individual level).</td>
</tr>
<tr>
<td><strong>Understanding</strong></td>
<td>Modelling a complex problem to improve patient-centred care that cannot be solved analytically?</td>
<td>Yes, prescribing outcome measures are determined by the decision-making processes of doctors, which cannot be solved analytically.</td>
</tr>
<tr>
<td><strong>Loops</strong></td>
<td>Modelling feedback loops that change the behaviour of future interactions and the consequences for the delivery system?</td>
<td>Yes, cause-effect relationships existed between prescribing behaviour and influence factors within healthcare systems. The change in prescribing behaviour changes the system environment, which causes further changes in the factors influencing prescribing behaviour.</td>
</tr>
<tr>
<td><strong>Agents</strong></td>
<td>Modelling multiple stakeholders with behavioural properties that interact and change the performance of the system?</td>
<td>Yes, stakeholder involved in prescribing decision-making processes are intelligent agents who make rational decisions in response to the changes in the system.</td>
</tr>
<tr>
<td><strong>Time</strong></td>
<td>Time-dependent and dynamic transitions in a health care delivery system, either between or within health care system levels or in health status change?</td>
<td>Yes, doctors’ prescribing behaviour changes at different time points during the processes.</td>
</tr>
</tbody>
</table>
Emergence

| Considering the intended and unintended consequences of health system interventions to address policy resistance and achieve target outcomes? | Yes, policy resistance emerged in AMS interventions were implemented in secondary care in the UK. Prescribing outcomes as consequences of existing interventions must be considered to inform the formulation of interventions in future. |

All the elements of the SIMULATE checklist were involved in the problem of antibiotic prescribing decision-making processes. The checklist indicated that dynamic simulation modelling is required to analyse the problem and will be an efficient approach to help develop the understanding of prescribing decision-making (Briggs et al., 2012).

4.1.3 System Dynamics modelling to inform efficient and effective use of resources in health systems

NHS and healthcare systems in the UK are facing significant financial pressure with no sign of easing. The ever-increasing pressure has encouraged policy makers and health researchers to turn to system modelling and simulation solutions to ensure the most efficient and effective use of limited health research resources (Pitt et al., 2016). Computer-based modelling methods are considered efficient as they required less resources when compared to the traditional ‘try it and see’ approaches (Kirwan et al., 2017). As a simulation method, SD modelling meets the requirement of providing evidence to support intervention and policy formulation with no extra research resources needed. In addition, SD modelling is an approach where the validity cannot be verified using statistical testing. Hence, SD
modelling has little demand in the size of source dataset used to formulate the model (Barlas, 1989). The discussion of SD approach and statistical significance will be expanded in Chapter 7 (Chapter 7, 7.3.2 Correlational and causal-descriptive models, 7.3.3 Statistical significance in System Dynamics modelling).

So far, various modelling and simulation methods have been reviewed through a screening process (Table 4.3).

<table>
<thead>
<tr>
<th>Table 4.3 Modelling and simulation method screening</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modelling and simulation method screening</td>
</tr>
<tr>
<td>Cognitive mapping</td>
</tr>
<tr>
<td>Process mapping</td>
</tr>
<tr>
<td>Soft Systems Methods (SSM) Strategic Options and Decision Analysis (SODA)</td>
</tr>
<tr>
<td>Causal loop diagrams (CLDs)</td>
</tr>
<tr>
<td>Regression</td>
</tr>
<tr>
<td>Forecasting</td>
</tr>
<tr>
<td>Optimisation</td>
</tr>
<tr>
<td>Queuing theory</td>
</tr>
<tr>
<td>Markov models</td>
</tr>
<tr>
<td>Analytic models</td>
</tr>
<tr>
<td>Discrete-event simulation</td>
</tr>
<tr>
<td>System Dynamics (SD)</td>
</tr>
</tbody>
</table>
Over the years, simulation modelling has become an effective and robust part of management science toolkit widely used in practice (Brailsford et al., 2004). It has been successful used as scientific tool for management thinking and decision support for process systems (Pidd, 2003). Simulation of a process system involves building a valid model of such a system and using this model in order to gain insight into the system’s functioning under alternative scenarios. In the context of simulation modelling in management science, the existing literature mainly explores the possibilities of individual, combined, or integrated application of DES and SD approaches (Brailsford et al., 2004; Peña-Mora et al., 2008). Discrete-event simulation (DES) is considered the closest alternative of SD modelling (Sweetser, 1999). There is a large area of overlap between the two approaches. Both methods, used appropriately, can help provide increased understanding and serve as an aid to decision-making. In both approaches, structure determines system performance, and reply heavily on computer-based simulation to produce quantitative results.

DES and SD can be positioned closely on the spectrum of ontology. The ontological and epistemological bases on a given scientific discipline postulate the way human beings comprehend knowledge about what is perceived to exist’ (Burrell & Morgan, 1979).
Critical realism is a philosophy of science primarily presented by the abductive mode of reasoning (Bhaskar, 1978, 1979, 1989). The critical realism ontology divides reality into three domains of being, referred to as the domains of real, actual, and empirical. The domain of real consists of underlying generative mechanisms and causal structure activated by these mechanisms. The activation of the causalities of the generative mechanisms triggers patterns of events and behaviours of the process systems that reside in the domain of actual. Those events and behaviours that are experienced or observed by humans are in the domain of empirical. The critical realism argues that conceptualisation of the problem behaviour of a system without data is ontologically separated from the experienced (perceived) behaviour of the system – it is difficult to build realistic conceptual model based on limited and personalized view of the real world. The general direction of critical realism in scientific generalization (in DES and SD) is from the available empirical data to the postulation of the ‘actual events’ and ‘real causes’. DES and SD approaches share similar model development processes: from problem articulation, to model conceptualisation, validation, simulation, and result interpretation. The model development steps can be separated into the three domains of beings aforementioned. Model conceptualisation, reflecting the underlying mechanisms and structures of the system, is related to the domain of real. Model validation and simulation are both empirical. Result interpretation is related to the domain of actual, where all the events and behaviours produced by underlying mechanism of the system are actualized. The validation of both
DES and SD models is the process to first validate the hypothesized conceptual model, then identify the correct generative mechanism that is tested against the actual behaviour of the modelled system. The validation of the conceptual model often involves expert opinion, which can be subjective.

DES and SD approaches are distinct in system structures, modelling techniques, and requirement in source data. DES models systems as networks of queues and activities. The state changes in the system occur at discrete time points. The objects in the systems are distinct individuals, each possessing characteristics that determine what happens to that individual, and the activities durations are sampled for each individual from probability distributions. SD models systems as networks of stocks and flows in with state changes occur continuously. The objects in the system are a continuous quantity. SD is essentially a deterministic approach. It does not handle individual entities. The main criteria of which a selection could be based on is presented in the table below (Table 4.4) (adapted from Brailsford et al., 2004).

<table>
<thead>
<tr>
<th><strong>Table 4.4 Criteria for selection of modelling approach</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scope</strong></td>
</tr>
<tr>
<td>Operational, tactical</td>
</tr>
<tr>
<td><strong>Importance of variability</strong></td>
</tr>
<tr>
<td><strong>Importance of tracking individuals</strong></td>
</tr>
<tr>
<td><strong>Number of entities</strong></td>
</tr>
</tbody>
</table>
### Table

<table>
<thead>
<tr>
<th>Control (of activities)</th>
<th>Holding (queues)</th>
<th>Rates (flows)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative timescale</td>
<td>Short</td>
<td>Long</td>
</tr>
<tr>
<td><strong>Purpose</strong></td>
<td>Decisions: optimisation, prediction and comparison (probabilities of individual behaviour under different scenarios)</td>
<td>Policy making: gaining understanding (of system behaviour under different scenarios)</td>
</tr>
</tbody>
</table>

SD can be used at a higher, more aggregated and strategic level (‘system’ perspective) than DES and the data requirements of an SD model are much less (Brailsford et al., 2004). It is more useful for clarifying the complexities of organisational behaviour. SD modelling is selected for this research, as this thesis aimed to examine doctors’ prescribing decision-making processes in medical wards collectively in a systematic manner. SD has the capability to deal with problems within inherently complex health systems consisting of multiple tiers of sub-systems and processes that are adaptive to changes in the environment as results of cause-effect relationships and behave in a non-linear fashion (Marshall et al., 2015). Also, SD was chosen for its capability to include ‘soft’ variables related to human behaviour.

Other modelling methods can be embedded in the stage of building an SD model. For example, process mapping can be utilised at the model conceptualisation stage to help set the scene of the modelled scenario, define sub-systems and system boundaries. The qualitative stage of SD modelling, which is to capture the causal relationships in modelled system using causal loop diagrams (CLD), can be completed in separation from the quantitative formulation stage to produce a qualitative model. Using SD, logical
consequences of the ‘what if’ assumptions can be computed infallibly under controlled conditions, allowing conduction of experiments of policy alternatives which are resource consuming, time consuming, not feasible or ethical in the real system. Other modelling and simulation methods are also operationalised in this research at different stage to solve specific research questions.

### 4.2 Data

SD modelling has been selected as the method in this study to analyse doctors’ prescribing decision-making processes. After deciding the modelling method, available databases or sources of information from which the qualitative maps and the computer-based simulation model can be constructed must be considered (Forrester, 2009). In Forrester’s opinion, the world’s store of information lies primarily in people’s heads – in mental databases. SD modelling should build on all available information, including the voluminous mental databases. By contrast, most analyses in the social sciences have been limited to information that has been numerically recorded. The numerical information is an extremely small part of all the information that is available (Figure 4.1) (Forrester 1968; Forrester, 1994; Forrester, 1997; Forrester, 2009).
In this study, three data sources were selected to provide information required to build the model. The data sources are discussed in the next section of this chapter, in relation to the purpose of the model and Forrester’s opinion on information sources for SD modelling.

### 4.3 Data sources

Both primary data and secondary data were included as source data for SD modelling. Employing secondary data is a practice to follow the lead given in the *OECD Principles and Guidelines for Access to Research Data from Public Funding*, that publicly-funded research data should be openly available to the scientific community to maximise the return on the investment in public sector (Pilat & Fukasaku, 2007).

The source data included both qualitative and quantitative evidence. Employing qualitative
data collected from in-depth, semi-structured interviews was a practice of utilising Forrester’s mental data base and written (textual) data base (Forrester 1968; Forrester, 1994; Forrester, 1997; Forrester, 2009). Though findings from qualitative studies cannot be translated into quantitative model parameters, they help enrich the textual knowledge base of prescribing behaviour management, strengthen the understanding of cause-effect relationships between doctors’ behaviour and influence factors, and increase the confidence in the overall credibility of the model.

Three data sources were included in this study to provide the required qualitative and quantitative information for SD modelling. Secondary data collected in earlier studies were employed, as well as primary data collected for the purposes of this thesis. Secondary data was collected from two sources, including 1) a cross-sectional survey of qualified doctors in training (referred as Foundation Year 1 and 2 doctors) in five NHS Trust teaching hospitals across West London to assess their skills, attitude and educational needs in antimicrobial prescribing in 2014 (Gharbi et al., 2016); and 2) semi-structured in-depth interviews conducted with doctors newly qualified to consultant level in three NHS Trust teaching hospitals to discuss their antibiotic prescribing decision-making processes for acute infection management in hospitals in 2015 (Rawson et al., 2016). Both studies were undertaken by fellow researchers at the Health Policy Research Unit (HPRU) at Imperial College London.

Primary data was collected specifically for purpose of this study. During 1 March 2016 to
1 August 2016, 150 patients with *E. coli* bloodstream infection (either admitted due to the infection or developed the infection during the admission) were enrolled as ‘hospital inpatients’ and stayed in the medical wards in the three NHS Trust teaching hospitals. The inpatient notes of these 150 patients were retrospectively reviewed to extract the data on antibiotic prescribing decision-making processes when doctors were treating these patients.

The analysis of the primary and secondary source data provides qualitative and quantitative information to support SD model formulation. The qualitative data was used in the mapping stage to help set the scene and define the boundaries of the system modelled and provide information in causal relationships between key variables occurring in the antibiotic prescribing decision-making processes, which are captured using CLDs presented in Chapter 5 (Chapter 5, 5.2.2 Causal Loop Diagram). The quantitative data, on the other hand, is incorporated to provide estimates of SD model parameters in the quantitative formulation stage.

In the later sections, brief details of the data collection in the primary studies is included for the two sources that provided secondary data (survey with Foundation Year doctors\(^1\) and interviews with specialty registrars\(^2\) and consultants\(^3\)) as well as the source of the primary data (inpatient hospital notes). The analysis performed on each of the secondary

\(^1\) **Foundation Year doctors**: doctors completing a 2-year Foundation Training programme after obtaining undergraduate medical degree in the UK. The training comprises Foundation Year 1 and Foundation Year 2.

\(^2\) **Specialty registrars**: doctors working in the 3-year Specialty Training programme in the UK. Doctors enter a 3-year specialty training programme after completing the 3-year Core Training programme.

\(^3\) **Consultants**: senior hospital-based doctors (physicians or surgeons) who have completed all specialty training and been placed on the specialty registrars in their chosen specialties in the UK.
and primary data source is described.

4.4 Secondary research

4.4.1 Quantitative research: survey with Foundation Year doctors

Though knowledge and experience are essential for optimal prescribing practices, prescribing decisions are often left to junior doctors (including Foundation Year doctors and core trainees\(^4\)) who may not have the expertise, knowledge or confidence. Meanwhile these newly qualified doctors are a large, mobile prescribing group. The survey was conducted to examine junior doctors’ knowledge, attitude, and self-perceived barriers to antimicrobial prescribing.

The survey participants were recruited during weekly teaching sessions for Foundation Year doctors to complete a 45-item questionnaire. Direct recruitment continued until saturation was reached (>85% doctors in one training session reporting that they had completed the survey) (Gharbi et al., 2016). 130 doctors were approached, 109 completed the paper-based questionnaires (84% response rate). Additionally, the electronic version of the questionnaire was sent by email to 759 junior doctors (below consultant) registered with North West London region, 31 completed the electronic-based questionnaires (4% response rate). Among all the respondents, 102 were Foundation Year 1 and 2 doctors

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\(^4\) Core trainees: doctors working in the 3-year Core Training programme in the UK. Doctors enter a 3-year specialty training programme after completing the 2-year Foundation Training programme.
(during their 1st or 2nd post-qualification years when they completed the survey).

Secondary analysis was performed using the data collected for Foundation Year doctors from this survey. All the variables of interest were tabulated or entered multivariate analysis.

4.4.2 Qualitative research: interviews with senior doctors

Studies have been conducted to generate evidence describing knowledge, attitude and cultural factors influencing antibiotic prescribing. However, existing data describing doctors’ decision-making processes are limited. Hence, a series of interviews were conducted to map the decision-making processes of medical physicians in secondary care for acute infection management and investigate the factors that may hinder or facilitate the effective use of antimicrobials.

8 consultants and 3 specialty registrars from non-infection medical specialties were interviewed. The characteristics of doctors included in this study are presented in Table 4.5.

Table 4.5 Characteristics of senior doctors included in the interview

<table>
<thead>
<tr>
<th>Doctor</th>
<th>Specialty</th>
<th>Experience (years of practising)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consultant 1</td>
<td>Haematology</td>
<td>5 years</td>
</tr>
<tr>
<td>Consultant 2</td>
<td>Haematology</td>
<td>25 years</td>
</tr>
<tr>
<td>Consultant 3</td>
<td>Geriatrics</td>
<td>4 years</td>
</tr>
<tr>
<td>Consultant 4</td>
<td>Endocrinology</td>
<td>Not stated</td>
</tr>
<tr>
<td>Consultant 5</td>
<td>Acute medicine</td>
<td>5.5 years</td>
</tr>
<tr>
<td>Consultant 6</td>
<td>Gastroenterology</td>
<td>Not stated</td>
</tr>
<tr>
<td>Consultant 7</td>
<td>Respiratory</td>
<td>5.5 years</td>
</tr>
</tbody>
</table>
The interviewed doctors described the procedure they would go through when treating a patient, the typical process of how an empiric decision was made on the medical ward, the barriers and facilitators they experienced in infection management, the attitude towards guidelines and microbiology laboratory test results, and the level of empowerment they perceived in their current post.

The interview transcripts were analysed by a single researcher. A grounded theory approach was applied to explore all topics that were considered to be important or interest (Heath & Cowley, 2004). Analysis of the data identified and labelled relevant factors influencing antibiotic decision-making processes, and established categories for these influence factors. The findings were discussed with the researcher who conducted the interviews (TMR) to enhance the rigor of the secondary analysis.

### 4.5 Primary research

The survey and the interviews provided both quantitative and qualitative evidence of ‘what doctors said that they would do/had been doing’. However, the assessment of doctors’ behaviour could not be done if there were no measures of their prescribing practices. An
inpatient note review was performed to extract data on decisions made when treating patients with bacterial infections by doctors from the same hospitals in which the survey and the interviews were conducted to provide evidence of ‘what doctors have actually done’ and to examine whether the findings from the survey and the interviews reflected the reality of doctors’ daily practices.

4.5.1 Documentary analysis: hospital inpatient notes review

The electronic records for the patients were extracted from the Cerner™ database. The ‘inpatient notes’ section (plain text of patients’ condition, history, co-morbidity, doctors’ impression and preliminary diagnosis, prescriptions, instructions of other procedures), ‘pharmacy notes’ section (type, dosage, route, duration, nurses/pharmacists who admitted, start/switch/stop time of medicines), and ‘laboratory records’ section (type of tests, test results) were reviewed for each patient for the latest inpatient episode during the time period from 1 March 2016 to 1 August 2016.

Associations between patient’s age, doctor’s seniority and prescribing behaviour at empiric stage, and the level of guideline compliance, were explored by cross tabulations. Multivariate logistic regression was performed to assess the correlation. The odds ratio was calculated to quantify how strongly a patient’s age, and a doctor’s seniority were associated with the guideline compliance level at empiric stage. Firstly, the odds ratio was calculated
for patient’s age and doctor’s seniority as single predictors, secondly, the analysis was performed adjusting for specialty and hospital as two confounders. The reported p-values were considered as two-tailed, and a p-value <0.01 was considered to be statistically significant. Statistical analysis was performed using Microsoft Excel® 2017 and STATA® v13.

The findings from the three separate studies discussed above provided the full picture of prescribing decision-making. The qualitative and quantitative findings from the analysis of data from each source are presented and discussed in Chapter 6 (6.3.1 Data sources for model parameterisation). A way to synthesize the findings of these studies is required to combine qualitative and quantitative evidence to evaluate complex prescribing behaviour and allow comparison of results around the same research topics using different methods. The qualitative and quantitative findings are integrated together using a data integration protocol for mixed-method study developed by O’Cathain to develop in-depth understanding of doctors’ prescribing decision-making processes and provide estimates of SD model parameters (O’Cathain, Murphy, & Nicholl, 2010). The data integration protocol and the integrated results are presented and discussed in Chapter 6 (6.3.2 Integration of qualitative findings, 6.3.3 Integration of qualitative findings).
4.6 System Dynamics modelling

Current approaches to the development of SD models include 1) approaches based on CLDs, which construct the qualitative model structure first based on the causal interconnections between key variables and transit the qualitative structure into quantitative simulation-based model; 2) approaches based on the identification of resources and their states, which identify system resources and the location in association with key variables, and construct models based on the movement of the resources; 3) usage of generic structures for specific domain field, which develop models based on existing operating systems, such as control systems in a nuclear power plant; and 4) component strategy for the formulation of SD models, which develop models based on the components included in the systems of interest (Coyle, 1996; Wolstenholme, 1990; Wolstenholme, 2004; Forrester, 1968). All these approaches are widely used in different research fields based on the purpose of individual studies and the resources available.

In this study, an approach combining usage of CLDs and component strategy was employed to construct an SD model that represents doctors’ antibiotic prescribing decision-making processes. The SD model building process described by Sterman in his well-recognised guidance ‘System Dynamics Modelling: Tools for Learning in a Complex World’ was followed in this study (Sterman, 2001). In Sterman’s guidance, building a simulatable SD model based on the causal relationships within the system modelled goes through the process of drawing CLDs, translating CLDs into stock and flow diagrams (SFDs),
formulating equations, and performing simulations (Sterman, 2001).

The model development process includes 6 broad stages of 1) conceptualisation, 2) source data analysis, 3) qualitative mapping, 4) quantitative formulation, 5) validation and testing, and 6) simulation and interpretation. In Chapter 3, the procedure of model conceptualisation was discussed. In this chapter, the steps undertaken to analyse the source data were described. In Chapter 5, the SD model is qualitatively described using through a series of mapping activities. In Chapter 6, the results of source data analysis, and the procedure followed to formulate and parameterise the model are presented and discussed. In Chapter 7, the tests performed to verify the validity of the SD model are described. In Chapter 8, results of the model simulation and the interpretation of the simulation results are presented. Figure 4.2 shows the actual process taken to build the SD model. The search of literature evidence, the analysis of source data, and the validation of SD model components were undertaken concurrently with model construction.

**Figure 4.2 System Dynamics model building process**
In the next chapter, the structure of the model is qualitatively described using a sub-system diagram, a model boundary chart, and a series of CLD (Chapter 5, 5.1 Defining the system, 5.2 Causal relationships of the System Dynamics model). The schematic map of prescribing decision-making processes in Chapter 2 provided the structural base for the SD model (Chapter 2, 2.2.4 Results: schematic map of prescribing pathway, Figure 2.2).

4.7 Research ethics approval

All persons and hospitals involved in this study are kept anonymous in order to maintain the confidentiality of respondents. Full ethics approval was obtained from the National Health Service (NHS) Research Ethics Committee (REC) (reference number 14/LO/2217) to access the hospital inpatient data. The use of the data was approved by NHS/HSC (Health and Social Care) R&D office and NHS REC. All identifiable information was removed for all patients and healthcare professionals after the analysis of the dataset in this study.
4.8 Discussion

4.8.1 Building a grounded model

An SD model can only be considered successful if it is ‘sound, defensible and well-grounded’ (Coyle & Exelby, 2000). A successful SD model must meet the requirements of the stakeholders and pass a series of model validation tests to verify the validity of different aspects of an SD model, including model structure, model parameters, and system behaviour simulated using the model (sound and defensible). The model validation tests performed in this study will be described in Chapter 5. In addition, the SD model must be well grounded in both theory and empirical evidence to establish validity, reliability, and practical utility (well-grounded) (Tulinayo, van Bomme, & Proper, 2011).

The source data used in formulating the SD model was selected based on the purpose of the model and the scene set and the boundaries defined for the system of interest. The system was described to be contextually and functionally equivalent to an NHS Trust teaching hospital in London. Hence, the qualitative and quantitative data was required to be collected from the similar settings to ensure that evidence was valid in the modelled system. Healthcare professionals and researchers from NHS Trust teaching hospitals provided input to help construct and validate the model. The model was grounded in the empiric knowledge of antibiotic prescribing decision-making processes provided by the experts from the same context.
In this chapter, the primary and secondary data from multiple sources were analysed to provide qualitative and quantitative information to support the formulation of the SD model. The findings from the analysis of each data set will be presented in Chapter 6 and synthesized together to draw a full picture of antibiotic prescribing decision-making processes and provide estimates of parameter values. In the next chapter, the SD model is described using qualitative maps. The scene of the system modelled is set and presented in a sub-system diagram. The boundaries of the system are defined and presented in a model boundary chart. The key variables included in the system, and the causal relationships between the key variables are presented in a series of causal loop diagrams.

Key points in Chapter 4:

- SD modelling was compared with alternative simulation modelling approaches. It was selected as the analytical tool in this research for its philosophical and theoretical adequateness.
- Multiple data sources were employed in this research to provide quantitative and qualitative information for SD model development.
- The primary data was collected from hospital inpatient notes. The secondary data was collected from a survey with junior doctors and in-depth interviews with senior doctors.
In the previous chapter, the rationale for selecting SD modelling in this study was discussed. Primary and secondary data from multiple sources was analysed to provide qualitative and quantitative information to support the formulation of the SD model.

In this chapter, the SD model is described using qualitative maps.

The qualitative mapping process included the following activities:

- Setting the scenes for the system to be modelled, constructing a sub-system diagram to visualise the system components included in the SD model;
- Defining the boundaries of the system, constructing a model boundary chart for excluded variables, exogenous variables, and endogenous variables;
- Drawing CLDs based on the sub-system diagram, model boundary chart, and the schematic map of prescribing decision-making processes presented in Chapter 2 (Chapter 2, 2.2.4 Results: schematic map of prescribing pathway, Figure 2.2);
- Developing a list of model parameters to guide construction of SFDs and quantitative formulation of the simulation model in the later stage.
5.1 Defining the system

In this section, the ‘system’ of interest, its components, and its boundaries are described. Before the system is described, the purpose of the SD model is defined, as the model is developed to study the system of interest.

The purpose of the SD model is to simulate prescribers’ decision-making processes and how such processes could be improved when the variables associated with the factors influencing decision-making were adjusted within the context of an NHS Trust teaching hospital.

5.1.1 Setting the scene

The system in this study is defined as a hospital that is contextually and functionally equivalent to an NHS Trust teaching hospital in West London. A sub-system diagram is presented in Figure 5.1 to represent the overall structure of the model and articulates the linkages between the ‘blocks’ of key variables in the model. It reflects the general structure and the level of aggregation in an SD model.
The system of interest consists of two sub-systems, the microbiology laboratory sub-system and the medical ward sub-system. Information and materials are transmitted freely within and between the two sub-systems. The information transmitted includes doctors’ prescribing decisions and microbiology laboratory test results. There is no restriction on the amount of information that can be transferred, however, the timing of information transmission is associated with other influence factors (i.e. the delivery of microbiology laboratory test results, and the time when microbiologists are involved in decision-making processes are determined by the laboratory turnaround time). The materials transferred include patients’ blood samples. There is not restriction on the number of blood samples that can be transferred either.

The prescribers in the modelled system are classified into two groups, as two different
types of prescribing behavioural patterns existed in medical wards. Senior doctors include specialty registrars and consultants, while junior doctors include Foundation Year 1 and 2 doctors, core trainees, and nurses. Nurses are categorised into the group of junior doctors because of their identical pattern of decision-making processes compared to other junior doctors. The prescribing guidelines and the influence from senior doctors have impacted on all doctors’ decision-making processes.

A group of patients with symptoms of bacterial infection enter the system, either by being admitted to medical wards directly, or by being admitted to the Accident and Emergency (A&E) Department first then being transferred to medical wards.

5.1.2 Defining the boundaries of the system

Every system simulated by an SD model has closed boundaries within which the behaviour of interest is generated. The model boundaries contain all components present in the final model. The boundaries are determined by a series of assumptions made at qualitative stage to simplify the system modelled:

- The model focuses on the description of prescribers’ decision-making processes in medical wards and microbiology laboratory. Inside the system, patients only passively accept the treatment and are not involved in the decision-making processes.
- The doctors are the intelligent agents who are capable to actively make decisions and
respond to changes in the environment within the system, doctors perceive, think, and act when the internal environment of the system changes. For example, if the amount of non-compliant prescribing decisions increases, doctors will perceive an increased risk of potential adverse patient outcome due to inappropriate prescribing practices and be motivated to take actions to reduce the negative impact caused by those non-compliant prescribing decisions.

- The total number of doctors and each doctor’s seniority remain constant within the system overtime.
- Only one empiric decision will be made and only one blood sample will be taken for each patient inside the system.
- All doctors have the same probability of treating patients and all doctors prescribe. Their behaviour is predictable, their habit of prescribing does not change randomly over time. They only change their behaviour in response to the change in influence factors of interest. Doctors’ behaviour change under various scenarios with influence factors adjusted in different ways will be simulated and discussed in later chapters (Chapter 8 and 9).

A model boundary chart is developed to present exogenous variables, endogenous variables, and the variables excluded by the model (Figure 5.2). Exogenous variables are the variables that change independently, affect the system behaviour without being affected by it. The values of exogenous variables remain constant (static) in the model. Endogenous variables
are the variables that change dependently, affect the system behaviour and are, in turn, affected by the system. Endogenous variables in an SD model are involved in feedback loops of the system. The values of endogenous variable change over time as a result of the cause-effect relationships between the variables.

**Figure 5.2 Model boundary chart of the prescribing decision-making model**

<table>
<thead>
<tr>
<th>Excluded variables</th>
<th>Exogenous variables</th>
<th>Endogenous variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patients’ demand</td>
<td>Admission</td>
<td>Doctors’ decision-making processes</td>
</tr>
<tr>
<td>Decision-making of other healthcare professionals inside hospital</td>
<td>Patients’ demographic characters (age, gender, etc)</td>
<td>Microbiologists’ decision-making processes</td>
</tr>
<tr>
<td>Influence factors existing above institutional level</td>
<td>Number of doctors</td>
<td>Microbiology laboratory turnaround time</td>
</tr>
<tr>
<td>Patients’ clinical condition</td>
<td>Doctors’ seniority</td>
<td>Blood sampling</td>
</tr>
<tr>
<td></td>
<td>Senior doctors relying on their own experiences</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Foundation Year doctors’ self-confidence</td>
<td></td>
</tr>
</tbody>
</table>

After defining the model boundaries, the cause-effect relationships between endogenous variables are described in the section below.

### 5.2 Causal relationships of the System Dynamics model

In this section, the causal relationships between the key variables are described.
5.2.1 System behaviour and causality

The ‘behaviour’ of the system of interest is predicted based on causal relationships between key variables. System behaviour is the changes in the values of dependent variables due to the change in the values of independent variables linked by cause-effect relationship (Sterman, 2001). System behaviour over time includes both anticipated and unanticipated status of the system in response to the change in system environment, such as implementation of policies and interventions. In this study, the system behaviour is defined as doctors’ decision-making processes, and assessed by whether prescribing decisions were in compliance with prescribing guidelines. The status of the system is considered ‘better’ with increased amount of prescribing decisions in compliance with guidelines.

Inside the system of interest, a change in one variable can cause the change in other variables either in the same or the opposite direction (Sterman, 2001). For example, the number of doctors relying on their own experience rather than following prescribing guidelines and the level of guideline compliance level among all doctors are two variables moving in the opposite direction, if the number of doctors relying on own experience increases, the level of guideline compliance among all doctors decreases. Such relationship can be presented using an arrow with a mark ‘O’, meaning the two variables linked by the arrow change in the opposite directions. The risk of prescribing inappropriately and the motivation to change policy environment inside the system, however, are two variables that change in the same direction. The higher the risk of prescribing inappropriately is, the
stronger the motivation the healthcare professionals would have to implement policies and interventions to reduce the risk of inappropriate prescribing. Such relationships can be presented using an arrow with a mark ‘S’, meaning the two variables linked by the arrow change in the same direction.

Change in one variable can cause changes in variables inside the system, and eventually change system behaviour (Sterman, 2001). The chain reaction linked by causal relationships among variables generates ‘loops’. Change in system behaviour that feeds back on the variable that changed in the first place, creates closed loops. For example, if the number of doctors relying on their own experience rather than following prescribing guidelines increases, doctors’ guideline compliance level decreases, which will result in the increase in the risk of inappropriate prescribing and the risk of adverse health outcomes among patients, which will increase the motivation to implement interventions to reduce the number of doctors relying on own experience and improve the level of guideline compliance within the system as response.

All complex dynamic behaviour is produced by two types of feedback loops: balancing loops and reinforcing loops (Sterman, 2001). If the change in variable X in a feedback loop causes a series of variables to change collectively, and eventually cause a greater change in the initial variable X in the same direction, the feedback loop is ‘reinforcing’, otherwise the loop is ‘balancing’. A reinforcing loop will keep reinforcing the change in variables until the boundaries of a system are reached. Alternatively, a balancing loop involves a gap
between the desired behaviour and the actual behaviour. The balancing loop will take corrective actions to decrease the discrepancy between the desired behaviour and actual behaviour until the desired behaviour is achieved and the system reaches its equilibrium. Using the example described before, if the number of doctors relying on own experience rather than following guidelines increases, the variables connected by causal relationships, including guideline compliance level, risk of inappropriate prescribing, risk of adverse health outcomes among patients, and motivation to implement policies and interventions to improve guideline compliance level will change in response and produce a balancing loop. This closed feedback loop will diminish the initial change of ‘increased number of doctors relying own experience rather than following guidelines’ through a series of behaviour changes within the system.

5.2.2 Causality in System Dynamics

Establishing and validating causality are the very steps in the model development process that distinguish SD modelling from other regression analysis or ‘data-fitting’ models. Cause-effect relationships, causal linkages, causal relationships, and causality are interchangeable terms in SD modelling. In the context of process system simulation, the causality underlying the behaviour of a process is not necessarily a reflection of the succession of distinct causes and effects, but
rather an emergent property of the complex interaction between the agency and technical components of an open socio-technical process system (Brailsford et al., 2014). The causal relationship between two variables can be defined, when the change in one variable will always result in the change in another variable within a range of operation, and the reason behind such changes can be explained (meaningful in real-life scenarios). The process of establishing causality in SD modelling is actually the process of establishing a linkage that can be validated based on the purpose of the model. According to the traditional reductionist (logical empiricist) philosophy, a valid model is an objective representation of a real-life system. The validity of a model is solely a matter of accuracy, rather than its usefulness. In contrast, the comparatively recent relativist (holistic) philosophy argues that a model is one of the many possible ways to describe a situation. Hence, a model, and the model validation process, cannot be entirely objective, quantitative and formal (Barles & Carpenter, 1990). The causal linkages in an SD model are therefore constructed based on both ‘hard’ and ‘soft’ relationships. Hard relationships can be described and tested quantitatively using mathematical equations, while soft relationships, are defined and validated using empiric knowledge and expert opinion. To summarise, the process of defining and validating causality in SD modelling is highly context-dependent. In this thesis, the causal relationships are the interlinks between doctors’ prescribing decision-making processes and the identified influence factors. The causal relationships are validated by a group of doctors who are the representatives of decision-makers themselves.
and other healthcare professionals who were closely involved in antibiotic prescribing management in hospitals. Within the set boundaries of the modelled system, the changes in doctors’ prescribing decisions can be predicted based on the causal relationships when the influence factors change.

Recently, complexity is much talked about, but the discussion has been largely superficial both theoretically and empirically in health and health research (Greenhalgh, 2018). Researchers acknowledged the existence of complexity (complex interventions, complex systems) but failed to engage with the underlying logic of complexity. A shift of paradigm is urgently required to research health and health systems. In 2001, Medical Research Council (MRC) published a framework for the development and testing of complex interventions. The framework has been updated in 2008 and again in 2015 to provide extended definition of complexity and other relative concepts to introduce an underlying philosophical shift from a conventional linear and cause-effect perspective to a system perspective that embrace non-linear causality. In traditional approach, causality is often a linear cause-and-effect relationship, while in the new complexity-informed approach, causality is multiple interacting influences account for a particular outcome but none can be said to have a fixed ‘effect size’ (Moore, 2015). In this thesis, the key research question of causality in antibiotic prescribing decision-making processes is investigated using a new research paradigm approach (SD modelling).
5.2.3 Causal loop diagrams

A causal loop diagram (CLD) is an analytic tool to help visualise the key variables and the causal relationship among these variables in a system (Forrester, 1994). Nodes, representing the identified key variables, are connected by arrows to generate feedback loops. The arrows are marked by ‘+’ sign or ‘S’, indicating that the connected variables changed in the same direction, or ‘-’ sign or ‘O’, indication that the connected variables changed in the opposite direction. For example, findings from the rapid literature review reported the existence of ‘prescribing etiquette’, when senior doctors considered themselves exempt from following policy and practice within a culture of perceived autonomous decision-making that relied more on personal experience and knowledge than prescribing guidelines. Such causality in decision-making processes can be captured by a causal diagram (Figure 5.3).

Figure 5.3 Causal relationship of ‘prescribing etiquette’

In the CLD of ‘prescribing etiquette’, when the first variable representing the level of relying on own experience and knowledge increases among senior doctors (including
registrars and consultants), the second variable representing the number of registrars and consultants not complying with prescribing guidelines increases. The two variables are connected by an arrow marked by ‘S’, indicating that these two variables change in the same direction. The third variable in the CLD is connected with the second variable by an arrow marked by ‘O’ showing the opposite direction of changing, representing the amount of empiric decisions in compliance with guidelines, will decrease as the first two variables increase.

In a real life, the causal relationships between variables inside a system are more complex. One variable can be affected by multiple variables, and in turn affecting multiple variables. For example, the number of specialty registrars and consultants not complying with guidelines will be increased, if more senior doctors rely on their own experience and knowledge rather than following guidelines, or senior doctors have stronger fear that they would under treat infections especially among elderly patients. The increased number of non-compliant specialty registrars and consultants will result in a decrease in the amount of compliant empiric decisions and an increase in the amount of non-compliant empiric decisions. These causal relationships can be captured in the causal diagram presented below in Figure 5.4.
The key variables and the causal relationships among these variables included in the CLD of the model were identified based on the findings of the rapid literature review. When evidence in literature was not sufficient to support the establishment of a cause-effect relationship, the data analysis results were also incorporated as supplement, using primary data collected from hospital inpatient data, secondary data collected from a survey with Foundation Year doctors and interviews with consultants and specialty registrars (Chapter 4, 4.4 Secondary research; Chapter 6, 6.3.1 Data sources for model parameterisation). After the CLDs were constructed, multiple expert panel workshops were organised to verify the validity of the causal relationships captured by the CLDs to ensure that the CLDs provided a valid reflection of doctors’ decision-making processes when treating hospital inpatients with bacterial infections. The details of the validation process will be discussed in Chapter 7 (Chapter 7, 7.2.1 Test the model structure).
5.2.3.1 Causal loop diagram of prescribing decision-making at empiric stage

The causal relationships among key variables at empiric stage are listed in Table 5.1, as well as the literature evidence that supported the causal relationships.

Table 5.1 Literature evidence supporting the causal relationships at empiric stage

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Dependent variable</th>
<th>Direction of changing</th>
<th>Literature evidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relying on own experience and knowledge</td>
<td>Specialty registrars and consultants not complying with guidelines</td>
<td>S</td>
<td>Charani et al., 2013</td>
</tr>
<tr>
<td>Fear of undertreating infections</td>
<td>Specialty registrars and consultants not complying with guidelines</td>
<td>S</td>
<td>Llor &amp; Bjerrum, 2014</td>
</tr>
<tr>
<td>Patient’s age</td>
<td>Fear of undertreating infections</td>
<td>S</td>
<td>Xu et al., 2013</td>
</tr>
<tr>
<td>Foundation Year doctors’ self confidence in prescribing appropriately</td>
<td>Foundation Year doctors, core trainees and nurses not complying with guidelines</td>
<td>O</td>
<td>Gharbi et al., 2016</td>
</tr>
<tr>
<td>Specialty registrars and consultants not complying with guidelines</td>
<td>Compliant empiric decisions</td>
<td>O</td>
<td>Mathematical deduction</td>
</tr>
<tr>
<td>Foundation Year doctors, core trainees and nurses not complying with guidelines</td>
<td>Compliant empiric decisions</td>
<td>O</td>
<td>Mathematical deduction</td>
</tr>
<tr>
<td>Specialty registrars and consultants not complying with guidelines</td>
<td>Non-compliant empiric decisions</td>
<td>S</td>
<td>Mathematical deduction</td>
</tr>
<tr>
<td>Foundation Year doctors, core trainees and nurses not complying with guidelines</td>
<td>Non-compliant empiric decisions</td>
<td>S</td>
<td>Mathematical deduction</td>
</tr>
<tr>
<td>Non-compliant empiric decisions</td>
<td>Inappropriate prescribing decisions</td>
<td>S</td>
<td>Mo et al., 2005</td>
</tr>
<tr>
<td>Inappropriate prescribing decisions</td>
<td>Perceived risk of undesired health outcomes due to inappropriate prescribing</td>
<td>S</td>
<td>Eccles et al., 2007</td>
</tr>
<tr>
<td>Perceived risk of undesired health outcomes due to inappropriate prescribing</td>
<td>Motivation to shorten laboratory turnaround time</td>
<td>S</td>
<td>Llor &amp; Bjerrum, 2014</td>
</tr>
<tr>
<td>Motivation of shortening laboratory turnaround time</td>
<td>Microbiology laboratory turnaround time</td>
<td>O</td>
<td>Skodvin et al. (2017)</td>
</tr>
<tr>
<td>---------------------------------------------------</td>
<td>--------------------------------------</td>
<td>---</td>
<td>----------------------</td>
</tr>
<tr>
<td>Microbiology laboratory turnaround time</td>
<td>Fear of undertreating infections</td>
<td>S</td>
<td>Gharbi et al., 2016</td>
</tr>
<tr>
<td>Perceived risk of undesired health outcomes due to inappropriate prescribing</td>
<td>Motivation to improve specialty registrars and consultants’ guideline compliance</td>
<td>S</td>
<td>Eccles et al., 2007</td>
</tr>
<tr>
<td>Motivation to improve specialty registrars and consultants’ guideline compliance</td>
<td>Specialty registrars and consultants not complying with guidelines</td>
<td>O</td>
<td>Knox &amp; Holmes, 2002</td>
</tr>
</tbody>
</table>

**Figure 5.5** is the CLD that captured all the causal relationships among key variables in the antibiotic prescribing decision-making processes at empiric stage, supported by evidence in literature and data analysis results from the hospital inpatient notes, the survey, and the interviews. 4 balancing feedback loops (B1, B2, B3 and B4) emerged in the system.

**Figure 5.5 Causal loop diagram of doctors’ decision-making processes at empiric stage**
Balancing loop B1 captured the causal relationships between senior doctors’ prescribing decision-making processes at empiric stage and the influence from shortening microbiology laboratory turnaround time (Figure 5.6).

**Figure 5.6 Balancing loop B1 of senior doctors’ decision-making processes**

The ‘fear of under-treating infections’ arises when specialty registrars and consultants have to make empiric decisions with no support in diagnostic information (microbiology laboratory test results). The level of fear is associated with patient’s age. The fear increases as the patient gets older, as their clinical conditions are more complex and critical. Specialty registrars and consultants tend to prescribe antibiotic drugs broader than the recommendations in the prescribing guidelines to cover all possible infections when the
pathogen information is not available. The increase in ‘fear of under-treating infections’ results in the increase in the number of specialty registrars and consultants not complying with guidelines, and the number of non-compliant empiric decisions. The increase in the number of non-compliant empiric decisions is followed by the increase in the number of inappropriate prescribing decisions, the perceived risk of undesired health outcomes among patients due to inappropriate prescribing. It increases the motivation among healthcare professionals to implement policies and interventions to shorten microbiology laboratory turnaround time, which will reduce the ‘fear of under-treating infections’ among specialty registrars and consultants as diagnostic information will become available sooner. The feedback loop balances the change in the variable of ‘fear of under-treating infections’. In theory, as the system evolves, the ‘fear of under-treating infections’ will eventually be diminished by the system through shortening microbiology laboratory turnaround time. The number of specialty registrars and consultants is also associated with an exogenous variable, which is the level of relying on their own experience rather than following prescribing guidelines.

Balancing loop B2 captured the causal relationships between senior doctors’ prescribing decision-making processes at empiric stage and the influence from improving specialty registrars and consultants’ guideline compliance (Figure 5.7).
When the number of specialty registrars and consultants not complying with guidelines increases and results in the increase in the perceived risk of undesired health outcomes among patients due to inappropriate prescribing through a series of causal connections between variables, it increases the motivation among healthcare professionals to implement policies and interventions to improve the level of prescribing guideline compliance among specialty registrars and consultants. Changing specialty registrars and consultants’ behaviour can not only improve their own decision-making and prescribing practices but can also influence doctors with lower seniority (Foundation Year doctors, core trainees and nurses). The number of specialty registrars and consultants not complying with guidelines decreases as the motivation of improve their practices becomes stronger. The
feedback loop balances the change in the variable of ‘number of specialty registrars and consultants not complying with guidelines’. In theory, as the system evolves, the number of specialty registrars and consultants not complying with guidelines will eventually be reduced to zero by the system through improving guideline compliance level among specialty registrars and consultants.

Balancing loop B3 captured the causal relationships between junior doctors’ prescribing decision-making processes at empiric stage and the influence from shortening microbiology laboratory turnaround time (Figure 5.8).

**Figure 5.8 Balancing loop B3 of junior doctors’ decision-making processes**

When the ‘fear of under-treating infections’ arises among specialty registrars and consultants, it does not only affect the prescribing decision-making processes of senior
doctors, but also the prescribing behaviour of Foundation Year doctors, core trainees and nurses. These junior doctors decision-making processes are influenced by senior doctors due to the existence of ‘prescribing etiquette’ (Chapter 2, 2.2.3 Results: influence factors on different levels across health systems). When the number of specialty registrars and consultants not complying with guidelines increases, the number of Foundation Year doctors, core trainees and nurses not complying with guidelines increases as senior doctors’ influence overrides prescribing guidelines. The number of non-compliant empiric decisions increases as a consequence. Through the chain reaction of increasing risk of inappropriate prescribing, increasing perceived risk of adverse patient health outcomes, increasing motivation to shorten microbiology laboratory turnaround time, reducing ‘fear of under-treating infections’ among senior doctors, the number of junior doctors not complying with guideline will be reduced. The feedback loop balances the change in the variable of ‘fear of under-treating infections’. In theory, as the system evolves, the ‘fear of under-treating infections’ will eventually be diminished by the system through shortening microbiology laboratory turnaround time. The number of Foundation year doctors, core trainees and nurses is also associated with an exogenous variable, which is the level of self-confidence Foundation Year doctors had in themselves that they were prescribing appropriately. The stronger the self-confidence they had, the less junior doctors would follow senior doctors and allow senior doctors’ influence to override prescribing guidelines, therefore, more of them would comply with prescribing guidelines at empiric stage.
Balancing loop B4 captured the causal relationships between junior doctors’ prescribing decision-making processes at empiric stage and the influence from improving specialty registrars and consultants’ guideline compliance (Figure 5.9).

**Figure 5.9 Balancing loop B4 of junior doctors’ decision-making processes**

When the number of specialty registrars and consultants not complying with guidelines increases, the number of Foundation Year doctors, core trainees and nurses not complying with guidelines increases as senior doctors’ influence overrides prescribing guidelines. As discussed before, changing specialty registrars and consultants’ behaviour can not only improve their own decision-making and prescribing practices but can also influence doctors with lower seniority (Foundation Year doctors, core trainees and nurses). The number of non-compliant empiric decisions, the risk of inappropriate prescribing, and the perceived risk of adverse patient health outcomes change as consequences, which lead to
the change in the motivation to improve specialty registrars and consultants’ guideline compliance level. The feedback loop balances the change in the variable of ‘number of specialty registrars and consultants not complying with guidelines’, as well as the change in the variable of ‘number of Foundation Year doctors, core trainees and nurses not complying with guidelines’ as these two variables are interconnected and moving in the same direction. In theory, as the system evolves, the number of both senior and junior doctors not complying with guidelines will eventually be reduced to zero by the system through improving guideline compliance level among specialty registrars and consultants.

Causal loop diagram of prescribing decision-making at review stage.

The causal relationships among key variables at review stage are listed in Table 5.2, as well as the literature evidence that supported the causal relationships.

### Table 5.2 Literature evidence supporting the causal relationships at review stage

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Dependent variable</th>
<th>Direction of changing</th>
<th>Literature evidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patients with microbiology laboratory test results</td>
<td>Empiric decisions reviewed by microbiologists</td>
<td>S</td>
<td>Fournier et al., 2013</td>
</tr>
<tr>
<td>Microbiologists complying with guidelines</td>
<td>Compliant reviewed decisions</td>
<td>S</td>
<td>Mathematical deduction</td>
</tr>
<tr>
<td>Microbiologists complying with guidelines</td>
<td>Non-compliant reviewed decisions</td>
<td>O</td>
<td>Mathematical deduction</td>
</tr>
<tr>
<td>Empiric decisions reviewed by microbiologists</td>
<td>Compliant reviewed decisions</td>
<td>S</td>
<td>Mathematical deduction</td>
</tr>
<tr>
<td>Empiric decisions reviewed by microbiologists</td>
<td>Non-compliant reviewed decisions</td>
<td>S</td>
<td>Mathematical deduction</td>
</tr>
<tr>
<td>Non-compliant reviewed decisions</td>
<td>Inappropriate prescribing decisions</td>
<td>S</td>
<td>Mol et al., 2005</td>
</tr>
<tr>
<td>Inappropriate prescribing decisions</td>
<td>Perceived risk of undesired health outcomes due to inappropriate prescribing</td>
<td>S</td>
<td>Eccles et al., 2007</td>
</tr>
<tr>
<td>-------------------------------------</td>
<td>--------------------------------------------------------------------------</td>
<td>---</td>
<td>------------------</td>
</tr>
<tr>
<td>Perceived risk of undesired health outcomes due to inappropriate prescribing</td>
<td>Motivation to perform microbiology laboratory test for all patients</td>
<td>S</td>
<td>Llor &amp; Bjerrum, 2014</td>
</tr>
<tr>
<td>Motivation to perform microbiology laboratory test for all patients</td>
<td>Patients with microbiology laboratory test results</td>
<td>S</td>
<td>Data source 3: hospital inpatient notes</td>
</tr>
<tr>
<td>Perceived risk of undesired health outcomes due to inappropriate prescribing</td>
<td>Motivation to provide result for all microbiology laboratory tests performed</td>
<td>S</td>
<td>Llor &amp; Bjerrum, 2014</td>
</tr>
<tr>
<td>Motivation to provide result for all microbiology laboratory tests performed</td>
<td>Microbiology laboratory tests with result delivered to medical ward</td>
<td>S</td>
<td>Data source 3: hospital inpatient notes</td>
</tr>
<tr>
<td>Microbiology laboratory tests with result delivered to medical ward</td>
<td>Patients with microbiology laboratory test results</td>
<td>S</td>
<td>Mathematical deduction</td>
</tr>
</tbody>
</table>

**Figure 5.10** is the CLD that captured all the causal relationships among key variables in the antibiotic prescribing decision-making processes at review stage, supported by evidence in literature and data analysis results from the hospital inpatient notes, the survey, and the interviews. 2 balancing feedback loops (marked by B5 and B6) emerged in the system.
Balancing loop B5 captured the causal relationships between microbiologists’ decision-making processes at review stage and the influence from performing microbiology laboratory test for all patients (Figure 5.11).
The findings from the rapid literature review and the data analysis of hospital inpatient notes suggested that both *timeliness* and *availability* of microbiology laboratory tests were important to support appropriate prescribing decision-making. In real life, a portion of patients in medical wards did not have microbiology tests performed during their admission. While shortening microbiology laboratory turnaround time help senior doctors make empiric decisions in compliance with guidelines, increasing the number of patients who had microbiology laboratory test results will allow more microbiologists to review decisions made by other doctors when treating these patients at empiric stage. When analysing the hospital inpatient notes, the guideline compliance level among
microbiologists was found to be significantly higher than that for doctors working in medical wards. All review decisions made by the microbiologists were in line with guidelines. Thus, the variable of microbiologist complying with guidelines was included in the CLD at review stage as an exogenous variable. Microbiologists’ guideline compliance level remained constant in the modelled system.

The number of non-compliant reviewed decisions increases when the number of empiric decisions reviewed by microbiologists decreases, which will result in the increase in risk of appropriate prescribing and the perceived risk of undesired patient health outcomes. The potential adverse health outcomes will motivate healthcare professionals to perform microbiology laboratory tests for as many patients as possible, ideally for all patients admitted, to increase the number of patients with microbiology laboratory test result and create more opportunities for microbiology review. In theory, as the system evolves, the number of non-compliant reviewed decisions will eventually be reduced to zero by the system through increasing the number of patients with microbiology laboratory test results by performing tests for all patients.

Balancing loop B6 captured the causal relationships between microbiologists’ decision-making processes at review stage and the influence from providing results for microbiology laboratory tests performed (Figure 5.12).
As mentioned before, in real life, a portion of patients did not have microbiology tests performed during their admission. The findings from the analysis of hospital inpatient notes also suggested that a part of microbiology tests performed did not have result provided. Though this group of patients did have microbiology tests, they had no diagnostic information to support decision-making either. The number of patients with microbiology laboratory test result can also be increased by providing results for all tests performed.

Similar to balancing loop B5, in balancing loop B6, the number of non-compliant reviewed decisions increases when the number of empiric decisions reviewed by microbiologists decreases, which will result in the increase in risk of appropriate prescribing and the perceived risk of undesired patient health outcomes. The potential adverse health outcomes
will motivate healthcare professionals to provide results for as many microbiology laboratory tests performed as possible, ideally for all tests performed, to increase the number of patients with microbiology laboratory test results and create more opportunities for microbiology review. Again, as the system evolves, the number of non-compliant reviewed decisions will eventually be reduced to zero by the system through increasing the number of patients with microbiology laboratory test result by providing results for all tests performed.

5.3 Discussion

5.3.1 Limitations of causal loop diagrams

In this study, the CLDs of the SD model focused on the non-compliant decisions at empiric and review stage. The purpose of the SD model is to reduce the number of non-compliant decisions to the maximal degree through different causal pathways. Before moving on to the next stage of constructing a simulatable SD model based on the causal relationships captured in the CLDs, the limitations of CLDs must be discussed first.

CLDs are an important tool to represent the feedback structures of a system. The benefits of CLD include the ability to 1) quickly capture hypothesis about the causes of dynamics, 2) elicit the mental models (psychological representations of real, hypothetical, or imaginary situations, which explain a person’s thought processes about how something
works in the real world and visualise the relationship between a person’s intuitive perception about his or her own acts and their consequences and the surrounding world) of individuals and teams, and communicate the important feedbacks which were considered to be responsible for a problem needing to be solved (Bala, Arshad, & Noh, 2017; Jones et al., 2011). However, certain limitations must also be taken into consideration when using CLD as a tool to support decision-making. CLDs have four major limitations (Schaffernicht, 2010). First, CLDs can lack precision, since CLDs only contain variable names, polarised links (with delay marks in some cases) and feedback loops, it is easy to over-aggregate and not display relevant variables. Second, CLDs have limited power to capture a variable’s full character, such as variable types. The distinction between stock variables (quantities) and flow variables (the rate of change of quantities) and the distinction between material flows and information flows are absent in CLDs. However, variable types have behavioural consequences. For example, ‘birth rate’ and ‘population’ are two variables with causal relationship between them. However, both increase and decrease in birth rate cause increase in population if birth rate is higher than zero. Thus, a polarised link between birth rate and population can lead to erroneous deduction of system behaviour (Schaffernicht, 2010). Third, CLDs can lead to mislabelling of loop polarities and misunderstanding of feedback mechanisms, especially if the polarities of the links are marked by ‘+’ and ‘−’ signs as a standard practice (Richardson, 1997). Inexperienced SD modellers sometimes mislabel the polarities of links between variables when tracing
around the loop and the up-and-down implications of a change in variable. For example, in this study, the link between ‘fear of under-treating infections’ and ‘the number of compliant senior doctors’ can be described as ‘when the fear of under-treating infections is reduced, the number of compliant senior doctors increases’. Some SD modellers have a tendency to put a positive sign on the link to signify the ‘increase’, instead of a negative sign to indicate that the two variables changed in the opposite direction. To prevent confusion, ‘S’ and ‘O’ signs were used in the CLDs in this study instead of ‘+’ and ‘-’ signs.

The last limitation of CLDs is in association with using CLDs to predict system behaviour. SD modelling involves the study of the relationships between feedback structure and dynamic behaviour using two sources: diagramming and simulating. CLDs are a great impetus to study the system from representations of system structure. However, behaviour can only be inferred from diagramming. Simulation is needed to alter undesired system behaviour.

Simulating system behaviour using computer-based software programmes starts from translating qualitative CLDs into quantitative stock and flow diagrams (SFDs). In the next section, the process of constructing the SFDs of the SD model of prescribing decision-making is discussed.
5.3.2 Dealing with ‘soft’ variables

Although there is general agreement about the importance of qualitative data during the development of an SD model, there is not a clear description about how or when to use it. The lack of a standard set of procedures to obtain, analyse, and integrate qualitative information creates a gap between ‘the problem modelled’ and ‘the model of the problem’ (Luna-Reyes & Andersen, 2003). This gap is more noticeable when an SD model involves the use of ‘soft’ variables.

In SD modelling, variables are classified into two groups. A ‘hard’ variable is one which is used to describe attributes or relationships in a problem to which mathematical or physical laws apply, or where governing business rules are readily formulated using algebraic operators linking other variables (McLucs, 2003). ‘Hard’ variables are quantifiable, and the quantification processes can be validated. The connection of ‘hard’ variables in SD modelling are established by quantitative metrics and numerical data. In contrast, ‘soft’ variables, sometimes referred as ‘intangibles’, are used to describe attributes of human behaviour or effects that variations in such behaviour produce. Numerical data are often unavailable or non-existent when estimating values for ‘soft’ variables. However, ‘soft’ variables are important components of the system structure. They can strongly influence the performance of the system. When modelling human behaviour, ‘soft’ variables of emotion are critical to decision-making and, therefore should be incorporated into SD models despite the difficulty in quantitatively measuring these variables. The challenge is
to incorporate ‘soft’ variables into SD models in ways that are both scientifically sound and logically defendable (McLucas, 2005).

When constructing the CLDs of prescribing decision-making processes, a ‘soft’ variable emerged in the system, which is ‘fear of under-treating infections’. The ‘fear of under-treating infections’ is a predictor of specialty registrars and consultants’ prescribing behaviour at empiric stage. It is an important link in the feedback loops included in the CLDs, therefore it cannot be excluded despite the challenge to quantify it. The ‘fear of under-treating’ is defined as an exogenous variable which remained constant at qualitative mapping stage, and included in CLDs and SFDs to maintain the completeness of feedback loops. This exogenous variable is determined by the auxiliary variable ‘patients’ age’. In the later stage of model simulation, no adjustment can be made directly on the variable ‘fear’, this variable will be eliminated from the SD model in simulation stage. In future, ‘fear of under-treating’ can be defined as an endogenous variable which can be measured and altered quantitatively by creating an ‘indexed variable’. The use of ‘indexed variable’ will be discussed again in Chapter 9 when recommendation for future research is made (Chapter 9, 9.4.1.2 The ‘soft’ variable: fear).

5.3.3 Modelling time delays

Time delays are a critical source of dynamics in nearly all systems (Hamilton, 1980). Time
delays in general fall into two categories, material delay, which is caused by transferring materials or completing a task within the system (i.e. delivering patients’ blood samples to microbiology laboratory), and information delay, which is associated with behaviour change of the intelligent agents (human beings) in response to information. In the real world, it takes time to collect and report information, to make decisions, to implement decisions, and for decisions to affect the state of the system. An example of various delays in a decision process is presented in Figure 5.13 below. The arrows marked by two short straight lines represent the delays.

**Figure 5.13 Various delays in a decision process**

Delay 1 would occur in the process of perceiving the current state of the system. The process could include measurement reporting and perception delays. Delay 2 would occur in the process of initiating corrective actions to reduce the perceived discrepancy between the current state of the system and the desired state of the system. This delay would occur
due to the time required to reach a decision of what kind of actions should be taken. Delay 3 would occur between the initiation of corrective actions and the emergence of effect of the corrective actions on the state of the system.

Notice that the delays are captured by a CLD with an aim to use corrective actions to reduce the discrepancy between the current state of the system and the desired state of the system. The desired state of the system can be considered as an exogenous variable, as it sets a ‘goal’ for the system to operation towards, and it is not affected by the state of the system. The ‘higher’ the ‘goal’ is, the bigger the discrepancy is between the current state of the system and the ‘goal’. Thus, the arrow connecting desired state and the system and discrepancy is marked by a positive sign, indicating the same direction of changing. The discrepancy is also influenced by the current state of the system, the ‘higher’ the current state of the system is, the closer it is to the ‘goal’, and the smaller the discrepancy is. The arrow connecting current state and the system and discrepancy is marked by a negative sign, indicating the opposite direction of changing. When the perceived discrepancy increases, more corrective actions will be taken to drive the system towards the desired state. The arrow connecting discrepancy and corrective actions and the arrow connecting corrective actions and state of the system are both marked by a positive sign, indicating the same direction of changing.

In this study, delays occurred in the process of doctors taking actions and adjusting prescribing behaviours to improve prescribing outcomes when the risk of inappropriate
prescribing practices was perceived. Delay 1 occurred in the process of assessing and reporting prescribing practices and determining whether the ‘discrepancy’ existed in the current state. Delay 2 occurred in the process of making decisions to change prescribing habit if discrepancy was perceived by healthcare professionals within the system. Delay 3 occurred due to the time consumed from initiating behaviour adjustment among doctors till the prescribing outcomes started to improve (Figure 5.14).

**Figure 5.14 Delays in the process of adjusting prescribing behaviour**

At this current stage, the evidence from the source data was not sufficient to tell whether the time delays existed in the modelled system and how long the delays would be if they existed. Therefore, time delays were eliminated from the SD model at qualitative mapping stage. Future work to include time delays in this model is discussed in Chapter 9 (Chapter 9, 9.4.1.3 Time delays in behaviour change).
In this chapter, the process to conceptualise the SD model of doctors’ antibiotic prescribing decision-making processes was discussed. A sub-system diagram, a model boundary chart, a series of causal loop diagrams, and stock and flow diagrams were constructed to describe the SD model. A list of quantitative model parameters was generated to allow formulation and simulation of the SD in the later stage. In the next chapter, the process of estimating values for the model parameters will be discussed.

Key points in Chapter 5:

- Causal loop diagrams (CLDs) were constructed to capture the causal relationships between doctors’ prescribing behaviour and the factors influencing it, which are microbiology laboratory turnaround time and senior doctors’ guideline compliance.
- CLDs represented the modelled system qualitatively. The quantitative simulation model will be presented in the next chapter.
Chapter 6 System Dynamics Model

Description: Simulation Model

In the previous chapter, the SD model of prescribing decision-making processes was described using qualitative maps. In this chapter, the qualitative map is translated into a rigorous simulation model. The processes of constructing stock and flow diagrams (SFDs) and parameterising the SD model using findings from the analysis of the source data are described.

6.1 Principles of simulation in System Dynamics

6.1.1 Overcome ‘bounded rationality’

Model and simulation are two inseparable concepts in operational research. A model is an approach combining diagrams, algorithms, and equations used to capture the behaviour of the system modelled. By contrast, simulation is the imitation of the operation of a real-world process or system, often with the help of computer-based software programmes (Richardson & Pugh, 1981, Roberts, 1981). Simulation is the actual running of the programme that contains the algorithms and equations of a model. A researcher would first build a model, then simulate the model.
As discussed in Chapter 3 (Chapter 3, 3.2.2 ‘Bounded rationality’), when studying a system, diagramming the causal relationships within the system help infer system behaviour to a limited extent only when the system structure is relatively simple (Chapter 5, 5.3.1 Limitation of causal loop diagrams). If a feedback structure includes more than 3 to 4 feedback loops, it becomes extremely difficult to infer its behaviour. This is due to the ‘bounded rationality’ principle of human brains, which reflects the limitations of the human brain in front of the sheer complexity present in real-world systems (Simon, 1957; Selten, 1990). Bounded rationality and its resulting poor performances are due to two basic and related deficiencies of humans’ mental models. First, humans’ cognitive maps of the causal structure of systems are vastly simplified compared to the complexity of systems themselves. Second, the dynamics of causal maps cannot be inferred correctly by humans. In this case, systems’ behaviour over time cannot be inferred. No mental model can assess adequately the impact of externally imposed changes or allocate responsibility for delay and disruption occurred in complex real-world systems (Sterman, 1992). Learning about the system is only possible through simulation. With the aid of computer-based simulation, SD models can predict possible responses of complex systems to different decisions so that their leverage points are identified, so that the opportunities are created for external interference to re-design the system structures enhance desired behaviour or to eliminate undesirable behaviour (Lane & Oliva, 1998). In order to predict doctors’ antibiotic prescribing behaviour when facing changes in policy environment with multiple influence
factors interrelated simultaneously, computer-based simulation is performed.

6.1.2 Computer-based simulation software

Computer-based simulation of the SD model is performed using two widely adopted SD modelling software packages: Vensim® (Ventana Systems Inc., 1998) and iThink® (iSee Systems, 2005) in this study. These two software packages not only provide platforms for simulation, qualitative mapping, quantitative formulation, and model validity test can also be performed.

6.2 Structure of the simulation model

A complete SD model contains feedback loops, which provide a qualitative description of a system by visualising the causal relationships. Stocks and flows, then enable quantitative simulation. Stocks are accumulations that occur as a result of a difference in input and output flow rates to a component in a system. For example, number of prescribing decisions accumulated at a time point when treating a group of patients is a stock variable. Flows are the movement between stocks. Stocks are quantities of variables accumulated by a certain time point, flows are the rates of variable quantities moved during a period of time. For example, number of a specific prescribing decisions made per day is a flow variable.
Defining the quantitative description of the key variables in the system and providing them numeric values is the process of model parameterisation.

### 6.2.1 Defining stock and flow variables

To establish the quantitative description of the model, a series of parameters were defined to construct the SFDs. Similar to a CLD, an SFD is a technique in SD modelling that helps visualise system behaviour. In an SFD, a stock variable is represented by a rectangle, a flow variable is represented by an arrow with a tap, with the arrow pointing either into the stock, which is an inflow, or out from the stock, which is an outflow. The source of an inflow, and the sink of an outflow, can be either another stock, or external quantities that come into the system represented by a cloud. The value of a stock variable at a time point is the sum of the initial value, the inflow rate and the outflow rate multiplied by time unit.

An example of senior doctors’ prescribing decision-making processes can be represented quantitatively by the SFD below (Figure 6.1). The first stock variable represents the number of decisions made by senior doctors (specialty registrars and consultants) at empiric stage. The second stock variable represents the number of non-compliant decisions made by senior doctors at empiric stage. These two stock variables are linked by the flow variable ‘senior doctors’ rate of prescribing (non-compliant)’, meaning the number of non-compliant decisions made by senior doctors at empiric stage per day. This flow variable of
‘rate of not complying’ might have little meaning in real life, instead, the ‘proportion of doctors not complying’ is the variable that can be interpreted easily. However, in a simulatable SD model, two stock variables can only be connected by a flow variable. Thus, the measure of proportion is converted into a flow variable with time element incorporated (rate). Both stock variables have the same unit, which is the number of decisions. The rate variable has the unit of number of decisions made per day.

**Figure 6.1 Stock and flow diagram of senior doctors making non-compliant empiric decisions**

The value of the stock variable ‘Non-compliant empiric decisions by specialty registrars and consultants’ is calculated as

\[
N_{(\text{Non-compliant empiric decisions by specialty registrars and consultants})}(t) = N_{(\text{Non-compliant empiric decisions by specialty registrars and consultants})}(0) + \int N(\text{empiric decisions made by specialty registrars and consultants}) \times [\text{Senior doctors' rate of prescribing (non - compliant)}] dt,
\]
where $N_{(\text{Non-compliant empiric decisions by specialty registrars and consultants})}(0) = 0$, meaning at the initial stage of the system, there is no decision made by specialty registrars or consultants.

In the previous section, key variables included in the SD model were connected by CLDs based on the causal relationships among these variables. Notice that the variables included in the CLDs can have different units. For example, the variable ‘number of senior doctors not complying’, which has the unit of ‘number of doctors’, and the variable ‘number of non-compliant empiric decisions’, which has the unit of ‘number of decisions’, can be linked together in a CLD. However, all the stock variables included in an SFD must have the same unit, and the flow variables must have the unit of the stock variables divided by time unit. In the prescribing decision-making SD model constructed later, all the stock variables have the unit of ‘number of decisions’, and all the flow variables have the unit of ‘number of decisions made per day’. Whenever there is a quantity with different unit, unit convert function will be used to convert the unit for consistency.

Based on the CLDs of doctors’ prescribing decision-making processes presented in the previous chapter (Chapter 5, 5.2.2 Causal Loop Diagram), a series of SFDs was constructed. Again, the prescribing decision-making processes were divided into two stages: empiric stage and review stage.
6.2.2 Stock and flow diagram

6.2.2.1 Stock and flow diagram of prescribing decision-making at empiric stage

The SFD of doctors’ prescribing decision-making processes at empiric stage is presented below (Figure 6.2). There are three main stock-and-flow structures and one system behaviour indicator (outcome measure) in the SFD at empiric stage. Patient’s age is included in the SFD as an auxiliary variable. Auxiliary variables are those variables not attached to any stock or flow variable. The value of auxiliary variables changes independently of the system behaviour. Adding or eliminating auxiliary variables do not change the mathematical structure of the model.

Figure 6.2 Stock and flow diagram of doctors’ decision-making processes at empiric stage
The three main stock-and-flow structures are discussed herewith.

**Figure 6.3 Stock and flow diagram of the empiric decision stock-and-flow structure**

The empiric decision stock-and-flow structure is presented in **Figure 6.3.** Two stock variables ‘empiric decisions by specialty registrars and consultants’ and ‘empiric decisions by Foundation Year doctors, core trainees and nurses’ (unit: number of decisions) are fed into by inflow rates ‘senior doctors’ rate of prescribing’ and ‘junior doctors’ rate of prescribing’ (unit: number of decisions/per day) for the two groups of doctors. Senior doctors and junior doctors’ rate of prescribing are derived using the number of admitted patients per day multiplied by the proportion of prescribing of senior and junior doctors. Notice that in the process of calculation, the unit of quantities involved was converted from ‘number of patients’ to ‘number of decisions’. As in the modelled system, each patient received one empiric decision, therefore, the number of patients and the number of empiric
decisions made are numerically identical.

**Figure 6.4 Complying stock-and-flow structure**

The complying stock-and-flow structure is presented in Figure 6.4. The stock variables ‘compliant empiric decisions’ (unit: number of decisions) are fed into by two inflow rates ‘senior doctors’ rate of complying’ and ‘junior doctors’ rate of complying’ (unit: number of decisions/per day) for the two groups of doctors. The rates of complying are derived from the number of empiric decisions made by the two groups of doctors and determined by the proportion of senior and junior doctors complying with guidelines at empiric stage.

**Figure 6.5 Non-complying stock-and-flow structure**
The non-complying stock-and-flow structure is presented in Figure 6.5. The stock variables ‘non-compliant empiric decisions’ (unit: number of decisions) are fed into by two inflow rates ‘senior doctors’ rate of not complying’ and ‘junior doctors’ rate of not complying’ (unit: number of decisions/per day) for the two groups of doctors. The rates of not complying are derived from the number of empiric decisions made by the two groups of doctors and the proportion of senior and junior doctors not complying with guidelines. Foundation Year doctors, core trainees and nurses’ guideline compliance level is also associated with specialty registrars and consultants’ guideline compliance level as the literature evidence suggested that senior doctors’ decisions would sometimes override prescribing guidelines (the existence of ‘prescribing etiquette’). The interlink between the rate of senior doctors not complying and the rate of junior doctors not complying is represented by the blue arrow marked by ‘+’ sign in the SFD. Specialty registrars and consultants are reported to have lower guideline compliance level due to the fear of under-treating complex infections cases, especially among elderly patients when they perceived themselves as the ones taking responsibilities of patients’ safety in medical wards. In the SFD of prescribing decision-making processes at empiric stage, the auxiliary variable ‘patients’ age’ and the exogenous variable ‘fear of under-treating’ are connected to this stock-and-flow structure, as these two variables are determining the specialty registrars and consultants’ guideline compliance (rate of not complying). The percentage of non-
compliant empiric decisions is used as the outcome measure at empiric stage.

To perform ‘what if’ scenario simulation, the system is expected to react to the change in outcome measures. Captured by the CLDs, when the amount of non-compliant decisions increases, the risk of inappropriate prescribing and the perceived risk of adverse patient health outcomes increase to motivate healthcare professionals to take action to either shorten microbiology laboratory turnaround time or improve guideline compliance level among specialty registrars and consultants. Four balancing loops emerged in the CLD of prescribing decision-making processes at empiric stage. These four balancing loops are now presented again using SFDs to allow the SD model to perform quantitative simulation based on the causal relationships between key variables in the CLDs.

**Balancing loop 1: senior doctors and microbiology laboratory turnaround time**

One of the scenarios is when the outcome measure (percentage of non-compliant empiric decisions) worsens and the risk of inappropriate prescribing increases inside the system, healthcare professionals will be motivated to shorten microbiology laboratory turnaround time to allow specialty registrars and consultants to make empiric decision-making processes based on diagnostic information and reduce the ‘fear of under-treating infections’. The SFD of this balancing loop is presented below (Figure 6.6).
All the stock variables included in the SFD have the identical unit of ‘number of decisions’. The ‘microbiology laboratory turnaround time’ is a variable with unit of days, it does not appear as a stock variable. However, the microbiology laboratory turnaround time is translated into the transit time of a conveyer stock presenting the process of testing patients’ blood samples. The conveyer stock will be described later in this section, and the mathematical equations included in the conveyer stock will be discussed in Chapter 6 (6.2.2.3 The conveyer stock of microbiology laboratory, 6.3.4.5 Parameters in the conveyer stock) when the impact on doctors’ decision-making processes from shortening microbiology laboratory turnaround time is simulated.
Balancing loop 2: senior doctors and guideline compliance

Besides shortening microbiology laboratory turnaround time to reduce the ‘fear of undertreating infections’ among senior doctors, improving guideline compliance among specialty registrars and consultants can also balance the undesired change in the outcome measure. The SFD of the balancing loop describing the causal relationship between system outcome and motivation to improve senior doctors’ guideline compliance is presented below (Figure 6.7).

Figure 6.7 Stock and flow diagram of the balancing loop B2

Balancing loop 3: junior doctors and microbiology laboratory turnaround time

Similar to the balancing loop B1, shortening microbiology laboratory turnaround time can
also change junior doctors’ decision-making process through the influence from senior doctors. When senior doctors’ rate of not complying decreases, junior doctors’ rate of not complying decreases as a consequence. The SFD of this balancing loop is presented below in Figure 6.8.

**Figure 6.8 Stock and flow diagram of the balancing loop B3**

**Balancing loop 4: junior doctors and guideline compliance**

When worsened prescribing outcome measure motivates healthcare professionals in the system to take actions to improve specialty registrars and consultants’ guideline compliance, junior doctors will also be influenced. The SFD of this balancing loop is presented in Figure 6.9.
6.2.2.2 Stock and flow diagram of prescribing decision-making at review stage

The SFD of doctors’ prescribing decision-making processes at review stage is presented below (Figure 6.10). There is one main stock-and-flow structure and one system behaviour indicator (outcome measure) in the SFD at review stage. Microbiologists’ guideline compliance level is included in the SFD as an exogenous variable, and the evidence from the source data to support this decision is discussed later in this chapter (Chapter 6, 6.5.2.2 Prescribing behaviour at review stage).
The main stock-and-flow structure in the SFD at review stage is discussed herewith.

**Figure 6.11 Microbiology review stock-and-flow structure**

The microbiology review stock-and-flow structure is presented in Figure 6.11. The stock variable ‘empiric decisions reviewed by microbiologists’ (unit: number of decisions) is fed into by the rate of reviewing of microbiologists (unit: number of decisions/per day). The rate of reviewing is calculated using the sources of total empiric guidelines made by all
doctors in medical wards multiplied by the proportion of empiric decisions reviewed by microbiologists, then divided by the time unit (day). The proportion of empiric decisions reviewed by microbiologists is determined by the proportion of patients with microbiology laboratory test results, as the microbiologists can only review the empiric decisions for the patients with test results. Therefore, by increasing the number of patients with microbiology laboratory test results, more opportunity will be created for the microbiologists to review empiric decisions.

As discussed before, the guideline compliance level among microbiologists was treated as exogenous variable in the SD model. 100% review decisions made by microbiologists were found to be in compliance with guidelines when analysing the data extracted from hospital inpatient notes. Thus, the purpose of the SD model at review stage is to increase the number of patients with microbiology test results to the maximal degree to allow microbiology review. Two balancing loops (B5 and B6) emerged in the SFD at review stage when the risk of inappropriate prescribing increases and motivates healthcare professionals to either perform microbiology laboratory tests for all patients or provide results for all tests performed. These two balancing loops are represented using SFDs again.

**Balancing loop 5: performing microbiology laboratory tests for all patients**

When the risk of inappropriate prescribing increases, healthcare professionals inside the system are motivated to perform microbiology laboratory tests for all patients. The SFD of
this balancing loop is presented below (Figure 6.12).

**Figure 6.12 Stock and flow diagram of the balancing loop B5**

![Stock and flow diagram of the balancing loop B5](image)

**Balancing loop 6: providing results for all microbiology laboratory test performed**

When the risk of inappropriate prescribing increases, healthcare professionals inside the system are also motivated to provide results for microbiology laboratory tests performed.

The SFD of this balancing loop is presented below (Figure 6.13).
6.2.2.3 The conveyer stock of microbiology laboratory

In SD modelling, sometimes ‘delay’ occurs during the process of system operation. When dealing with delay, a time element must be incorporated in SD model development. There are two types of delay in SD modelling: 1) information delay, which is associated to the time consumed to delivery and interpret information, change perception and alter behaviour, the time delays caused by the lag time in behaviour change were discussed in the previous chapter (Chapter 5, 5.3.3 Dealing with time delays); and 2) material delay, which is caused by the process of delivering materials from stock to stock. For example, in this study, patients' blood samples are delivered to the microbiology laboratory for pathogen identification. The diagnostic information is not available immediately. The time
consumption of blood sample processing must be considered. Such delay, which is essentially the microbiology laboratory turnaround time, provided the opportunity for intervention implementation.

A special type of stocks, named ‘conveyers’, are designed to simulate such ‘delay’ processes in iThink® software package. A conveyor is like a moving sidewalk in the airport. The quantity rides until the conveyor deposits it at the other end, the trip takes a certain amount of time to complete (transit time), a proportion of the quantity does not make it all the way through (leakage). A conveyer is used to simulate the variable ‘microbiology laboratory turnaround time’ as it reflects the process of delay and unifies the units of the quantities modelled. The SFD of the conveyer was constructed using iThink® 10.0.3 and presented in the figure below (Figure 6.14).

**Figure 6.14 Conveyer stock of microbiology laboratory**
The convey stock was fed by ‘microbiology laboratory inflow’, which represents the blood samples arriving in the laboratory. After the process of testing pathogens is completed, a portion of blood samples that arrived do not have test result delivered back to medical wards, which is represented by the outflow of ‘missing blood samples’. The processed blood samples leave the microbiology laboratory and accumulate in the stock of ‘processed blood samples’. Before the system moves on to the next stage of microbiology review, the unit of the quantity model is converted from ‘number of blood samples’ back to ‘number of decisions’ to maintain the dimensional consistency of the SD model.

The microbiology laboratory turnaround time is simulated using the transit time of the conveyer stock. The transit time can be a single time constant or a series of values. To increase the robustness of the SD model, the transit time of the microbiology laboratory conveyer is set to be a distribution of turnaround time. The turnaround time distribution is calculated using the data extracted from the hospital inpatient notes and stored in the graph function ‘TAT_value’. The details of calculation will be discussed later in this chapter (Chapter 6, 6.3.4.5 Parameters in the conveyer stock).

### 6.3 Model parameterisation

After the construction of the CLDs and SFDs of the SD model was completed, a list of quantitative parameters to be included in the SD model was generated to guide the data
analysis and model parameterisation in the later stage.

The parameters included in the SD model of prescribing decision-making processes are presented in Table 6.1. Converter is a type of variable used in SD model to hold the values of auxiliary variables and exogenous variables, which are normally constants.

**Table 6.1 System Dynamics model parameters**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Senior doctors’ rate of prescribing</td>
<td>Flow</td>
<td>Number of decisions per day</td>
<td>Empiric decisions made by specialty registrars and consultants per day</td>
</tr>
<tr>
<td>Proportion of senior doctor prescribing</td>
<td>Converter</td>
<td>-</td>
<td>Proportion of empiric decisions made by specialty registrars and consultants</td>
</tr>
<tr>
<td>Junior doctors’ rate of prescribing</td>
<td>Flow</td>
<td>Number of decisions per day</td>
<td>Empiric decisions made by Foundation Year doctors, core trainees and nurses</td>
</tr>
<tr>
<td>Proportion of junior doctor prescribing</td>
<td>Converter</td>
<td>-</td>
<td>Proportion of empiric decisions made by Foundation Year doctors, core trainees and nurses</td>
</tr>
<tr>
<td>Empiric decision by specialty registrars and consultants</td>
<td>Stock</td>
<td>Number of decisions</td>
<td>Number of empiric decisions made by specialty registrars and consultants</td>
</tr>
<tr>
<td>Empiric decisions by Foundation Year doctors, core trainees and nurses</td>
<td>Stock</td>
<td>Number of decisions</td>
<td>Number of empiric decisions made by Foundation Year doctors, core trainees and nurses</td>
</tr>
<tr>
<td>Senior doctors’ rate of complying</td>
<td>Flow</td>
<td>Number of decisions per day</td>
<td>Compliant empiric decisions compliant made by specialty registrars and consultants per day</td>
</tr>
<tr>
<td>Proportion of senior doctors complying</td>
<td>Converter</td>
<td>-</td>
<td>Proportion of specialty registrars and consultants compliant with guidelines at empiric stage</td>
</tr>
<tr>
<td>Junior doctors’ rate complying</td>
<td>Flow</td>
<td>Number of decisions per day</td>
<td>Compliant empiric decisions made by Foundation Year doctors, core trainees and nurses per day</td>
</tr>
<tr>
<td>Proportion of junior complying</td>
<td>Converter</td>
<td>-</td>
<td>Proportion of Foundation Year doctors, core trainees and nurses complying with guidelines at empiric stage</td>
</tr>
<tr>
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<td>Stock</td>
<td>Number of decisions</td>
<td>Number of empiric decisions not compliant with guidelines made by specialty registrars and consultants</td>
</tr>
<tr>
<td>Compliant empiric decisions by Foundation Year doctors, core trainees and nurses</td>
<td>Stock</td>
<td>Number of decisions</td>
<td>Number of empiric decisions not compliant with guidelines made by Foundation Year doctors, core trainees and nurses complying with guidelines</td>
</tr>
<tr>
<td>Non-compliant empiric decisions by specialty registrars and consultants</td>
<td>Stock</td>
<td>Number of decisions</td>
<td>Number of empiric decisions not compliant with guidelines made by specialty registrars and consultants</td>
</tr>
<tr>
<td>Non-compliant empiric decisions by Foundation Year doctors, core trainees and nurses</td>
<td>Stock</td>
<td>Number of decisions</td>
<td>Number of empiric decisions not compliant with guidelines made by Foundation Year doctors, core trainees and nurses complying with guidelines</td>
</tr>
<tr>
<td>Percentage of compliant empiric decisions</td>
<td>Outcome measure</td>
<td>%</td>
<td>Percentage of empiric decisions in compliance with guidelines</td>
</tr>
<tr>
<td>Microbiology laboratory turnaround time</td>
<td>Transit time in conveyer</td>
<td>Days</td>
<td>Days before the microbiology laboratory test results become available</td>
</tr>
<tr>
<td>Empiric decisions reviewed by microbiologists</td>
<td>Stock</td>
<td>Number of decisions</td>
<td>Number of empiric decisions reviewed by microbiologists</td>
</tr>
<tr>
<td>Microbiologists’ rate of reviewing</td>
<td>Flow</td>
<td>Number of decisions per day</td>
<td>Number of empiric decisions reviewed microbiologists per day</td>
</tr>
<tr>
<td>Proportion of microbiologist complying</td>
<td>Converter</td>
<td>-</td>
<td>Proportion of microbiologists complying with guidelines at review stage</td>
</tr>
<tr>
<td>Percentage of reviewed empiric decisions</td>
<td>Outcome measure</td>
<td>%</td>
<td>Percentage of empiric decisions made by all doctors reviewed by microbiologists</td>
</tr>
</tbody>
</table>

The parameter list provided the direction of data collection and analysis to formulate the SD model that enables simulation of doctors’ decision-making processes and prediction of prescribing outcomes assessed by percentage of compliant empiric decisions and
percentage of reviewed empiric decisions.

6.3.1 Data sources for model parameterisation

In Chapter 4, the data sources included in this study to support SD model development were described, as well as the methods used to analyse the primary and secondary source data (Chapter 4, 4.3 Data sources, 4.4 Secondary research, 4.5 Primary research). In this chapter, the results of data analysis are presented.

6.3.1.1 Data Sources 1: survey with Foundation Year doctors

Data Source 1 is the survey with Foundation Year doctors recruited from 5 NHS Trust teaching hospitals in North West London. Characteristics of the Foundation Year doctors included in this study are presented in Table 6.2. All of the Foundation Year doctors were prescribing antibiotics in their post when they participated the survey.

<table>
<thead>
<tr>
<th>Table 6.2 Characteristics of Foundation Year doctors included in the study</th>
</tr>
</thead>
<tbody>
<tr>
<td>N total Foundation Year doctors = 103</td>
</tr>
<tr>
<td>N* (%)</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
</tr>
<tr>
<td>Male</td>
</tr>
<tr>
<td>47 (45.7%)</td>
</tr>
<tr>
<td>Female</td>
</tr>
<tr>
<td>56 (54.3%)</td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
</tr>
<tr>
<td>20-24</td>
</tr>
<tr>
<td>42 (40.8%)</td>
</tr>
</tbody>
</table>
Foundation Year 1 doctors rarely (n = 7, 12.1%) reported prescribing independently without the instruction from more senior doctors. Most Foundation Year 2 doctors (n = 34, 76.6%) reported feeling increased confidence in prescribing in the second year post-qualification compared to the first year (n = 36, 62.1%). Lacking knowledge (18.9%), lacking experience (16.2%), and lacking diagnosis (12.6%) were reported to be the factors decreasing Foundation Year doctors’ confidence in prescribing, while confidence in senior doctors (45.9%), diagnosis/information to confirm pathogens (39.1%) and experience (25.2%) were reported as key factors to improve confidence. When Foundation Year doctors needed support in decision-making, they would likely to seek help from specialty registrars, microbiologists, and consultants from their own specialty. They reported experiencing difficulties to find help in the evening/at night, during weekends and public holidays.

Foundation Year 1 doctors reported complying with national prescribing policy infrequently (n = 12, 20.1%), while Foundation Year 2 doctors complied with guidelines
Foundation Year doctors reported that a non-optimal prescription would most probably get corrected by a doctor on the next patient round or a pharmacist. 5.5% Foundation Year doctors estimated that none of the non-optimal prescriptions would be reported back to the prescribing doctor, 28.1% estimated 1-33%, 15.5% estimated 34-66%, and 20.0% estimated 67-99%, 2.7% estimated 100%. 28.1% Foundation Year doctors were not able to make the estimation. The findings suggested that a high proportion of Foundation Year doctors were prescribing antibiotics independently while not feeling confident that these decisions were optimal. However, increasing knowledge in antibiotic prescribing through training programmes as an isolated factor may not increase confidence. Providing support and supervision from senior doctors and diagnosis of pathogens were more likely to improve confidence.

6.3.1.2 Data Source 2: Interviews with senior doctors

Data Source 2 is the in-depth interviews with specialty registrars and consultants recruited from 3 NHS Trust teaching hospitals in West London. 5 key research question themes were identified based on a review of extant literature and discussion among the researchers that conducted the three studies. The 5 research topic themes are listed in Table 6.3.
Table 6.3 Research topic themes emerged in interviews with senior doctors

<table>
<thead>
<tr>
<th>Research topic theme</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Procedure</td>
<td>The procedure doctors followed when treating infections</td>
</tr>
<tr>
<td>Perception</td>
<td>Doctors’ perception of the service quality provided by themselves</td>
</tr>
<tr>
<td>Interaction</td>
<td>Doctors’ interaction with colleagues</td>
</tr>
<tr>
<td>Guideline compliance</td>
<td>Awareness, accessibility, compliance level, and evaluation of antibiotic prescribing guidelines</td>
</tr>
<tr>
<td>Barriers</td>
<td>Environmental (e.g. emerged multi-resistance), structural (e.g. delayed delivery of microbiology laboratory test results), behavioural (e.g. senior doctors’ instruction overriding prescribing guidelines) barriers occurred on different levels across healthcare systems.</td>
</tr>
</tbody>
</table>

The findings from Data Source 2 are particularly helpful as they are the views of the senior group of prescribers and confirm the causality mechanism captured in the CLDs. The in-depth nature of the interviews helped understand doctors’ reasoning behind prescribing decision-making. Delayed delivery of microbiology test results was identified repeatedly by senior doctors as a barrier to the optimal infection management. Senior doctors relied on their own experience when making empiric decisions considering a series of factors: 1) the microbiology laboratory test results were not available when a prescribing decision must be made as soon as possible, hence, microbiologists were not involved in the decision-making processes in empiric stage; 2) prescribing guidelines were considered useful however needed improvement or regular update.
6.3.1.3 Data Source 3: Hospital inpatient notes review

Data Source 3 is the hospital inpatient notes of 150 patients admitted in 3 NHS Trust teaching hospitals in West London from 1 March to 1 August 2016 who either admitted with *E. coli* bacteraemia or developed *E. coli* bacteraemia during their hospital stay. Among 150 enrolled patients, 23 were excluded due to data incompleteness. Characteristics of the 127 included patients are presented in Table 6.4.

Table 6.4 Characteristics of patients included in the study

<table>
<thead>
<tr>
<th></th>
<th>N enrolled notes = 127</th>
<th>N* (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td></td>
<td>57 (44.9%)</td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td>70 (55.1%)</td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20-29</td>
<td></td>
<td>6 (4.7%)</td>
</tr>
<tr>
<td>30-39</td>
<td></td>
<td>9 (7.1%)</td>
</tr>
<tr>
<td>40-49</td>
<td></td>
<td>5 (3.9%)</td>
</tr>
<tr>
<td>50-59</td>
<td></td>
<td>17 (13.4%)</td>
</tr>
<tr>
<td>60-69</td>
<td></td>
<td>23 (18.1%)</td>
</tr>
<tr>
<td>70-79</td>
<td></td>
<td>33 (26.0%)</td>
</tr>
<tr>
<td>80-89</td>
<td></td>
<td>26 (20.5%)</td>
</tr>
<tr>
<td>90-99</td>
<td></td>
<td>8 (6.3%)</td>
</tr>
<tr>
<td><strong>Survival during admission</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alive</td>
<td></td>
<td>101 (79.5%)</td>
</tr>
<tr>
<td>Deceased</td>
<td></td>
<td>26 (20.5%)</td>
</tr>
<tr>
<td><strong>Hospital</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital A</td>
<td></td>
<td>33 (26.0%)</td>
</tr>
<tr>
<td>Hospital B</td>
<td></td>
<td>47 (37.0%)</td>
</tr>
<tr>
<td>Hospital C</td>
<td></td>
<td>47 (37.0%)</td>
</tr>
<tr>
<td>Specialty</td>
<td>Count (Percentage)</td>
<td></td>
</tr>
<tr>
<td>--------------------------------------------------------------------------</td>
<td>--------------------</td>
<td></td>
</tr>
<tr>
<td>Acute medicine/acute assessment unit/A&amp;E</td>
<td>16 (12.6%)</td>
<td></td>
</tr>
<tr>
<td>Cancer/chemotherapy</td>
<td>3 (2.4%)</td>
<td></td>
</tr>
<tr>
<td>Cardiology</td>
<td>4 (3.1%)</td>
<td></td>
</tr>
<tr>
<td>Endocrinology/metabolism medicine/hepatobiliary/hepatology</td>
<td>11 (8.7%)</td>
<td></td>
</tr>
<tr>
<td>Gastrointestinal/gastroenterology</td>
<td>9 (7.1%)</td>
<td></td>
</tr>
<tr>
<td>General ICU</td>
<td>8 (6.3%)</td>
<td></td>
</tr>
<tr>
<td>General surgery/neurosurgery</td>
<td>14 (11.0%)</td>
<td></td>
</tr>
<tr>
<td>Geriatric/elderly care</td>
<td>7 (5.5%)</td>
<td></td>
</tr>
<tr>
<td>Gynaecology/maternity</td>
<td>11 (8.7%)</td>
<td></td>
</tr>
<tr>
<td>Haematology</td>
<td>8 (6.3%)</td>
<td></td>
</tr>
<tr>
<td>High dependency unit</td>
<td>8 (6.3%)</td>
<td></td>
</tr>
<tr>
<td>Kidney/transplant medicine/renal</td>
<td>10 (7.9%)</td>
<td></td>
</tr>
<tr>
<td>Rehabilitation/therapeutics</td>
<td>5 (3.9%)</td>
<td></td>
</tr>
<tr>
<td>Respiratory</td>
<td>4 (3.1%)</td>
<td></td>
</tr>
<tr>
<td>Trauma/orthopaedics</td>
<td>1 (0.8%)</td>
<td></td>
</tr>
<tr>
<td>Urology</td>
<td>6 (4.7%)</td>
<td></td>
</tr>
<tr>
<td>Vascular</td>
<td>2 (1.6%)</td>
<td></td>
</tr>
</tbody>
</table>

The length of stay of the patients included is presented in Figure 6.15.

**Figure 6.15 Patients’ length of stay in Data Source 3**
**Prescribing behaviour at empiric stage**

The prescriptions made for these 127 patients at empiric stage were analysed. The prescribed antibiotics were categorised into narrow spectrum and broad spectrum according to the activities using the antibiotic activity ranking (Braykov et al., 2014). The documented empiric decisions in terms of types and routes of the antibiotic drugs made by doctors at different positions are presented in Figure 6.16.

**Figure 6.16 Empiric decisions made by doctors at different positions**

![Bar chart showing empiric decisions by different positions.]

The empiric decisions were assessed using the local guideline (NHS Trust teaching hospital treatment of infection clinical guideline for adults) and national guideline (NICE guideline of bacterial infections for adults), a decision was considered ‘non-compliant with
guidelines’ if the prescription did not follow the recommendations provided by the local or national guidelines. Non-compliant decisions included the decisions using the antibiotics with broader spectrums, using higher doses, and with longer duration when compared to the recommendations in guidelines, the decisions of which patients’ physiological parameters and biomarkers did not justify the incompliance, and the decisions with no documentation of whether these decisions were validated by microbiologist. Guideline compliance of empiric decisions is presented in Table 6.5.

Table 6.5 Guideline compliance level of empiric decisions against other factors

<table>
<thead>
<tr>
<th></th>
<th>Total decisions</th>
<th>Compliant</th>
<th>Non-compliant</th>
<th>Unknown</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Seniority</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foundation Year 1 doctors</td>
<td>3</td>
<td>3 (100.0%)</td>
<td>0 (0.0%)</td>
<td>0</td>
</tr>
<tr>
<td>Foundation Year Y2 doctors</td>
<td>22</td>
<td>21 (95.5%)</td>
<td>1 (4.5%)</td>
<td>0</td>
</tr>
<tr>
<td>Core trainees</td>
<td>23</td>
<td>22 (95.7%)</td>
<td>1 (4.3%)</td>
<td>0</td>
</tr>
<tr>
<td>Specialty registrars</td>
<td>48</td>
<td>43 (89.6%)</td>
<td>5 (10.4%)</td>
<td>0</td>
</tr>
<tr>
<td>Consultants</td>
<td>15</td>
<td>12 (80.0%)</td>
<td>3 (20.0%)</td>
<td>0</td>
</tr>
<tr>
<td>Microbiologists</td>
<td>14</td>
<td>14 (100.0%)</td>
<td>0 (0.0%)</td>
<td>0</td>
</tr>
<tr>
<td>Nurses</td>
<td>2</td>
<td>2 (100.0%)</td>
<td>0 (0.0%)</td>
<td>0</td>
</tr>
<tr>
<td><strong>Hospital</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital A</td>
<td>33</td>
<td>28 (84.8%)</td>
<td>5 (15.2%)</td>
<td>0</td>
</tr>
<tr>
<td>Hospital B</td>
<td>47</td>
<td>43 (91.5%)</td>
<td>4 (8.5%)</td>
<td>0</td>
</tr>
<tr>
<td>Hospital C</td>
<td>47</td>
<td>45 (95.7%)</td>
<td>2 (4.3%)</td>
<td>0</td>
</tr>
<tr>
<td><strong>Specialty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acute medicine, acute assessment unit, A&amp;E</td>
<td>16</td>
<td>16 (100.0%)</td>
<td>0 (0.0%)</td>
<td>0</td>
</tr>
<tr>
<td>Cancer, chemotherapy</td>
<td>3</td>
<td>3 (100.0%)</td>
<td>0 (0.0%)</td>
<td>0</td>
</tr>
</tbody>
</table>
The level of guideline compliance was assessed against two associated factors 1) patient’s age, and 2) prescribing doctor’s seniority. Binomial logistic regression analysis (as the dependent variable was set to fit into either one of the two categories: in compliance or not in compliance) provided the unadjusted odds ratio and odds ratio with specialty and hospital adjusted as confounders. An adjusted odds ratio of 0.97 (95% CI, 0.92-1.01, P-value = 0.09) suggested a smaller likelihood of doctors to follow the guidelines at empiric stage when treating older patients. The results of the regression analysis for doctors’ seniority were listed in Table 6.6.
Table 6.6 Binomial logistic regression examining guideline compliance at empiric stage associated with prescribing doctors’ seniority

<table>
<thead>
<tr>
<th>Associated factors</th>
<th>Unadjusted OR</th>
<th>[95% CI]</th>
<th>Crude p-value</th>
<th>Adjusted OR</th>
<th>[95% CI]</th>
<th>Adjusted p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seniority</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foundation Year 1 doctors</td>
<td>1*</td>
<td></td>
<td>1*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foundation Year 2 doctors</td>
<td>1.61</td>
<td>0.09 to 28.11</td>
<td>0.74</td>
<td>1.88</td>
<td>0.10 to 35.16</td>
<td>0.67</td>
</tr>
<tr>
<td>Core trainees</td>
<td>1.69</td>
<td>0.10 to 29.41</td>
<td>0.72</td>
<td>1.72</td>
<td>0.10 to 30.48</td>
<td>0.71</td>
</tr>
<tr>
<td>Specialty registrars</td>
<td>0.66</td>
<td>0.07 to 6.18</td>
<td>0.72</td>
<td>0.71</td>
<td>0.07 to 6.74</td>
<td>0.76</td>
</tr>
<tr>
<td>Consultants</td>
<td>0.31</td>
<td>0.03 to 3.38</td>
<td>0.34</td>
<td>0.29</td>
<td>0.03 to 3.37</td>
<td>0.33</td>
</tr>
<tr>
<td>Microbiologists</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Pharmacists</td>
<td>N/A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nurses</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

The highest guideline compliance level was predicted among Foundation Year 2 doctors and core trainees at empiric stage, while the lowest level was predicted for consultants.

**Prescribing behaviour at review stage**

During empiric stage, patients’ blood samples were taken and delivered to microbiology laboratory. The pathogen of the infection (*E. coli*) was confirmed for the majority of the patients. The microbiology laboratory turnaround time varied from less than 24 hours to more than 3 days (Figure 6.17).
The microbiologists were involved significantly in the decision-making processes after the microbiology laboratory test results became available. 64.6% of the decisions were made by microbiologists at the review stage, 17.3% of the decisions were made by consultants and specialty registrars with the input of microbiologists. All the decisions (including de-escalation and escalation) at the review stage complied with the guidelines, suggesting that the process of treating *E. coli* infection was policy driven.

The finding of the inpatient note review suggested that specialty registrars, core trainees and Foundation Year 2 doctors made the most decisions at empiric stage, meanwhile Foundation Year 1 doctors documented and followed the decisions made by senior staff. Nurses and pharmacists’ involvement in empiric prescribing decision-making processes was negligible. The level of guideline compliance decreased as the doctor’s seniority increased. All the empiric decisions made by Foundation Year 1 doctors and nurses complied with guideline recommendations. The lowest compliance level was observed.
among consultants and specialty registrars.

The findings of this study have several limitations. First, the data was extracted from hospital inpatient notes retrospectively to support the assessment of guideline compliance. Doctors could possibly have taken additional steps (i.e. discuss with microbiologists, discuss with patients) to justify their empiric decisions, however such processes could be undocumented. Secondly, due to the limited number of documented empiric decisions made by Foundation Year 1 doctors, nurses and microbiologists, it could not be confirmed that such high compliance level reflected the real prescribing behaviour or was caused by random error.

6.3.2 Integration of qualitative findings

Qualitative studies have the capability to provide details of human behaviour, which quantitative studies cannot match. Methods commonly used to collect qualitative data include interviews, focus groups, ethnographic studies, and observation (Luna-Reyes & Andersen, 2003). Most qualitative data collection techniques are devoted to the elicitation of knowledge about a particular research topic, enriching the written database to be used in the SD model development process (McLucas, 2003). Researchers could benefit from the process of combing quantitative and qualitative data and gain more knowledge about the research topic than analysing different studies separately. A study has been published
by O’Cathain et al to propose a ‘performative protocol’ to integrate the results of qualitative and quantitative studies (O’Cathain, Murphy, & Nicholl, 2010). Three techniques, data triangulation, following a thread, and mixed-method matrix, were introduced in the study. Data triangulation protocol is the technique used to merge qualitative results generated in the three studies on doctors’ decision-making processes.

**6.3.2.1 Summary of qualitative findings**

In this study, qualitative data has been incorporated at different stages. In the stage of model conceptualisation, the qualitative findings helped connect the key variables in the defined system of prescribing decision-making processes. The qualitative findings from the rapid literature review and the analysis of hospital inpatient notes helped identify the key variables and influence factors to be included in the system. The schematic map of the process of antibiotic prescribing was constructed based on the qualitative findings. The causal relationships between key variables captured by CLDs of the SD model were established using the same information. A 2x2 table was used to combine the qualitative findings from the rapid literature review and the analysis of the data from multiple sources, including the factors influencing prescribing decision-making processes assessed by guideline compliance level for two groups of doctors (Table 6.7).
### Table 6.7 Synthesized qualitative findings from the three studies

<table>
<thead>
<tr>
<th>Compliance Level</th>
<th>Junior doctors</th>
<th>Senior doctors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>High</strong></td>
<td>Use prescribing guidelines as instruction when feel unsupported by senior doctors or microbiologists; In special environments, such as A&amp;E.</td>
<td>Perceive themselves as role models; Have support from microbiologists at empiric stage; Feedback on their practices.</td>
</tr>
<tr>
<td><strong>Low</strong></td>
<td>Decision-making influenced by cultural and hierarchical factors in medical wards; Lack of knowledge and experience in prescribing, or lack of confidence that they are prescribing appropriately, which result in obedience to senior doctors and thus low guideline compliance level.</td>
<td>Rely on own experience and knowledge rather than prescribing guidelines; Fear of undertreating infections when pathogen information is not available, especially when treating elderly patients.</td>
</tr>
</tbody>
</table>

When the ‘soft’ variable (‘fear of under-treating infections’) emerged in the causal relationships within the system, qualitative data supported the interpretation of the feedback loops containing such ‘soft’ variable and helped translate this variable into the quantitative simulatable SD model.

#### 6.3.2.2 Qualitative data integration: data triangulation

The information reported by the three studies covered all aspects of prescribing decision-making processes when treating hospital inpatients with bacterial infections. Following the triangulation protocol provided by O’Cathain *et al*, a ‘convergence coding matrix’ was produced by displaying findings emerging from each study on the same page to investigate where findings from each method agree (convergence), offer complementary information on the same issue (complementarity), or appear to contradict each other (discrepancy or
dissonance) (O’Cathain, Murphy, & Nicholl, 2010). ‘Silence’ - where a theme or finding arises from the result of one study and not another, was also included in the convergence coding matrix. Silence might be expected because of the strengths of different methods to examine different aspects of a phenomenon, but surprise silences might also arise that help to increase understanding or lead to further investigations. The findings from the analysis of each data set were listed in the convergence coding matrix and arranged into the 5 research themes established when analysing the secondary data collected from the interviews with specialty registrars and consultants (Chapter 6, 6.3.1.2 Data Source 2: interviews with senior doctors). The 5 research themes established are procedure, perception, interaction, guideline compliance, and barriers. The convergence coding matrix is presented in the table below (Table 6.8).

**Table 6.8 Convergence coding matrix**

<table>
<thead>
<tr>
<th>Procedure</th>
<th>Data Source 1: Survey with Foundation Year 1 and 2 doctors</th>
<th>Data Source 2: Interview with consultants and specialty registrars</th>
<th>Data Source 3: Hospital inpatient notes review</th>
<th>Convergence assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnose an infection case</td>
<td>Silent</td>
<td>Consultants and specialty registrars made diagnosis considering patient history, biomarkers, and physiology parameters</td>
<td>Doctors made preliminary diagnosis considering patient history, biomarkers, and physiology parameters</td>
<td>Convergence</td>
</tr>
<tr>
<td>Make empiric decisions</td>
<td>Silent</td>
<td>Whoever on ward (normally a junior doctor) would make empiric decision as early as possible.</td>
<td>Specialty registrars made the most decisions at empiric stage on medicine wards (35.2%), foundation year doctors made the most empiric decisions in A&amp;E (61.9%). Empiric treatment were initiated in less than 24 cases for all cases.</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Review of previous decisions on weekdays</td>
<td>Foundation year doctors were involved in reviewing processes daily and consider de-escalation case by case.</td>
<td>Consultants reviewed and adjusted previous decisions daily considering microbiology laboratory results and microbiologists’ advice.</td>
<td>All doctors reviewed previous decisions for multiple times (four times) daily on weekdays, specialty registrars and consultants adjust empiric decisions considering microbiology laboratory results and microbiologists’ advice.</td>
<td>Complementarity</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Review of previous decisions during weekends/out-of-hour</td>
<td>Silent</td>
<td>Whoever on call would review previous decisions (including 24/7 SHO, specialty registrars, and microbiologists) daily.</td>
<td>Whoever on call would review previous decisions (24/7 SHO in most cases) daily.</td>
<td>Convergence</td>
</tr>
<tr>
<td>Make decisions to stop treatment</td>
<td>Silent</td>
<td>Consultants made decisions to stop treatment.</td>
<td>Consultants made decisions to stop treatment, considering microbiologists’ advice.</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Confidence in prescribing appropriately</td>
<td>Most of the foundation year doctors felt fairly confident that they were prescribing appropriately (73.9%), senior doctors’ instruction, guidelines and diagnostic information increases the confidence among foundation year doctors.</td>
<td>Silent</td>
<td>Silent</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Empowerment at current position</td>
<td>Silent</td>
<td>Consultants and specialty registrars felt empowered.</td>
<td>Foundation year doctors’ decisions were sometimes overridden by consultants’ decisions.</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Perceived role in antibiotic decision-making processes</td>
<td>Foundation year doctors were involved in the decision-making processes.</td>
<td>Consultants believed that they were final decision makers and take full responsibility.</td>
<td>Senior doctors (consultants, specialty registrars and core trainees) were final decision makers to initiate, switch and stop treatment, while foundation year doctors documented senior doctors’ decisions and make decisions to continue a current treatment plan.</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Interaction among foundation year doctors</td>
<td>Silent</td>
<td>Silent</td>
<td>Silent</td>
<td>N/A</td>
</tr>
<tr>
<td>Interaction between senior doctors and foundation year doctors</td>
<td>Most foundation year doctors (67.5%) sometimes or often prescribed with a more senior doctor and sought help from senior staff (primarily from specialty registrars) whenever needed.</td>
<td>Consultants made decisions considering information provided by junior doctors (including foundation year doctors).</td>
<td>Silent</td>
<td>Complementarity</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Interaction between senior doctors and microbiologists</td>
<td>Silent</td>
<td>Microbiologists' advice was only important during later stage, as pathogen information is usually not available at empiric stage. Microbiology laboratory results are confirmative information.</td>
<td>Microbiologists were involved in review process, especially when escalation is needed, or when patient is discharged with OPAT.</td>
<td>Convergence</td>
</tr>
<tr>
<td>Interaction between Foundation Year doctors and microbiologists</td>
<td>Foundation year doctors sought help from microbiologists in training and daily practices.</td>
<td>Silent</td>
<td>Silent</td>
<td>N/A</td>
</tr>
<tr>
<td>Awareness of guidelines</td>
<td>All foundation year doctors reported being aware of the local guidelines.</td>
<td>All consultants and specialty registrars reported being aware of the local guidelines.</td>
<td>Silent</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Accessibility of guidelines</td>
<td>Foundation year doctors found local guidelines easy to access, from smartphone App, intranet, handbook or posters on ward).</td>
<td>Foundation year doctors found local guidelines easy to access, mainly from intranet), and external guidelines easy to access from internet.</td>
<td>Silent</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Guideline compliance</td>
<td>Foundation year doctors reported following local guidelines.</td>
<td>Consultants sometimes trusted their own experience.</td>
<td>Consultants sometimes prescribed broader than local guidelines.</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Feedback regarding guidelines</td>
<td>Foundation year doctors find both local guidelines help support decision-making and increase confidence.</td>
<td>Consultants find both local and external guidelines help support decision-making and increase confidence.</td>
<td>Silent</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Other materials supporting decision-making</td>
<td>Foundation year doctors found education programmes helpful.</td>
<td>Consultants sometimes read literature to support decision-making.</td>
<td>Silent</td>
<td>Complementarity</td>
</tr>
</tbody>
</table>
6.3.3 Integration of quantitative findings

Data Source 2 and Data Source 3 provided quantitative data to support SD model formulation. The findings from these two sources were synthesized to help confirm causal relationships and assign the key variables with numerical values. At the qualitative mapping stage, the ‘soft’ variable ‘fear of under-treating’ was discussed (Chapter 5, 5.3.2 Dealing with ‘soft’ variables). In this chapter, regression analysis is performed to determine whether the association existed between patient’s age and doctor’s prescribing habit.

6.3.3.1 The regression analysis of ‘fear’

Correlation was detected between patient’s age and doctor’s guideline compliance level. Specialty registrars and consultants had a tendency to prescribe antibiotics with broader spectrum than the recommendations in the guidelines. Using the empiric knowledge of antibiotic prescribing and input from experts, such correlation can be explained as doctors avoiding risks of not covering all possible infections when treating older, sicker patients by prescribing antibiotics with broader spectrum. However, the regression analysis has
only demonstrated the existence of the correlation. It was not sufficient to help establish mathematical equations to quantitatively relate patient’s age, ‘fear of under-treating’, and doctors’ prescribing habit assessed by guideline compliance level. Hence, the ‘soft’ variable ‘fear of under-treating’ was eliminated from the simulatable model after qualitative stage of the SD model was completed. Further discussion of such an issue is included in Chapter 9 (Chapter 9, 9.4.1.2 The ‘soft’ variable: fear).

6.3.4 Methods for estimation of model parameters

6.3.4.1 Assumptions made before parameter value estimation

The SD model was constructed to represent the salient features of the prescribing decision-making processes. When estimating values of the parameters, the following assumptions were made to simplify the simulation model in addition to the assumptions made at qualitative mapping stage (Chapter 5, 5.1.2 Defining the boundaries of the system):

The number of patients admitted per day remain constant. In reality, for example, the rate of treating would be lower during weekends.

All the doctors inside the system had an equal probability of treating patients;

All the doctors made prescribing decisions based on own knowledge, experience, prescribing guidelines, or other doctors’ instruction, other factors, such as stock level of medications, financial incentives, were not considered.
The number of patients entering the system per day and the number of patient’s blood samples entering the microbiology laboratory per day were assumed not to exceed the maximal sample processing capacity of the microbiology laboratory.

### 6.3.4.2 Parameter value estimation

The estimated values for the model parameters are presented in Table 6.9, as well as how the parameter values were deduced using the results of source data analysis.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Unit</th>
<th>Description</th>
<th>Value</th>
<th>Derivation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admitted patients</td>
<td>Converter</td>
<td>Number of patients per day</td>
<td>Number of patients admitted with symptoms of bacterial infections in medical wards per day</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Senior doctors’ rate of prescribing</td>
<td>Flow</td>
<td>Decisions per day</td>
<td>Rate of specialty registrars and consultants making empiric decisions</td>
<td>Patients admitted* Proportion of senior prescribing</td>
<td></td>
</tr>
<tr>
<td>Proportion of senior prescribing</td>
<td>Converter</td>
<td>-</td>
<td>Proportion of empiric decisions made by specialty registrars and consultants</td>
<td>0.496</td>
<td>63 per 127</td>
</tr>
<tr>
<td>Junior doctors’ rate of prescribing</td>
<td>Flow</td>
<td>Decisions per day</td>
<td>Rate of Foundation Year doctors, core trainees, and nurses making empiric decisions</td>
<td>Patients admitted* Proportion of junior prescribing</td>
<td></td>
</tr>
<tr>
<td>Proportion of junior prescribing</td>
<td>Converter</td>
<td>-</td>
<td>Proportion of empiric decisions made by Foundation Year doctors, core trainees, and nurses</td>
<td>0.394</td>
<td>50 per 127</td>
</tr>
<tr>
<td>Empiric decision by senior doctors</td>
<td>Stock</td>
<td>Number of decisions</td>
<td>Number of empiric decisions made by specialty registrars and</td>
<td>Initial value = 0</td>
<td>-</td>
</tr>
</tbody>
</table>

*Table 6.9 System Dynamics model parameters with values*
<table>
<thead>
<tr>
<th>Consultant Type</th>
<th>Stock Type</th>
<th>Number of Decisions</th>
<th>Description</th>
<th>Initial Value</th>
<th>Compliant Empiric Decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Empiric decisions by junior doctors</strong></td>
<td><strong>Stock</strong></td>
<td><strong>Number of decisions</strong></td>
<td>Number of empiric decisions made by Foundation Year doctors, core trainees, and nurses</td>
<td>Initial value = 0</td>
<td>-</td>
</tr>
<tr>
<td><strong>Senior doctors’ rate of complying</strong></td>
<td><strong>Flow</strong></td>
<td><strong>Decisions per day</strong></td>
<td>Rate of specialty registrars and consultants complying with guidelines at empiric stage</td>
<td>Empiric decision by senior* Proportion of senior complying</td>
<td>0.873</td>
</tr>
<tr>
<td><strong>Proportion of senior complying</strong></td>
<td><strong>Converter</strong></td>
<td>-</td>
<td>Proportion of specialty registrars and consultants complying with guidelines at empiric stage</td>
<td>0.873</td>
<td>-</td>
</tr>
<tr>
<td><strong>Junior doctors’ rate of complying</strong></td>
<td><strong>Flow</strong></td>
<td><strong>Decisions per day</strong></td>
<td>Rate of Foundation Year doctors, core trainees, and nurses complying with guidelines at empiric stage</td>
<td>Empiric decisions by junior*Proportion of junior complying</td>
<td>0.960</td>
</tr>
<tr>
<td><strong>Proportion of junior complying</strong></td>
<td><strong>Converter</strong></td>
<td>-</td>
<td>Proportion of Foundation Year doctors, core trainees, and nurses complying with guidelines at empiric stage</td>
<td>0.960</td>
<td>-</td>
</tr>
<tr>
<td><strong>Microbiologists’ rate of complying</strong></td>
<td><strong>Flow</strong></td>
<td><strong>Decisions per day</strong></td>
<td>Rate of microbiologists complying with guidelines</td>
<td>Empiric decisions by senior*Proportion of microbiologist complying</td>
<td>1.000</td>
</tr>
<tr>
<td><strong>Proportion of microbiologist complying</strong></td>
<td><strong>Converter</strong></td>
<td>-</td>
<td>Proportion of microbiologists complying with guidelines</td>
<td>1.000</td>
<td>-</td>
</tr>
<tr>
<td><strong>Compliant empiric decisions</strong></td>
<td><strong>Stock</strong></td>
<td><strong>Number of decisions</strong></td>
<td>Number of empiric decisions in compliance with guidelines</td>
<td>Initial value = 0</td>
<td>-</td>
</tr>
<tr>
<td><strong>Non-compliant empiric decisions</strong></td>
<td><strong>Stock</strong></td>
<td><strong>Number of decisions</strong></td>
<td>Number of empiric decisions not in compliance with guidelines</td>
<td>Initial value = 0</td>
<td>-</td>
</tr>
<tr>
<td><strong>Percentage of compliant empiric decisions</strong></td>
<td><strong>Auxiliary</strong></td>
<td>-</td>
<td>Percentage of compliant decisions at empiric stage</td>
<td>Initial value = 0</td>
<td>-</td>
</tr>
<tr>
<td><strong>Perceived risk of inappropriate prescribing practices</strong></td>
<td><strong>Eliminated at quantitative stage</strong></td>
<td>-</td>
<td>Simulate by adjusting other variables</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><strong>Motivation to shorten turnaround</strong></td>
<td><strong>Eliminated at</strong></td>
<td>-</td>
<td>Simulate by adjusting other variables</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Motivation to increase specialty registrars and consultants' guideline compliance</td>
<td>Eliminated at quantitative stage</td>
<td>-</td>
<td>Simulate by adjusting other variables</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Microbiology laboratory turnaround time</td>
<td>Transit time in conveyer stock</td>
<td>Days</td>
<td>Days before the microbiology laboratory test results become available</td>
<td>1.22 days</td>
<td>-</td>
</tr>
<tr>
<td>Processed blood samples</td>
<td>Stock</td>
<td>Number of samples</td>
<td>Number of processed blood samples converted into number of patients, then number of decisions</td>
<td>Initial value = 0</td>
<td>-</td>
</tr>
<tr>
<td>Fear of under-treating infections</td>
<td>Eliminated at quantitative stage</td>
<td>-</td>
<td>Simulate by adjusting other variables</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Patient’s age</td>
<td>Eliminated at quantitative stage</td>
<td>Years (not involved in calculation)</td>
<td>Patient’s age when admitted</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Proportion of patients without blood sample taken</td>
<td>Converter</td>
<td>-</td>
<td>Proportion of patients admitted with no blood sample taken and no microbiology laboratory test performed</td>
<td>0.102</td>
<td>13 per 127</td>
</tr>
<tr>
<td>Microbiologists’ rate of reviewing</td>
<td>Flow</td>
<td>Decisions per day</td>
<td>Rate of microbiologists reviewing empiric decisions after microbiology laboratory test results become available</td>
<td>Processed blood samples* Proportion of reviewing</td>
<td></td>
</tr>
<tr>
<td>Review decisions by microbiologists</td>
<td>Stock</td>
<td>Number of decisions</td>
<td>Review decisions made by microbiologists</td>
<td>Initial value = 0</td>
<td>-</td>
</tr>
<tr>
<td>Percentage of reviewing</td>
<td>Converter</td>
<td>-</td>
<td>Percentage of empiric decisions reviewed by microbiologists</td>
<td>0.863</td>
<td>82 per 95 tested</td>
</tr>
</tbody>
</table>
6.3.4.3 Estimation of senior doctors’ influence: table function

An important aspect of SD model development is to recognise the linear relationships and non-linear relationships within the modelled system and construct the model accordingly (Mohapatra, 1980). A model is considered linear if a state variable is related to its rate of change in a linear fashion. Mathematically, a linear system obeys the principle of superposition (Luenberger, 1964). The linearity of a system can be tested using homogeneity and additivity. When the magnitude of the input variable is doubled in a system, if it can be predicted that the output function will also be doubled, homogeneity is obeyed. When there are more than one input variables, if the overall output of the system is the sum of the outputs for each input variable, additivity is obeyed. The rules of homogeneity and additivity are together referred as the principle of superposition. Systems that satisfy both homogeneity and additivity are considered to be linear systems (Mohapatra, 1980). However, there is no accepted definition of non-linearity. Relationships between variables in complex systems existing in real life normally do not obey the principle of superposition. These relationships/systems are considered as non-linear relationships/systems. When building an SD model, researchers may be faced with a situation where there is a relationship between two variables but no simple algebraic equation to define the non-linear relationship (Wang & Boyd, 2010). In this case, a table function can be generated to connect independent and dependent variables and represent the relationship. In a table function, values of independent and dependent variables are
listed in pairs. The numerical values of dependent variable correspond measurements of the dependent variable. The number of pairs of independent and dependent variables, also referred as the number of data points, is determined by the availability of source data. The more data points are included in a table function, the more accurately the non-linear relationship can be described. In SD modelling, a table function containing 6 or more pairs of independent and dependent variables is generally considered acceptable (Lei & Choge, 2001). Table function is a ‘black-box’ approach, which records observed states of inputs and outputs with no inner logic available for inspection. More details of black-box approaches are discussed in the model validation stage (Chapter 7, 7.3.2 Correlational and causal-descriptive models).

In this study, the findings from the rapid literature review, the survey with Foundation Year doctors, the interviews with specialty registrars and consultants, and the hospital inpatient notes all suggested that senior doctors’, including specialty registrars and consultants’, decision-making processes had influence on junior doctors’ prescribing habit at empiric stage. The causal relationship between senior doctors’ and junior doctors’ decision-making certainly existed but could not be captured quantitatively by a simple equation. A table function was generated to contain 6 pairs of independent variables, which were the proportion of non-compliant empiric decisions made by senior doctors, and dependent variables, which were the proportion of non-compliant empiric decisions made by junior doctors. The values of the independent and dependent variables for each pair of data were
estimated using Data Source 3 (hospital inpatient notes) collected from hospital inpatient notes of 150 patients with *E. coli* bacteraemia during their hospital stay. 6 days were selected randomly from the 154-day time period (from 1 March 2016 to 1 August 2016). All empiric decisions made to treat the patient group on these 6 days were reviewed and categorised based on whether the empiric decisions were made by junior or senior doctors. The information of empiric prescribing decisions made on these 6 days was presented in the table below (Table 6.10).

<table>
<thead>
<tr>
<th>Day</th>
<th>Junior doctors</th>
<th>Senior doctors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Compliant empiric decisions</td>
<td>Non-compliant empiric decisions</td>
</tr>
<tr>
<td>Day 1</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>Day 2</td>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>Day 3</td>
<td>13</td>
<td>0</td>
</tr>
<tr>
<td>Day 4</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>Day 5</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>Day 6</td>
<td>14</td>
<td>1</td>
</tr>
</tbody>
</table>

The table function was then generated to connect the independent variable (proportion of non-compliant empiric decisions made by senior doctors) and the dependent variable (proportion of non-compliant empiric decisions made by junior doctors) (Table 6.11). As mentioned before, this table function was a black-box approach that provides numerical values of the dependent variable observed at different data points. The exact algebraic relationship between senior and junior doctors’ guideline compliance remained unknown.
### Table 6.11 Table function of senior and junior doctors’ guideline compliance

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data point 1</td>
<td>0.133</td>
</tr>
<tr>
<td></td>
<td>0.125</td>
</tr>
<tr>
<td>Data point 2</td>
<td>0.200</td>
</tr>
<tr>
<td></td>
<td>0.091</td>
</tr>
<tr>
<td>Data point 3</td>
<td>0.125</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
</tr>
<tr>
<td>Data point 4</td>
<td>0.056</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
</tr>
<tr>
<td>Data point 5</td>
<td>0.071</td>
</tr>
<tr>
<td></td>
<td>0.125</td>
</tr>
<tr>
<td>Data point 6</td>
<td>0.100</td>
</tr>
<tr>
<td></td>
<td>0.067</td>
</tr>
</tbody>
</table>

#### 6.3.4.4 Parameters in the conveyer stock

A conveyer stock was used to simulate the process of patients’ blood samples being tested in the microbiology laboratory. The following parameters were included and estimated in the conveyer stock:

- Type of conveyer: discrete;
- Transit time: average time of processing = microbiology laboratory turnaround time;
- Inflow limit: maximal number of patients = 1000;
- Capacity: maximal number of samples processed per day;
- Initial value: initial number of blood samples = 0;
- Leakage fraction: fraction of blood samples arriving at the laboratory but without test results delivered back to medicine wards = 0.066.

The transit time (microbiology laboratory turnaround time) is calculated using the distribution of turnaround time extracted from Data Source 3 (hospital inpatient notes).
First, the cumulative distribution function (CDF) of microbiology laboratory turnaround time was plotted, using the data extracted from the hospital inpatient notes (Chapter 6, 6.3.1.3 Data Source 3: hospital inpatient notes review, Figure 6.17). The plot described the probability the blood sample of a patient could be processed within certain period of time. (Figure 6.18).

**Figure 6.18 Cumulative distribution function of laboratory turnaround time**

![Cumulative distribution function of laboratory turnaround time](image)

In order to use the CDF to draw random values of the probability distribution of microbiology laboratory turnaround time, the CDF was inverted and plotted again (Figure 6.19). The process of inverting CDF converted the uniformly distributed number between 0 and 1 into the desired discrete probability distribution. The y-axis of the inverse cumulative distribution function (ICDF) plot represents the number of days spent to process a blood sample (0.5 days is used in cases of turnaround time less than 24 hours),
the x-axis represents the probability distribution.

**Figure 6.19 Inverse cumulative distribution function of laboratory turnaround time**

The ICDF was inserted into *iThink* software to create a graph function TAT_value = \( \text{GRAPH (RANDOM (0, 1)) (0.66, 0)(0.942, 1)(0.981, 2)(1.000, 3)} \), which allowed generation of random integers in the range of 0 to 3, representing the simulated microbiology laboratory turnaround time measured in days, based on the probability distribution for the discrete event of ‘processing patients’ blood samples’. This graph function was used as the ‘transit time’ of the conveyer stock which represents the number of blood samples in the microbiology laboratory. The shortening of microbiology was achieved by adjusting the graph function to generate turnaround time from less than 24 hours to 3 days with varying probability distribution.
In this chapter, the SD model was formulated quantitatively by translating CLDs constructed at qualitative stage into SFDs on software platforms. The findings from the analysis of primary and secondary data from multiple sources were synthesized together to draw a full picture of antibiotic prescribing decision-making processes and provide estimates of parameter values. In the next chapter, the processes of validating the estimates of the model parameters as well as the model structure will be discussed.

Key points in Chapter 6:

- Stock and flow diagrams (SFDs) were constructed allow computer-based quantitative simulation of doctors’ prescribing decision-making processes. The stocks held the quantity as number of prescribing decisions and the flows were the rates of prescribing decisions being made. The microbiology laboratory sub-system captured the blood culture turnaround time using delay function.

- The variables in the model were parameterised using primary and secondary source data.
Chapter 7 Model Validation and Testing

In the previous chapter, the steps undertaken to analyse source data and make estimates of the SD model parameters were described. With the basic model structure and the list of parameters established, a series of tests must be performed to verify the model’s capability and credibility of providing valid prediction of doctors’ prescribing behaviour within the context defined by the model boundaries before the model is simulated to provide any policy recommendation. In this chapter, the tests performed to validate the SD model are described. In this study, the SD model validation guideline ‘Tests for Building Confidence in System Dynamics Models’ published by the System Dynamics Group, Massachusetts Institute of Technology was followed (Senge & Forrester, 1980). Please be aware that more than one SD model validation guideline has been published, including ‘Multiple Tests for Validation of System Dynamics Type of Simulation Models’, and ‘Validation of Simulation Based Models: A Theoretical Outlook’ (Barlas, 1989; Martis, 2006). These practical guidelines were developed over time with the evolvement of computer-based simulating techniques. However, the fundamental concept of validating model structure, model parameters, and model behaviour was accepted by all these guidelines (Martis, 2006). The Senge guidance is recognised as the most comprehensive one that provided the validation tests supporting SD models constructed for all different purposes (Senge & Forrester, 1980). Hence, this guideline was followed.
7.1 Aims and principles of model validation in System Dynamics modelling

Confidence in SD models can be strengthened by a wide variety of tests for 1) model structure, 2) model parameter, and 3) model behaviour at different stages of model development. The validation of model structure was performed in parallel with the development of the schematic map, the CLD and the SFD. The validation of model behaviour was performed after model parameterisation. In this chapter, the processes of performing these tests and how these tests contributed to the model validation are discussed. The validation tests performed at different stages are presented in Figure 7.1.

Figure 7.1 Validation tests performed at different stages of the study
To the degree that an SD model passes test that it is ‘sound, defensible and well grounded’ it has that degree of validity and, hence, of being good enough for its purpose (Coyle, 2000). If an SD model passes no tests, the model would be completely invalid and hence useless. However, a model might pass many tests but fail one that is essential. Such a model would be invalid, as one would not know how much confidence could be placed in the model outputs. Thus, every single test performed to validate the model is critical. There is no discrimination in the necessity and the importance of each validation test.

**7.2 Model validation tests**

To ensure the model structure as a valid reflection of systems in real-life, 5 core tests were conducted to assess structure and parameters directly (without examining relationships between structure and behaviour). Structure-verification test, parameter-verification test, extreme condition test, boundary-adequacy test and dimensional-consistency test were performed on the SD model constructed for this study.

**7.2.1 Test the model structure**

**7.2.1.1 Structure-verification test**

The SD model went through structure-verification to make sure that the model structure
did not contradict *empiric* knowledge about the structure of the real system. Structure-verification tests included review of model assumptions by people highly knowledgeable about corresponding parts of the real system, and comparison of model assumptions to descriptions of decision-making and organisational relationships documented in literature. The model structure was considered valid after meeting two criteria, 1) the model structure is a simplified replication of a system existed in real-life, and 2) the most relevant structure for the purpose of the model was chosen from this system.

Multiple expert panel workshops were conducted to review the model structure that represented prescribing decision-making processes at different stages. The experts from NHS Trust teaching hospitals attended three workshops to validate the schematic map and the CLDs of prescribing decision-making processes, these included two consultants, two Foundation year doctors, two pharmacists, one nurse, and two researchers from the Infection Prevention and Control (IPC) team. The model structure validation started with the review of the sub-system diagram and the schematic map of prescribing decision-making processes presented in Chapter 2 (Chapter 2, 2.2.4 Results: schematic map of prescribing pathway) to confirm that 1) the sub-system diagram included adequate system components and 2) the map summarised the processes of prescribers making decisions to treat patients with symptoms of bacterial infections in hospital wards. The schematic map was reviewed again with influence factors overlaid on the system, the expert panel reached agreement on which level within healthcare systems the influence factors occurred. Finally,
the CLD of the SD model was reviewed to verify that the correct causal relationships among key variables in antibiotic prescribing decision-making processes were captured. The sub-system that simulated the process of testing blood sample in microbiology laboratory was compared to literature evidence then reviewed by two microbiologists from the same hospitals. The table below summarised the comments on the SD model structure from the expert panel Table 7.1.

Table 7.1 Comments on model structure from multiple expert panel workshops

<table>
<thead>
<tr>
<th>Expert attended</th>
<th>2 Foundation Year doctors, 2 pharmacists, 1 nurse from one NHS Trust teaching hospital</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>11 August 2015</td>
</tr>
<tr>
<td>Issue</td>
<td>Comments from the expert panel</td>
</tr>
<tr>
<td>How to categorise those influence factors that cannot be attributed to one level of healthcare system?</td>
<td>Antibiotic prescribing processes are dynamic and 'messy'. The processes vary between countries, hospitals, and physicians. Structural and procedural influence factors are relatively easier to be located inside healthcare systems. However, cultural, contextual, and behavioural determinants have impact on all levels across healthcare systems. This type of influence factors can be included in the hierarchical framework by placing them on multiple levels. However, further research should be conducted to study the multi-level aspects of antibiotic prescribing decision-making.</td>
</tr>
<tr>
<td>Which influence factors should be focused on in this study?</td>
<td>As this study aimed to understand prescribers’ decision-making, thus, the influence factors that had impact on individual prescribers’ prescribing habits should be studied thoroughly.</td>
</tr>
<tr>
<td>Reflection in the study</td>
<td>After the schematic map was constructed, various modelling and simulation approaches were evaluated to select a systems thinking method. SD modelling was selected for its capability to simulate the interconnection between influence factors and elements within a complex system. The SD model focused on the impact from senior doctors’ influence and microbiology laboratory turnaround time.</td>
</tr>
</tbody>
</table>
Which outcome measures should be used? How to quantitatively assess them?

Prescribing decision-making processes were measured by either prescribing outcomes in amount or types of drug prescribed, or prescribing behavioural outcomes in changed behaviour, or health outcomes of patients in earlier published studies. The ‘appropriateness’ of prescribing practices must be measured against prescribing guidelines. The totality, or the type (i.e. broad-spectrum or narrow spectrum) of the antibiotic drugs prescribed, or the length of the treatment are often used for the purpose of surveillance on healthcare system level. They are not sufficient enough to tell whether a decision was appropriate, unless each case was assess individually based on clinical conditions. In this case, prescribing guidelines would be the ‘standard’ for comparison. The expert panel suggested using guideline compliance level as the outcome measure. Guideline compliance level can be quantified using the percentage of doctors following guidelines, or the percentage of decisions in line with guidelines.

Are the assumptions to simplify the impact on different groups of doctors appropriate enough?

At first, the microbiology laboratory turnaround time overlaid on the schematic map only at review stage. But in real life, doctors in medical wards sometimes made empiric decisions based on pathogen information if the microbiology laboratory test results were available immediately after patients being admitted. The impact of turnaround time at empiric stage should be considered too. The assumptions made for senior doctors’ influence on junior doctors’ decision-making at empiric stage was appropriate. The impact from the facilitator ‘education programmes’ can be directly translated into improving guideline compliance level among doctors to simplify the scenarios even more.

The SD model used the level of guideline compliance among doctors at empiric stage (percentage of compliant empiric decisions), and the level of microbiology review (which equivalent to the level of guideline compliance of review decisions) at review stage (percentage of reviewed empiric decisions) as outcome measures.

Workshop 2: Validation of the causal loop diagrams

<table>
<thead>
<tr>
<th>Expert attended</th>
<th>2 consultants, 1 Foundation Year doctors, 1 nurse from one NHS Trust teaching hospital</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>1 Feb 2016</td>
</tr>
<tr>
<td>Issue</td>
<td>Comments from the expert panel</td>
</tr>
<tr>
<td>Do the CLDs constructed have valid structures? Do they include all key variables?</td>
<td>At first, only one CLD was constructed to cover all causal relationships between variables at empiric and review stage. The CLD is too complex. In addition, the key variables involved in decision-making were different at two stages. Since two different outcome measures were defined for the model, the expert panel suggested separating empiric and review stage when constructing the CLDs.</td>
</tr>
<tr>
<td>Reflection in the study</td>
<td>To address the comments, two CLDs have been constructed for empiric stage and review respectively.</td>
</tr>
</tbody>
</table>
Are the causal relationships captured in the CLDs valid and accurate reflection of the prescribing decision-making processes in real life?

The causal relationship between patient’s age and the fear of under-treating infections was not clear. The evidence in source data and literature was not strong enough to support the causal connection. The expert panel suggested that keeping these two variables (patient’s age and fear of under-treating) in the CLDs, assuming they were constants, and consulting experts in SD modelling at simulation stage. Further research for literature evidence must be conducted to justify the causal relationship. If these two variables are not quantitatively simulated, the limitation of treating these two variables as constants must be captured and discussed.

Multivariate logistic regression was performed to detect whether the correlation between patient’s age and doctors’ guideline compliance level at empiric stage existed, despite regression analysis was not a standard data analysis method in SD modelling. In addition, further search for literature evidence was conducted. Earlier published studies in cultural environment in medical wards, doctors’ perception of risks, and behavioural models in healthcare decision-making were cited to justify the causal relationship. In the simulation stage, patient’s age was treated as an auxiliary variable, and the fear of under-treating was treated as an exogenous variable.

### Workshop 3: Validation of the microbiology laboratory sub-system

<table>
<thead>
<tr>
<th>Expert attended</th>
<th>2 microbiologists and 2 researchers from the IPC team from one NHS Trust teaching hospital</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>5 Oct 2016</td>
</tr>
<tr>
<td>Issue</td>
<td>Comments from the expert panel</td>
</tr>
<tr>
<td>Does the SD model simplify the procedure of processing patients’ blood samples correctly?</td>
<td>All patients’ blood samples arrived in microbiology laboratory are tested. However, some samples might go missing or get contaminated during transmission or in the process of testing. These samples do not have test result delivered back to medical wards. As soon as microbiology laboratory test result is available, microbiologist will report the result by telephone. Delay might be caused if the result becomes available on Friday afternoons, or before public holidays. In general, the workload does not exceed the maximal capacity of the laboratory. However, the laboratory turnaround time will be elongated if there is a local outbreak.</td>
</tr>
<tr>
<td>What are microbiologists’ role in antibiotic prescribing decision-making processes? When do they provide input?</td>
<td>Microbiologists normally provide input after empiric decisions were made. When they report the microbiology test results by telephone, they also discuss patient’s clinical condition with the doctors in medical wards and advise whether the empiric decisions should be maintained or adjusted (to de-escalate or escalate). However, the opportunity of microbiology review is eliminated if the patients do not have microbiology test result to report.</td>
</tr>
</tbody>
</table>
7.2.2 Test the model parameters

7.2.2.1 Parameter-verification test

Similar to structure-verification test, a parameter-verification test was performed to determine whether the parameters correspond conceptually and numerically to real systems by comparing model parameters against observation of real life. Two expert panel workshops were organised to verify the definition of the model parameters and the selection of source data to support parameterisation.

The expert panel that reviewed the model structure also verified the model parameters. Each parameter was considered to match elements of real system. The categorisation of excluded variables, endogenous variables, exogenous variables, and auxiliary variables were considered appropriate based on the purpose of the model. A second expert panel attended by two health economics modellers and two infectious disease modellers from the Modelling & Economics Unit, Public Health England (PHE) and an SD modeller from University of Hertfordshire was conducted to verify the quality of the source data used, the methods used to analyse the source data and deduce the parameter values or provide estimates when certain information was missing from source data and literature, and the numerical values of parameters. The table below summarised the comments on the SD model parameters from the expert panel (Table 7.2).
Table 7.2 Comments on model parameters from multiple expert panel workshops

### Workshop 1: Validation of the inclusion of parameters

<table>
<thead>
<tr>
<th>Expert attended</th>
<th>2 consultants, 1 Foundation Year doctors, 1 nurse from one NHS Trust teaching hospital</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>02 September 206</td>
</tr>
<tr>
<td>Issue</td>
<td>Comments from the expert panel</td>
</tr>
<tr>
<td>Are the parameters included in the SD model appropriate and sufficient based on the purpose of the model?</td>
<td>The parameters included in the SD model represented quantitatively the key variables in the antibiotic prescribing decision-making processes in English hospitals. The inclusion of model parameters was entirely dependent on the purpose of the model. This model aimed to simulate doctors' behaviour and measure prescribing outcomes assessed guideline compliance level, thus, the exclusion of parameters in associated with patients' demands and other health outcomes was considered appropriate. When discuss the process of model parameterisation, the connection between the purpose of the model and the selection/inclusion of model parameters must be explained explicitly.</td>
</tr>
<tr>
<td>Are the included parameters categorised correctly?</td>
<td>Again, the categorisation of model parameters is dependent on the purpose of the SD model and the causal relationships between the key variables. The availability of source data could only determine how the quantitative value of a parameter was estimated, but not whether this parameter should be included/excluded. This is a common mistake made by a lot of SD modellers, it must be avoided in this study. The soft variable ‘fear of under-treating’ among specialty registrars and consultants was included in the model and categorised as exogenous variable at the current stage of the study due to lack to source data to support the establishment of quantitative causal connection between the measure of emotion ‘fear’ and senior doctors. This variable was included in the CLDs of the model, but not simulated quantitatively in the later stage. This limitation provided the scope for future expansion of the SD model, please address this when discussion future work.</td>
</tr>
</tbody>
</table>

### Workshop 2: Validation of multiple data sources

<table>
<thead>
<tr>
<th>Expert attended</th>
<th>2 health economics modellers, 2 infectious disease modellers from PHE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>3 Feb 2017</td>
</tr>
<tr>
<td>Issue</td>
<td>Comments from the expert panel</td>
</tr>
<tr>
<td>Are the data sources providing information suitable?</td>
<td>The SD model was considered well-grounded, as it was parameterised using data collected from the hospitals in which the prescribing behaviour of the junior and senior doctors was studied. The data was collected and processed using different methods, which provided comprehensive quantitative and qualitative information of antibiotic prescribing processes. The various data collection and analysis methods provided the opportunity of cross-validation to increase the confidence in the evidence. The data sources were considered suitable for the SD model.</td>
</tr>
</tbody>
</table>
The model parameterisation was supported by primary data collected from hospital inpatient data and secondary data collected from the survey with Foundation Year doctors and in-depth interviews with specialty registrars and consultants. The patients, the Foundation Year doctors, the specialty registrars, and the consultants were recruited from multiple NHS Trust teaching hospitals in West London. These hospitals provided similar environment for antibiotic prescribing practices. The consistency of the source data was maintained because of the homogeneity of the data sources. However, the validation of the results simulated by the SD model was ‘restricted’ to the hospitals with similar structures and geographic locations. The boundaries of the model must be described accurately.

In Chapter 3, the scene was set for the SD model in prior to model construction process to provide information about the boundaries within which the model was valid. When discussing future work in Chapter 7, the possible ways to expand the model to include healthcare organisations with different structures (e.g. GPs' prescribing practices in primary care) was discussion, as well as the requirement of source data to expand the model.

**Workshop 3: Validation of parameter estimation for the SD model**

<table>
<thead>
<tr>
<th>Expert attended</th>
<th>1 SD modeller from the University of Hertfordshire</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>15 Feb 2017, 08 May 2018</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Issue</th>
<th>Comments from the expert panel</th>
<th>Reflection in the study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are the methods used to derive parameter values from the source data appropriate?</td>
<td>The mathematical equations included in the SD model were presented in the expert panel workshop. The SD modelling expert validated that all equations were constructed correctly. A series of model parameter validation tests should be performed later to verify the validation of the estimates of the parameter values.</td>
<td>After the expert panel workshop, extreme condition test, boundary-adequacy test, and dimensional-consistency test were performed to validate the model parameters and increase the confidence in the soundness of the SD model.</td>
</tr>
</tbody>
</table>

### 7.2.2.2 Extreme condition test

A valid SD model should allow the represented system to operate under extreme conditions and be able to predict consequences, which are logical. Performing extreme condition tests helped improve the soundness and usefulness of the SD model in two ways. First, when using an SD model to predict system behaviour under various policy scenarios under extreme conditions, the model would be forced to operate outside of the historical operating regions. For example, a model of a healthcare institute might have to operate during an epidemic when patient flow increased beyond the historical maximum. Thus, the confidence in model’s ability to behave plausibly for a ‘wider than normal’ range of policy
conditions was developed. Second, when changing model parameters to approach extreme conditions, non-linearity was introduced into the system. Such non-linearity in the transition from normal to extreme conditions could help policy makers understand the asymptotes (i.e. the extreme value one variable could approach in theory) in the system of interest and prevent reaching such extreme conditions in real life. Using the example of an epidemic again, with increased patient flow towards infinitely large, the ‘productivity’ and the ‘service quality’ of the modelled healthcare institute would approach to zero due to limited resources, and occupational burnout of healthcare professionals. Simulating the system under extreme conditions would suggest a threshold magnitude of patient admission to ensure that below such threshold the maximal number of patients could get adequate services.

The SD model of prescribing decision-making processes was simulated for 1000 new patients for 100 days with various imaginary parameter values (minus infinity, plus infinity, zero) implying extreme conditions. The selection of arbitrary numbers is allowed when validating an SD model. The ‘total number of decisions in compliance with guidelines’ was selected as the performance indicator at empiric stage, and the ‘total number of decisions reviewed by microbiologists’ was selected as the performance indicator at review stage. The test results are presented in Table 7.3 below.
### Table 7.3 Extreme condition test results

<table>
<thead>
<tr>
<th>Tested variable</th>
<th>Extreme value 1</th>
<th>Performance indicator</th>
<th>Extreme value 2</th>
<th>Performance indicator</th>
<th>Extreme value 3</th>
<th>Performance indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Empiric stage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New patients</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Senior doctors’ rate of prescribing</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>969</td>
</tr>
<tr>
<td>Junior doctors’ rate of prescribing</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>896</td>
</tr>
<tr>
<td>Senior doctors’ rate of complying</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>488</td>
</tr>
<tr>
<td>Senior doctors’ rate of not complying</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>984</td>
</tr>
<tr>
<td>Junior doctors’ rate of complying</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>543</td>
</tr>
<tr>
<td>Junior doctors’ rate of not complying</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>937</td>
</tr>
<tr>
<td><strong>Review stage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Microbiologists’ rate of complying:</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>811</td>
</tr>
<tr>
<td>Microbiology laboratory conveyor transit time</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>Not simulatable</td>
</tr>
<tr>
<td>Blood sample without results</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>1000</td>
</tr>
<tr>
<td>Microbiologists’ rate of reviewing</td>
<td>$+\infty$</td>
<td>Not simulatable</td>
<td>$-\infty$</td>
<td>Not simulatable</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

When the values of rate parameters were adjusted to negative or positive infinity, *iThink®* software collapsed as the parameter values went beyond the simulatable range. The incidence of software collapse was expected, and the result was documented as ‘not simulatable’ in the table above.

The expert panel of mathematic modellers and SD modellers verified the selection of stock and flow variables, auxiliary variables, and performance indicators that went through the extreme condition tests were appropriate in two separate workshops after model parameterisation. The results of the extreme condition tests confirmed that the model logically simulated the causal relationships occurred in the prescribing decision-making
processes. For example, when the rate of complying was adjusted to zero for senior and junior doctors, the total number of empiric decisions in compliance with guideline dramatically decreased. When the leakage fraction of the microbiology laboratory conveyor, that represented the fraction of blood samples that arrived in the laboratory but without test results delivered back to medicine wards, was adjusted to zero, the total number of review decisions by microbiologists was equivalent to the total number of patients entering the system.

7.2.2.3 Boundary-adequacy test

The boundaries of the prescribing decision-making SD model were set according to the purpose of the model (3.1.1 setting the scene). The boundary-adequacy test assessed whether the model aggregation was appropriate and whether the model included all relevant structures (i.e. the boundary of the model is appropriately set to include all necessary components). The model’s ‘boundary adequacy’ was tested by developing a hypothesis relating the established model structure to a particular issue addressed by the model. The expert panel that reviewed the model structure also reviewed the model boundary chart to verify that the exclusion and the categorisation of endogenous and exogenous variables were performed appropriately.

After validating the model boundary chart, a hypothesis was established to see whether
additional model components or variables should be included. The prescribing decision-making SD model was developed to predict doctors’ decisions made when treating patients with symptoms of bacterial infections assessed by the number of prescribing decisions in/not in compliance with prescribing guidelines. A hypothesis for boundary-adequacy test would be improving the availability of pathogen information at empiric stage which would in turn improve guideline compliance levels. The expert panel verified that no extra model structure was required to simulate the causal relationship between the timeliness of pathogen information (microbiology laboratory test results) delivery and guideline compliance. Hence, the SD model satisfied the boundary-adequacy test.

7.2.2.4 Dimensional-consistency test

The dimensional-consistency test ensured that the units of all the simulated quantities were consistent. In an SD model, all the stock variables must have the same unit, and all the flow variables must have the same unit as stock variables divided by time unit. The units of measure of variables on both sides of the equations must be equal when assigning mathematical equations to each flow variable. The dimensions of variables in the SD model must correspond to the unit in which they can meaningfully express the real variables which exist in real life. In this study, the simulated quantities in the SD model shared the same unit of ‘number of prescribing decisions’, except at review stage when ‘number of
blood samples’ was included. The number of blood samples was converted back to the number of prescribing decisions to ensure the dimensional-consistency. First, the units of the simulated quantities were checked manually after the construction of SFDs. Before simulation, the units were checked again using the built-in unit check function in Vensim® and iThink® software to check all equations for consistency in units.

Controversy and limitations existed in unitising variables in SD models over time. The limitations of dimensional-consistency test of SD model will be discussed later in this chapter (5.3.4 controversy in unitising variables).

7.2.3 Test the model behaviour

Analysis of behaviour generated by the SD models is the step undertaken to evaluate adequacy of model after the model structure and parameters were verified. Behaviour reproduction test, and behaviour sensitivity analysis were performed on the SD model in this study.

7.2.3.1 Behaviour reproduction test

Behaviour reproduction test was performed by providing one (sometimes a few) input(s) to the model to reproduce historical behaviour. This test was sometimes referred as
‘baseline simulation’ as the model is simulated under baseline scenario without any adjustment of contextual parameters. The SD model was validated by how well the model behaviour matched the behaviour of the real system.

The prescribing decision-making SD model was simulated using the combination of arbitrary values of 1000 patients for 100 days again. The percentage of empiric decisions in line with prescribing guidelines was estimated to be 92.9%. The estimation was compared to the real-life data of 91.9% reported in the 2016/17 annual report. The statistics in the annual report was primary collected from same NHS Trust Teaching Hospitals.

English surveillance programme for antimicrobial utilisation and resistance (ESPAUR) is the initiative led by Department of Health (DOH) and Public Health England (PHE) reporting national data on antibiotic prescribing and resistance, and hospital antimicrobial stewardship implementation. The data in ESPAUR report has been used for benchmarking against national and regional antibiotic resistance and prescribing to determine appropriate local action by commissioners, individual organisations and health economies. The ESPAUR report of year 2014 included the survey sent to 146 NHS Trusts with 99 responses to investigate implementation and uptake of antimicrobial stewardship interventions in local hospitals. Overall empiric stage guideline compliance level of 93% was reported by the responding NHS Trusts. The simulated result of 92.9% compliant empiric decisions demonstrated the generalisability of the model when compared with the national level data.
Thus, the simulation result was considered a valid reflection of doctors’ guideline compliance level in real life by the expert panel.

7.2.3.2 Behaviour sensitivity analysis

The parameters in an SD can be estimated using statistical methods, literature evidence, market research data, expert opinion, or any other sources of information (Sterman, 2001). Hence, parameters of SD models are subject to uncertainty. Sensitivity analysis is to be performed to serve the purpose of exploring the effects of parameters uncertainty or behaviour patterns (Hekimoğlu & Barlas, 2010). Behaviour sensitivity analysis focused on sensitivity of model behaviour to changes in parameter values. It helped understand whether possible shifts in model parameters would cause a failure in model simulation, as well as which parameters (in most cases of SD modelling, rate variables) had the stronger impact on system behaviour. If certain model parameters demonstrated strong impact on model outcomes, SD modellers must ensure that these parameters were deduced from credible data sources using adequate data analysis techniques to increase the confidence in model validity. The expert panel helped verify that the sensitivity of the model behaviour was an appropriate reflection within the defined model boundaries.

The behaviour sensitivity test was performed right after the behaviour prediction test with the following flow variables adjusted to various levels: 0%, 25%, 50%, and 75% of the
original value (Table 7.4). Again, the ‘total number of decisions in compliance with
guidelines’ was selected as the performance indicator at empiric stage, and the ‘total
number of decisions reviewed by microbiologists’ was selected as the performance
indicator at review stage.

Table 7.4 Behaviour sensitivity test results

<table>
<thead>
<tr>
<th>Tested variable</th>
<th>0% original value</th>
<th>Outcome measure</th>
<th>25% original value</th>
<th>Outcome measure</th>
<th>50% original value</th>
<th>Outcome measure</th>
<th>75% original value</th>
<th>Outcome measure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Empiric stage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Senior doctors’ rate of prescribing</td>
<td>0</td>
<td>957</td>
<td>0.124</td>
<td>949</td>
<td>0.248</td>
<td>937</td>
<td>0.372</td>
<td>928</td>
</tr>
<tr>
<td>Junior doctors’ rate of prescribing</td>
<td>0</td>
<td>896</td>
<td>0.099</td>
<td>905</td>
<td>0.197</td>
<td>912</td>
<td>0.296</td>
<td>917</td>
</tr>
<tr>
<td>Senior doctors’ rate of complying</td>
<td>0</td>
<td>489</td>
<td>0.218</td>
<td>797</td>
<td>0.437</td>
<td>873</td>
<td>0.655</td>
<td>904</td>
</tr>
<tr>
<td>Senior doctors’ rate of not complying</td>
<td>0</td>
<td>913</td>
<td>0.032</td>
<td>917</td>
<td>0.064</td>
<td>920</td>
<td>0.095</td>
<td>926</td>
</tr>
<tr>
<td>Junior doctors’ rate of complying</td>
<td>0</td>
<td>539</td>
<td>0.240</td>
<td>870</td>
<td>0.480</td>
<td>907</td>
<td>0.720</td>
<td>916</td>
</tr>
<tr>
<td>Junior doctors’ rate of not complying</td>
<td>0</td>
<td>937</td>
<td>0.010</td>
<td>933</td>
<td>0.020</td>
<td>929</td>
<td>0.030</td>
<td>925</td>
</tr>
<tr>
<td>Microbiologists’ rate of complying</td>
<td>0</td>
<td>907</td>
<td>0.250</td>
<td>916</td>
<td>0.500</td>
<td>921</td>
<td>0.750</td>
<td>922</td>
</tr>
<tr>
<td><strong>Review stage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Microbiologists’ rate of reviewing</td>
<td>0</td>
<td>832</td>
<td>0.216</td>
<td>832</td>
<td>0.432</td>
<td>832</td>
<td>0.648</td>
<td>832</td>
</tr>
</tbody>
</table>

A non-linear relationship emerged between the flow variables and the performance
indicators. A tornado plot was generated to demonstrate the sensitivity of the model
behaviour (assessed by the number of decisions in compliance with guideline at empiric stage compared to the baseline value of 929 complying decisions per 1000 empiric decisions) responding to adjusted rate variables (Figure 7.2).

The level of compliance among senior doctors, quantitatively represented as ‘senior doctors’ rate of complying’, had the strongest impact on the performance indicators at both empiric stage and review stage.

**Figure 7.2 Tornado plot of sensitivity analysis**

The information in literature was not sufficient to determine whether the system would exhibit similar high sensitivity to the corresponding variables in real life. Earlier published studies have only reported that the senior doctors’ guideline compliance
level had strong influence on all doctors’ decision-making processes. However, no quantitative evidence was available to verify the non-linear characters revealed by the sensitivity analysis. An additional sensitivity analysis was performed by adjusting the most dominant influence factor. Typically, ± 20% of the parameter value are used as the distribution range for simulation models (Sterman, 2000; Hekimoğlu & Barlas, 2010). The change in performance indicator (total number of compliant empiric decisions) was simulated when the most dominant variable (senior doctors’ rate of complying to guidelines) was varying in the range (± 20% of the parameter value). Senior doctors’ rate of complying is 0.873, hence the distribution range was set to be from 0.698 to 1.048 (the rate of complying beyond 1 has no meaning in real-life, as the percentage of compliant decisions cannot exceed 100%, the value of 1.048 is set for the purpose of testing system behaviour sorely). The model was simulated to predict the total number of compliant empiric decisions under the scenario when doctors with lower seniority are influenced by senior doctors’ decisions. The result of sensitivity test was plotted (with a moving average trendline added) (Figure 7.3). The observed behaviour pattern does not fit in any common behaviour mode (such S-shape mode, tipping point mode).
7.3 Discussion: The unique model validity for System Dynamics

7.3.1 Validation using expert opinion: philosophical positioning of System Dynamics on the spectrum of ontology

The employment of expert opinion is an important component of SD model validation. To discuss why such validation method is appropriate, one must first understand the philosophical assumptions held by SD.

Researchers employing quantitative modelling methods, or quantitative research methods in general, tend to maintain the distance and separateness from the studied subjects. The
researchers identify and classify features, count them, and construct statistical models to explain what is observed. Quantitative research deals in numbers, logic, and an objective stance and focuses on convergent reasoning rather than divergent reasoning – the generation of a variety of ideas about a research problem in a spontaneous, free-flowing manner. The validity of a model is often discussed in association with the limitation of the methods employed rather than the limitation of the researchers’ mental model.

In contrast, SD acknowledges the ‘bounded rationality’ in the researchers and recognises the influence of the researcher during the research process (Chapter 3, 3.3.2 ‘Bounded rationality’). A SD model representation can be thought of as the mental model that an individual modeller uses to characterise perceived reality.

In philosophical or sociological research, consistent sets of basic assumptions about ontology, epistemology, axiology, human nature, methodology, and causality and logic constitute different paradigms (Pruyt, 2006). These paradigms, which could be simply seen as ‘world view’, influence interpretations and frame philosophies, meta-methodologies, multi-methodologies, methodologies, techniques, and tools used. By using these, outcomes, interpretations, and decisions are made. Many SD modellers called SD a (modelling) paradigm (Anderson, 1980; Randers, 1980; Meadows, 1980; Forrester, 1994; Richardson, 1999; Sterman, 2002). However, David Lane, a professor of Business Informatics and a specialist in SD and systems thinking at Henley Business School, concluded that SD belonged to more than one paradigm when he tried to classify SD in the
well-known ‘four-paradigm framework’ developed by Burrell and Morgan (Figure 7.4). (Burrell & Morgan, 1980).

**Figure 7.4 Four-paradigm framework (Burrell & Morgan, 1980)**

Lane rejected the Burrell-Morgan framework which is characterised by rigid paradigm incommensurability and suggested embedding SD in lower-level philosophical theories. The argument continued with different SD modellers trying to locate SD on the hierarchy of concepts.

Some modellers would call systems thinking a philosophy, then SD might be seen as a part of such a holistic philosophy instead of being a philosophy on its own right. Some modellers suggested that SD is a ‘theory of structure’ that tells how the concept of feedback loop and stock should be used to construct models (Forrester, 1968). Hence, SD is at most a structural epistemological theory or language with which SD modellers used to describe reality. SD is a language that guided humans’ perceptions of the problems and actions, rewrote humans’ mental models. Others called SD a methodology or a group of methods.
However, it is clear that there are different types of SD methods in use ranging from very quantitative to purely qualitative ones, and the variations resulting from different procedures, model development scripts, and the modellers’ personal styles for each of them. Thus, SD cannot be equivalent to an assembly of techniques and tools.

My interpretation and application in this thesis is grounded in a perspective that, SD in itself is not a philosophy, methodology or method, set of techniques or tools, and it is indeed more than a theory of structure. It is promising to position SD on the paradigmatic level as it does provide a different lens to view the reality and develop an understanding from it.

It is also useful to locate SD on the natural of social science axis to help SD modellers to examine the validity of the models they built. Along a continuum of paradigms, objective view sits at one end while subjective view sits at the other end. The basic assumptions are made to answer the key questions in ontology, epistemology, human nature, and methodology (Table 7.5).

<table>
<thead>
<tr>
<th>Table 7.5 Subjective and objective view</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ontology: what is the nature of phenomena?</strong></td>
</tr>
<tr>
<td>Real world exists as a product of appreciation.</td>
</tr>
</tbody>
</table>

| **Epistemology: what ‘knowledge’ can we obtain?** | Subjective view | Objective view |
| Knowledge is subjective meaning. | Causal laws are deducted by objective observer. |

| **Human nature: what is the nature of human actions?** | Subjective view | Objective view |
| Free will allows humans to shape their environment. | Humans react mechanically to their environment. |
The SD concepts locate away from the objective extreme on the axis because of the importance of subjective elements such as subjective mental models, confidence in the model and insight gained (Forrester, 1961). SD models are built based upon the assumption that there are multiple realities and that conception of truth and values are not absolute, instead they are relative to the persons or groups holding them. The validity of an SD model is assessed in association with the purpose and the context of the model. When assessing the validity, experts’ opinions and other qualitative information are adopted to ensure that the model was capable to reflect reality to a certain extent. The SD model in this thesis was validated using expert opinions obtained in multiple discussion panels. The discussion panels included clinicians (both junior and senior doctors), pharmacists, nurses, hospital managers, modellers, and researchers in infectious diseases and AMR. The inclusion of a wide range of professionals involved in the antibiotic prescribing decision-making processes reduced the risk of building a biased model.

7.3.2 Model validation associated with the purpose of the model

The research areas, including public health management, in which simulation approach can be applied are expanding exponentially nowadays. Simulation approach is favoured for its
ability to help understand mechanisms, supporting decision-making and forecasting with manageable requirement of financial input (Lemke & Łatuszyńska, 2013). Evaluation of model credibility is an important yet controversial aspect of any model-based methodology (Barlas, 1996). The credibility of a model is assessed by 1) the accuracy of its representation of reality, 2) the ability to satisfy users’ requirements to support decision-making, and 3) the tolerance to uncertainties and unexpected and extreme conditions. The controversy of simulation model validation arises from the fact that validation, in the sense of confirmation, can never be absolute. The validity of a model is changing ‘here and there’, ‘now and then’, which means it largely depends on where and when the model was applied to. There is no clear binary measure to determine whether a model is valid. A model can never ‘be valid’, it can only ‘be considered valid’ for a certain period of time within defined boundaries. The judgement is made by the researchers who develop the model and the stakeholders who use the model, based on the purpose of the model (i.e. the problems needed to be solved, or the issues needed to be understood). In simulation modelling, a pragmatic approach is adopted to establish confidence (to some degree) in whether the model is sufficiently accurate enough for the intended purpose (Senge & Forrester, 1980).

### 7.3.3 Correlational and causal-descriptive models

Simulation models in general fall into two categories: correlational models and causal-
descriptive models (Barlas, 1989). ‘Correlation’ is a statistical measure that describes the size and direction of a relationship between two or more variables. A correlation between variables does not automatically mean that the change in one variable is the cause of the change in the values of the other variables. Causation, indicating the causal relationship between two or more variables, means that one event (effect) is the result of the occurrence of the other event (cause). A good example to differentiate correlation and causation is given here. A correlation might be observed between the increased market demand of soft beverage and increased prevalence of high blood pressure among the elderly. However, the increased prevalence of high blood pressure is not caused by the increased demand of soft beverage. The increased demand of soft beverage and the increased prevalence of high blood pressure among the elderly are both caused by the increased temperature in summer.

Correlational models, sometimes referred as ‘black-box’ approaches, are mainly data driven. Time-series models, or regression models belong to this category. The establishment of causal mechanisms in the model structure is not necessary, only the aggregate quantitative outputs of the model matter (Barlas, 1989). In black-box modelling, the model is considered valid if the outputs are accurate representation of the real world. How the outputs are generated by the model is irrelevant to the validity of the model (Martis, 2006). Black-box approaches are useful when the primary interest is in fitting data regardless of a particular mathematical structure of the model. They are applied when there is no sufficient evidence to support the understanding the exact interconnection mechanism
among modelled variables. The development of a black-box model is a trial-and-error process, where the parameters are estimated for various model structures and the results are compared for each structure. When building a black-box model, especially for forecasting purposes, the confidence in model validity is increased as the output of the model gets closer to the observed real-life statistics within some specific range of accuracy (Barlas, 1989; Balci, 1986; Carson, 2002, Robinson, 1997).

In contrast, theory-like causal-descriptive models, referred as ‘white-box’ approaches, aim to capture how systems actually operate in real life. An accurate output alone is insufficient to determine the validity of a white-box model. The internal causal structure is more crucial to ensure the validity of the model than the capability of providing accurate simulation results. A valid causal-descriptive model must predict a system’s behaviour, explain how the behaviour is generated, and suggest ways to alter the existing behaviour. SD models fall into this category. Thus, the validation of an SD model must include the validation of the causal structure, validation of data, validation of system behaviour and validation of capability to assess alternative policies (Barlas, 1989; Balci, 1986; Carson, 2002). It is said, a valid SD model “must generate the right output behaviour for the right reasons” (Barlas & Kanar, 2000).
7.3.4 Statistical significance in System Dynamics modelling

‘Statistical significance’ is a quantity used to determine whether the null hypothesis should be rejected or retained. When studying an event of interest, the null hypothesis is made as a default assumption that the event did not happen. For the null hypothesis to be rejected, an observed result related to the occurrence of the event has to be statistically significant, \textit{i.e.} the event did not happen because of random chance (Johnson, 2013). By performing statistic hypothesis testing, a $p$-value is reported. The $p$-value is the significance level of a study and is chosen before data collection. $P$-value represents the probability that random chance could explain the result. In general, a $p$-value of 5\% or lower is considered to be statistically significant, \textit{i.e.} the observed occurrence of the studied event happens not because of random chance (Robinson, 1997).

In practice, the appropriateness of the statistical hypothesis test is determined by sample size (the number of observations or replicates to include in the study sample). Interpretation of $p$-value must take sample size into consideration. The size of study sample dictates the amount of information to be collected by researchers, hence the precision, or ‘level of confidence’ in estimation made from studying the sample. The uncertainty in estimation increases when the variability of the samples (heterogeneity) increases, or, when the sample size decreases (Engels \textit{et al.}, 2000). Increasing sample size gives researchers greater power to detect differences and reduce uncertainty in estimation.

Statistical hypothesis testing is frequently used in validation models in social, behavioural
and economic science. It is also widely applied in health-related research. For example, statistical significance is used in clinical trials to test the effectiveness of new drugs. If the drug effect is observed among the studied population and a p-value lower than the chosen significance level is achieved, the researchers can conclude that the effect is caused by the drug rather than random chance (Jacobson & Truax, 1991).

During the past decades, SD modelling has been used to evaluate the effectiveness of policy alternatives in different research areas. There is a very little use of statistical significance testing and SD has often been criticised for it (Barlas, 1996). The controversy existed between SD modellers and social, behavioural and social scientists. SD modellers have responded to the criticism by arguing that statistical significance contributed very little to model validation in SD, due to the ‘white box’ characteristics of SD models discussed before. Logical and rational debate seems not likely to solve the issue, because statistical significance testing has evolved into being a ‘norm’ in some research areas in social and behavioural science (Morrison & Henkel, 1970). Both technical and philosophical problems exist when using statistical significance testing in validating SD models. The fundamental assumptions held for statistical tests to be valid are explained in Appendix 2. Data generated by SD models are auto-correlated and cross-correlated by their very nature. Using statistical tests to analyse serially correlated or cross-correlated data requires extensive model simplification and exclusion of model factors that are important to a model’s behaviour (Mass & Senge, 1978). In addition, there is no single output variable
that one can focus solely on when verifying the validity of an SD model. Multiple variables of importance should all be tested based on the purpose of the study. Statistical testing is not capable of providing reliable measure with a mathematical equation of ‘likelihood’ (Miller, 1981). If statistical testing is to be performed, it would be a simultaneous multiple-hypothesis test, instead of testing a single hypothesis. Computing the overall statistical significance for a simultaneous multiple-hypothesis test in an SD model is extremely difficult, as the variables in an SD model are often cross-correlated.

In this study, the most important variables processed in the SD model included ‘percentage of empiric decisions in compliance with prescribing guidelines’ and ‘percentage of empiric decisions reviewed by microbiologists’. The first variable is auto-correlated. A theory has been developed to describe how junior doctors’ decision-making processes were influenced by their senior colleagues. Thus, auto correlation is expected in the percentage measured for different doctors. The second variable, which measured the level of microbiology review after empiric stage, is cross-correlated to other variables included in the SD model, such as microbiology laboratory turnaround time, and the percentage of patients with microbiology laboratory test performed. The nature of the data processed in the SD model determined that statistical significance testing is neither appropriate, nor necessary, in verifying the validity of the SD model.

Apart from the technical issues caused by using statistical significance testing in SD model validation, philosophical problems also exist. These problems are associated with the
common practice of using significance level (p-value) to support a binary ‘true’ or ‘false’ decision to accept or reject a null hypothesis. If the ultimate goal of validating a model is to *fail to reject* a null hypothesis, statistical testing could possibly be used. However, in SD modelling, the goal of validation is to show ‘no significant difference’ between the model and the system in real life. It would make no sense to develop a null hypothesis then to reject it.

This study is a novel application of SD in the research topic of antibiotic prescribing management, which belongs to a broader research field of infection control. In infection control, it has become a ‘norm’ for researchers to use statistical testing to process data and validate models (Sickbert-Bennett *et al.*, 2004). Though it required extensive researching of literature in SD, it was important to understand why this well-established approach was not suitable in SD model validation, and why a valid SD model could still be constructed using data collected from a relatively small sample.

In the stage of model parameterisation, one type of statistical testing (regression analysis) was performed to detect the correlation between doctors’ seniority and their prescribing pattern at empiric stage (Chapter 6, 6.3.3.1 The regression analysis of ‘fear’). Doctors with higher seniority (specialty registrars and consultants) were found to prescribe antibiotics with broader spectrum. The use of regression analysis was a practice to help construct the CLDs of the model when the evidence in literature was not sufficient. In earlier published studies, it is reported that senior doctors, especially consultants, had lower guideline
compliance level because they relied on their own knowledge and experience when prescribing. However, how their prescribing decisions differed from the guidelines remained unclear. The difference could be in types of antibiotic drugs, the route of administration, or the length or therapy. In order to construct a causality link between doctors’ seniority and their prescribing pattern, whether these two variables had the same direction of change must be confirmed. Hence, the regression analysis was performed, knowing that the independent variable (doctors’ seniority) was not auto correlated. It demonstrated that though statistical testing was not appropriate in validating an SD model, it still plays a role in the process of model development - in this case, to detect correlation between two variables to help identify causal relationship.

7.3.5 Controversy in unitising variables

Apart from statistical significance and sample size in source data, unitising variables is another controversial topic in SD modelling (Malczynski, 2011). In the recent past, the controversy around system units stemmed mainly from the difficulty in applying and managing units of quantities modelled within SD software. Most SD software programmes have built-in functions or similar features to maintain the dimensional consistency within the modelled system by restricting the number of variable units. For example, in iThink programme, if more than one variable unit exists in the system, the software will generate
warning and the simulation cannot be performed. While these built-in features help SD modellers to maintain the dimensional consistency, they restrict the ‘size’ of an SD model. There is a belief among SD modellers that if an SD model stays below a certain small size, variable units are not required\(^\text{13}\). Small SD models, or aggregated SD models, are the models consisting of a few key variables and at most 7 to 8 major feedback loops (Ghaffarzadegan, Lyneis, & Richardson, 2011). Small SD models have the ability to capture important, and often counterintuitive insights relating behaviour to the feedback structure of the system. More specifically, small models are sufficient to explain ‘behaviour’ and help build intuition regarding policy responses (Sterman, 2001). The benefit of constructing small models has been highlighted in the research field of SD, not only because of small models’ ability to predict unexpected, counterintuitive behaviour, but also because of the general belief mentioned earlier. It is assumed that the modellers are more than capable of managing the syntax and semantics of the model construction without the overhead of unitising variables if the model is ‘small’ enough. For example, in this study, the number of decisions is numerically equal to the number of patients or the number of patient’s blood samples (assumed that one empiric decision is made for each patient, and each patient has no more than one blood sample taken). Thus, this model could be simulated without variable units as the variable units do not change simulation results. However, as a best practice of SD modelling, every model variable should have a unit assigned to it.
The controversy of unitising model variables has drawn more attention, as SD modelling has been applied to more complex systems accompanied by the development of computer-based simulation technology. The size of SD models grows to simulate the behaviour of a multi-level system. The conflict occurs between performing the best practice and not restricting the size of the model. In this study, the modelled system consisted of two sub-systems, which are medical ward sub-system and microbiology laboratory sub-system. The quantities of interest are different in these two sub-systems (number of prescribing decisions vs. number of patient’s blood samples). The variable units were converted in the conveyer stock of microbiology laboratory to maintain the dimensional consistency of the model. However, when expanding this model in future, difficulties are expected to unify the variable units.

So far, the SD model of prescribing decision-making passed a series of tests to verify model structure, model parameters, and model behaviour. The unique model validity in SD modelling was also discussed. In the next chapter, a series of ‘what if’ scenarios are simulated using the SD model to predict doctors’ prescribing decision-making processes when facing policy alternatives.

Key points in Chapter 7:

- The SD model went through a series of validation tests to verify the credibility of
model structure, model parameters, and system behaviour.

- Employing expert opinion is a unique method to verify the validity of an SD model. It is associated with the ontological and epistemological fundamental assumptions that SD was built upon.
Chapter 8 Analysis of Scenarios and Simulation Results

After going through a series of tests to verify the validity of the structure and the parameter estimation, the SD model of prescribing decision-making processes was used to simulate doctors’ prescribing behaviour under a series of ‘what if’ scenarios. The simulation results of ‘what if’ scenarios were compared to the prescribing behaviour under the baseline scenario simulated to reproduce the system behaviour in real life (Chapter 7, 7.2.3.1 Behaviour reproduction test). The simulation results are then interpreted to decide the CLDs dominating the system behaviour.

8.1 Defining ‘what if’ scenarios

A scenario is a potential circumstance or combination of circumstances that could have a significant impact on the system of interest (Swart, Raskin, & Robinson, 2004). Simulating system behaviour under ‘what if’ scenarios yields various projections for the outcome based on selectively changing inputs without requirement to implement interventions in real life. Doctors’ antibiotic prescribing decision-making processes are simulated under ‘what if’ scenarios to predict how doctors adjust their prescribing behaviour if the factors influencing their decision-making changed.
At empiric stage, the system behaviour is measured by the level of guideline compliance of all doctors (percentage of compliant empiric decisions). Factors influencing doctors’ decision-making processes at empiric stage include microbiology laboratory turnaround time and senior doctors’ (specialty registrar and consultants’) prescribing habits. The SD model is used to simulate all doctors’ prescribing behaviour when microbiology laboratory turnaround time is changed (shortened), when senior doctors’ prescribing habit is changed (guideline compliance level increases), and when the two changes happen together.

The scenarios simulated at empiric stage are:

- Scenario 1(a): Shortening microbiology laboratory turnaround time so that the all patient samples are processed in less than 3 days;
- Scenario 1(b): Shortening microbiology laboratory turnaround time so that the all patient samples are processed in less than 2 days;
- Scenario 1(c): Shortening microbiology laboratory turnaround time so that the all patient samples are processed in less than 24 hours;
- Scenario 2(a): Increasing specialty registrars’ guideline compliance level to 100% so that all consultants follow prescribing guidelines, while the prescribing habit of doctors with lower seniority is not influenced;
- Scenario 2(b): Increasing consultants’ guideline compliance level to 100% so that all consultants follow prescribing guidelines, while the prescribing habit of doctors with lower seniority is not influenced;
• Scenario 2(c): Increasing specialty registrars and consultants’ guideline compliance level to 100% so that all specialty registrars and consultants follow prescribing guidelines, while the prescribing habit of doctors with lower seniority is not influenced;

• Scenario 3(a): Increasing specialty registrars’ guideline compliance level to 100% so that all consultants follow prescribing guidelines, and the prescribing habit of doctors with lower seniority is influenced;

• Scenario 3(b): Increasing consultants’ guideline compliance level to 100% so that all consultants follow prescribing guidelines, and the prescribing habit of doctors with lower seniority is influenced;

• Scenario 3(c): Increasing specialty registrars and consultants’ guideline compliance level to 100% so that all specialty registrars and consultants follow prescribing guidelines, and the prescribing habit of doctors with lower seniority is influenced;

• Scenario 4: Combination of the scenario 1(c) and 3(c) which can improve guideline compliance to the maximal degree.

After empiric stage, the system behaviour is measured by the level of microbiology review (percentage of empiric decisions reviewed by microbiologists). The factor influencing microbiology review after empiric stage is the availability of microbiology laboratory test results. The SD model is used to simulate the level of microbiology review when the availability of microbiology laboratory test results is increased.
The scenarios simulated at review stage are:

- Scenario 5(a): Performing microbiology tests for all patients (including those who did not have test under baseline scenario);
- Scenario 5(b): Providing microbiology laboratory test results for all test performed (including the tests that did not have results returned to the medical ward).

All simulations were performed for 1000 patients over the time period of 100 days under each scenario. The number of patients entering the system per day was assumed to be constant, which was 10 patients per day, except the initial stage of simulation. At the initial stage, there were no patients inside the system. The number of patients inside the system started to increase from zero, until a steady speed of entering was achieved. The number of patients entering the system per day and the number of patient’s blood samples entering the microbiology laboratory per day were assumed not to exceed the maximal sample processing capacity of the microbiology laboratory.

The steps taken to adjust the model parameters under each scenario, perform the simulation, and interpret simulation results are discussed in this chapter.
8.2 Scenario simulation and analysis of results

8.2.1 Improving practices at empiric stage

At empiric stage, the level of prescribing guideline compliance of all doctors, quantitatively represented by the percentage of empiric decisions in compliance with guidelines, was selected as the outcome measure of the modelled system. The prescribing behaviour of all doctors alters in response to the change (shortening) in microbiology laboratory turnaround time, and the change (increase) in senior doctors’ guideline compliance level at empiric stage, and to the change in microbiology laboratory turnaround time and senior doctors’ guideline compliance level at empiric stage together.

8.2.1.1 Shortening microbiology laboratory turnaround time

The impact on guideline compliance from microbiology turnaround time was simulated through the following steps.

Simulation of microbiology laboratory convey under baseline scenario

Before performing the ‘what if’ scenario simulation for Scenario 1(a), 1(b), and 1(c), the number of blood samples processed per day was simulated for 1000 patients during the time period of 100 day under the baseline scenario (i.e. the laboratory turnaround time is
not shortened) to test whether the conveyer stock of microbiology laboratory was capable of reproducing the operation of a real-world microbiology laboratory. Assuming all 1000 patients had blood samples taken in medical wards, the microbiology laboratory processed and delivered the test results of 78.1% patient samples back to medical wards per day on average (Figure 8.1).

Figure 8.1 Number of blood samples processed per day under baseline scenario

![Graph of blood samples processed per day](image)

The simulation result was considered an accurate estimate of the average microbiology laboratory turnaround rate in real life, which is 79.7% (reported in the NHS Trust Board Committee Report of Fiscal Year 2017 published internally by the NHS Trust teaching hospitals in North West London). The results of the baseline simulation demonstrates that the stock-and-flow structure of microbiology laboratory is a valid reflection of the real-world system.
Simulation of microbiology laboratory convey under ‘what if’ scenarios

The stock-and-flow structure of microbiology laboratory was presented in Chapter 6 (6.2.2.3 The conveyer stock of microbiology laboratory, Figure 6.14). The parameters in the graph function TAT_value of the convey stock were adjusted to simulate prescribing behaviour under scenarios of shortened microbiology laboratory turnaround time. The graph function TAT_value was constructed to generate random integers between 0 to 3 to represent microbiology laboratory turnaround time measured in days. The random integers generated were fed into the conveyer stock as ‘transit time’. Every time a quantity (patient’s blood sample) arrived in the convey, the graph function generated an integer as the transit time, which determined for how long this quantity (patient’s blood sample) stayed inside the conveyer stock. The adjustment of microbiology laboratory turnaround time was made by changing the parameters in the graph function TAT_value which determined the distribution of probabilities for each integer (microbiology laboratory turnaround time measured in days) being generated.

Under Scenario 1(a): Shortening microbiology laboratory turnaround time so that the all patient samples are processed in less than 3 days, the graph function TAT_value = GRAPH (RANDOM (0, 1)) (0.66, 0.5)(0.942, 1)(0.981, 2)(1.000, 3) in baseline scenario was adjusted to TAT_value = GRAPH (RANDOM (0, 1)) (0.66, 0.5)(0.942, 1)(1.000, 2).

Under Scenario 1(b): Shortening microbiology laboratory turnaround time so that the all patient samples are processed in less than 2 days, the graph function TAT_value = GRAPH
(RANDOM (0, 1)) (0.66, 0.5)(0.942, 1)(0.981, 2)(1.000, 3) in baseline scenario was adjusted to TAT_value = GRAPH (RANDOM (0, 1)) (0.66, 0.5)(1.000, 1).

Under Scenario 1(c): Shortening microbiology laboratory turnaround time so that the all patient samples are processed in less than 24 hours, the graph function TAT_value = GRAPH (RANDOM (0, 1)) (0.66, 0.5)(0.942, 1)(0.981, 2)(1.000, 3) in baseline scenario was adjusted to TAT_value = GRAPH (RANDOM (0, 1)) (1.000, 0.5).

The number of blood samples processed per day was plotted. The curves in different colours represented the number of blood samples processed per day under baseline scenario (•), Scenario 1(a) (•), 1(b) (•) and 1(c) (•) was plotted (Figure 8.2).

**Figure 8.2 Number of blood samples processed per day under baseline scenario, Scenario 1(a), Scenario 1(b), and Scenario 1(c)**

At the beginning of simulation, patients gradually entered the system. Thus, the number of
blood samples processed per day kept increasing from Day 1 until the number of patients entering the system per day stabilised towards 10 patients per day.

The initial section with positive rate of changing on each of the curves overlapped, indicating that it took the same amount of time for the microbiology laboratory to reach the steady rate of blood sample processing under each scenario. This simulation result associated with the assumption that the number of patients entering the system per day and the number of patient’s blood samples entering the microbiology laboratory per day remained steady and did not exceed the maximum capacity of the laboratory. Hence, there was no ‘queueing’ inside the microbiology laboratory.

Under Scenario 1(a), 1(b) and 1(c), 78.1% patient samples were processed for all patients who had entered the system at the end of simulation, which was identical to the value simulated under baseline scenario. This result indicated that the shortened laboratory turnaround time only affected how fast a patient’s blood sample was processed, but not whether a patient’s blood sample was processed.

Specialty registrars and consultants had a short time window to make empiric decisions. Treatment plans must be made as quickly as possible after a patient is admitted in medical ward. By shortening laboratory turnaround time, more opportunities were created for specialty registrars and consultants to make empiric decisions based on the microbiology laboratory test results and follow prescribing guidelines (Chapter 5, 5.2.2.1 Causal loop diagram of prescribing decision-making at empiric stage). When microbiology laboratory
test results became timely available, the fear of under-treating infections was reduced among senior doctors. The guideline compliance level among these doctors was increased and all empiric decisions made based on microbiology laboratory test results were in compliance with guidelines, as a result of the decreased level of fear.

To simulate the impact of shortened turnaround time, the parameter representing specialty registrars and consultants’ level of complying was adjusted under Scenario 1(a), 1(b), and 1(c). Under Scenario 1(a), when the microbiology laboratory turnaround time was shortened to less than 3 days for all patients, the patients’ samples which were processed after the third day under baseline scenario were now being processed in three days. The distribution of these ‘extra’ portion of patient’s blood samples was determined by the distribution of microbiology laboratory turnaround time under each scenario. For example, under baseline scenario, a% of blood samples were processed in 1 day, b% of blood samples were processed in 2 days, c% of blood samples were processed in 3 days, and b% blood samples were processed after 3 days. Under Scenario 1(a), all patients’ blood samples were processed in 3 days with a new distribution of turnaround time, say x% of blood samples were processed in 1 day, y% of blood samples were processed in 2 days, and z% of blood samples were processed in 3 days. The ‘extra’ portion of d% blood samples were then processed within 3 days under Scenario 1(a), with turnaround time distributed as x% in 1 day, y% in 2 days, and z% in 3 days. Hence, an additional portion of patients, which was calculated as the total number of patients * d% * x%, had their empiric decisions made
based on microbiology laboratory test results and in compliance with prescribing guidelines under Scenario 1(a).

Under baseline scenario, 92.9% empiric decisions made by specialty registrars and consultants were compliant with guidelines. The level of compliance among senior doctors did not improve in Scenario 1(a) and 1(b) when the microbiology laboratory turnaround was shortened to less than 3 days and less than 2 days for all patients. However, in Scenario 1(c), when the laboratory turnaround time was shortened to less than 24 hours for all patient samples, the simulated percentage of compliant empiric decisions increased from 92.9% to 93.3%. The results suggested that the significant improvement in guideline compliance level through shortening microbiology laboratory turnaround time can only be achieved if all patient samples were processed within 24 hours.

8.2.1.2 Improving senior doctors’ guideline compliance

Senior doctors, including specialty registrars and consultants, are the group of doctors that had lower guideline compliance level, and were influencing decision-making processes of doctors with lower seniority. When senior doctors were making empiric decisions themselves, they had a tendency to prescribe antibiotics with broader spectrum than the recommendations in prescribing guidelines if the support in pathogen information was not available. When senior doctors were not making empiric decisions, doctors with lower
seniority made decisions under senior doctors’ influence. At empiric stage, senior doctors played the roles of decision makers in medical wards. Increasing the guideline compliance level among consultants and specialty registrars not only improve senior doctors’ prescribing practices, but also has a positive influence on Foundation Year doctors, core trainees, and nurses’ prescribing decision-making processes.

To simulate the impact on prescribing outcomes from increased guideline compliance among senior doctors (while all junior doctors remained unaffected), the parameters representing specialty registrars and consultants’ level of complying (‘senior doctors’ rate of complying’ and ‘senior doctors’ rate of not complying’) were adjusted under Scenario 2(a), 2(b), and 2(c). The percentage of compliant empiric decisions was simulated under Scenario 2(a), 2(b), and 2(c), assuming that increasing guideline compliance level among senior doctors only changed the empiric decisions made by themselves.

Under Scenario 2(a), the guideline compliance level among specialty registrars at empiric stage was adjusted to 100%. The simulated percentage of compliant empiric decisions made by all doctors was improved from 92.9% to 96.8%, if all specialty registrars followed prescribing guidelines.

Under Scenario 2(b), the guideline compliance level among consultants at empiric stage was adjusted to 100%. The simulated percentage of compliant empiric decisions made by all doctors was increased from 92.9% to 95.3%, if all consultants followed prescribing
guidelines.

Under Scenario 2(c), the guideline compliance level among specialty registrars and consultants at empiric stage was adjusted to 100%. The simulated percentage of compliant empiric decisions made by all doctors was increased from 92.9% to 99.0%, if all specialty registrars and consultants followed prescribing guidelines.

Later, the percentage of compliant empiric decisions was simulated under Scenario 3(a), 3(b), and 3(c), assuming that increasing guideline compliance level among senior doctors changed not only the empiric decisions made by themselves, but also the empiric decisions made by doctors with lower seniority. The simulations were performed by adjusting the values of parameters representing both senior doctors’ and junior doctors’ guideline compliance level. The adjusted parameters were ‘senior doctors’ rate of complying’, ‘senior doctors’ rate of not complying’, ‘junior doctors’ rate of complying’, and ‘junior doctors’ rate of not complying’, using the table function generated in Chapter 4 (4.4.4 Estimation of senior doctors’ influence: table function). The table function determined the correlation between senior doctors’ rate of complying and junior doctors’ rate of complying. For any given value of ‘senior doctors’ rate of complying’, the table function generated a value for ‘junior doctors’ rate of complying’ based on the correlation determined by the 6 data points inside the table function. Thus, under Scenario 3(a), 3(b), and 3(c), when the parameters representing senior doctors’ guideline compliance level were changed, the
parameters representing junior doctors’ guideline compliance level were changed accordingly. Hence, the percentage of compliant empiric decisions was changed as a result of adjusted prescribing habits among both senior and junior doctors.

Under Scenario 3(a), the guideline compliance level among specialty registrars at empiric stage was adjusted to 100%. The simulated percentage of compliant empiric decisions made by all doctors was improved from 92.9% to 96.9%, if all specialty registrars followed prescribing guidelines and influenced junior doctors’ decision-making.

Under Scenario 2(b), the guideline compliance level among consultants at empiric stage was adjusted to 100%. The simulated percentage of compliant empiric decisions made by all doctors was increased from 92.9% to 95.8%, if all consultants followed prescribing guidelines and influenced junior doctors’ decision-making.

Under Scenario 2(c), the guideline compliance level among specialty registrars and consultants at empiric stage was adjusted to 100%. The simulated percentage of compliant empiric decisions made by all doctors was increased from 92.9% to 99.2%, if all specialty registrars and consultants followed prescribing guidelines and influenced junior doctors’ decision-making.

8.2.1.3 Combination of earlier scenarios

The percentage of empiric decisions in compliance with guidelines was simulated under
Scenario 3, which combined Scenario 1(c) of shortening microbiology laboratory turnaround time for all patients to less than 24 hours and Scenario 3(c) of increasing specialty registrars and consultants’ guideline compliance level at empiric stage to 100% with junior doctors’ being influenced, to predict the maximal possible improvement in guideline compliance level at empiric stage. Under Scenario 3, 99.4% of empiric decisions were in line with guidelines. This result suggested that with that if all senior doctors followed prescribing guidelines (either because timely microbiology laboratory test result was available, or because their prescribing habit was improved), and junior doctors were influenced by senior doctors’ prescribing habit, an improvement in overall guideline compliance can be achieved at empiric stage.

8.2.2 Improving practices at review stage

At review stage, microbiologists review empiric decisions made by other doctors in medical wards. Knowing that the guideline compliance was 100% among microbiologists (Chapter 6, 6.3.1.3 Data Source 3: hospital inpatient notes review), the system behaviour was considered ‘better’ if the percentage of empiric decisions reviewed by microbiologists was higher. Under baseline scenario, 78.1% of the empiric decisions made by doctors in medical wards were reviewed by microbiologists. An assumption was made when simulating prescribing behaviour at review stage to simplify the model. It was assumed
that the microbiology would only review empiric decisions for the patients with microbiology laboratory test results available. Thus, in order to increase the guideline compliance level at review stage by increasing the number of empiric decisions reviewed by microbiologists, the number of patients who had microbiology laboratory test results available was to be increased.

In reality, blood sample result was not available for every patient admitted because of two reasons. First, a microbiology laboratory test was not performed for every patient. Second, some of the patients had blood samples taken and the blood samples arrived in the microbiology laboratory, however, the test results were not delivered back to medical wards due to missing samples or contamination in transmission or storage. The fraction of patients who did not have a blood sample taken was 0.102 under baseline scenario. The fraction of patients who had a blood sample taken but did not have a microbiology laboratory test result available was represented by the ‘leakage fraction’ in the conveyer stock of microbiology laboratory, which was 0.066 under baseline scenario. The review was not performed for those patients of ‘leakage’, who either did not have microbiology test performed, or had the test performed however the test result was not available.

8.2.2.1 Performing tests for all patients

Under Scenario 4(a), blood sample was taken, and microbiology test was performed for all
patients. The fraction of patients who did not have blood samples taken was adjusted to zero. The simulated percentage of empiric decisions reviewed by microbiologists increased from 78.1% to 88.3%.

8.2.2.2 Providing results for all tests

Under Scenario 4(b), test results were delivered back to medical wards with turnaround time less than 24 hours for all patients who had the test performed. The leakage fraction in the conveyer stock of microbiology laboratory was adjusted to zero. The simulated percentage of empiric decisions reviewed by microbiologists increased from 78.1% to 78.7%.

8.3 Interpretation of simulation results

Similar to sensitivity analysis performed at model validation stage to detect which parameters had the strongest impact on system behaviour (Chapter 7, 7.2.3.2 Behaviour sensitivity analysis), the simulation results are interpreted using CLDs of the modelled system to detect which feedback loop dominated the system behaviour.

The results of simulation under all ‘what if’ scenarios are listed in the Table 8.1.
Table 8.1 Results of ‘what if’ scenario simulations

<table>
<thead>
<tr>
<th>Policy implication</th>
<th>‘What if’ scenario</th>
<th>Simulation result</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Empiric stage</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shortening microbiology laboratory turnaround time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario 1(a): turnaround time shortened to 2 days or less for all patients</td>
<td>Insignificant</td>
<td></td>
</tr>
<tr>
<td>Scenario 1(b): turnaround time shortened to 1 day or less for all patients</td>
<td>Insignificant</td>
<td></td>
</tr>
<tr>
<td>Scenario 1(c): turnaround time shortened to less than 24 hours for all patients</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 93.3%</td>
<td></td>
</tr>
<tr>
<td>Increasing senior doctors’ guideline compliance level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario 2(a): all specialty registrars following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 96.8%</td>
<td></td>
</tr>
<tr>
<td>Scenario 2(b): all consultants following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 95.3%</td>
<td></td>
</tr>
<tr>
<td>Scenario 2(c): all specialty registrars and consultants following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.0%</td>
<td></td>
</tr>
<tr>
<td>Scenario 3(a): all specialty registrars following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 96.9%</td>
<td></td>
</tr>
<tr>
<td>Scenario 3(b): all consultants following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 95.2%</td>
<td></td>
</tr>
<tr>
<td>Scenario 3(c): all specialty registrars and consultants following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.3%</td>
<td></td>
</tr>
<tr>
<td>Scenario 4: combined scenario of shortening turnaround time to less than 24 hours and increasing specialty registrars and consultants’ guideline compliance level</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.4%</td>
<td></td>
</tr>
<tr>
<td><strong>Review stage</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Improving microbiology test practices</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario 5(a): performing microbiology tests for the patients who were not tested</td>
<td>Percentage of empiric decisions reviewed by microbiologists increased from 78.1% to 88.3%</td>
<td></td>
</tr>
<tr>
<td>Scenario 5(b): reporting results for the microbiology tests with no result</td>
<td>Percentage of empiric decisions reviewed by microbiologists Increased from 78.1% to 78.7%</td>
<td></td>
</tr>
</tbody>
</table>
8.3.1 Feedback loops at empiric stage

**Figure 8.3** is the CLD that captured all the causal relationships among key variables in the antibiotic prescribing decision-making processes at empiric stage.

**Figure 8.3 Causal loop diagram of doctors’ decision-making processes at empiric stage (re)**

Figure 8.3 is a replica of Figure 5.5 presented in Chapter 5 (5.2.2.1 Causal loop diagram of prescribing decision-making at empiric stage). It is presented again here for ease of reference for the reader. 4 balancing feedback loops (marked by B1, B2, B3 and B4) emerged in the system. Results of ‘what if’ scenario simulation are listed in the table below according to which feedback loop the scenario was associated with (Table 8.2).
At empiric stage, the maximal improvement in guideline compliance was achieved under Scenario 3(c). Under scenario 3(c), all specialty registrars and consultants were following prescribing guidelines and influencing junior doctors’ decision-making processes. During the 100-day simulation period, specialty registrars and consultants always followed prescribing guidelines when they were making empiric decisions themselves. When they were not making empiric decisions, their influence existed and affected junior doctors’ prescribing habit. The simulation result indicated that the balancing feedback loop B4 was dominating system behaviour at empiric stage (Figure 8.4).
Figure 8.4 Balancing loop B4 of junior doctors’ decision-making processes (re)

Figure 8.4 is a replica of Figure 5.9 presented in Chapter 5 (5.2.2.1 Causal loop diagram of prescribing decision-making at empiric stage).

8.3.2 Feedback loops at review stage

Figure 8.5 is the CLD that captured all the causal relationships among key variables in the antibiotic prescribing decision-making processes at review stage.
Figure 8.5 Causal loop diagram of doctors’ decision-making processes at review stage (re)

Figure 8.5 is a replica of Figure 5.10 presented in Chapter 5 (5.2.2.2 Causal loop diagram of prescribing decision-making at review stage). It is presented again here for ease of reference for the reader. 2 balancing feedback loops (marked by B5 and B6) emerged in the system. Results of ‘what if’ scenario simulation are listed in the table below according to which feedback loop the scenario was associated with (Table 8.3).

Table 8.3 ‘What if’ scenarios and feedback loops at review stage

<table>
<thead>
<tr>
<th>‘What if’ scenario</th>
<th>Simulation result</th>
<th>Feedback loops</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 5(a): performing microbiology tests for the patients who were not tested</td>
<td>Percentage of empiric decisions reviewed by microbiologists increased from 78.1% to 88.3%</td>
<td>B5</td>
</tr>
</tbody>
</table>
At review stage, the maximal improvement in microbiology review was achieved under Scenario 5(a). Under scenario 5(a), all patients admitted in medical wards had a blood sample taken and microbiology tests performed, and all these performed tests had result. More opportunities were created for microbiologists to review empiric decisions made for these patients and provide input according to prescribing guidelines. The simulation result indicated that the balancing feedback loop B5 was dominating system behaviour at review stage (Figure 8.6). Figure 8.6 is a replica of Figure 5.11 presented in Chapter 5 (5.2.2.2 Causal loop diagram of prescribing decision-making at review stage).

**Figure 8.6 Balancing loop B5 of microbiologists’ decision-making processes**
8.4 Discussion

In this chapter, the results of simulation verified the validity of the SD model to provide estimates of prescribing outcomes under various policy scenarios. Through multiple casual pathways, compliance level can be improved at empiric stage, and more empiric decisions can be reviewed by microbiologists to ensure that appropriate decisions can be made to escalate or de-escalate the empiric therapies. The greatest improvement can be achieved by shortening laboratory turnaround time to less than 24 hours for all patients, or by increasing the guideline compliance level among specialty registrars and consultants while doctors with lower seniority were influenced.

8.4.1 The strength of quantitative simulation

The increase in the percentage of compliant empiric decisions was achieved by either shortening microbiology laboratory turnaround time to less than 24 hours for all patients, or by increasing senior doctors’ guideline compliance level with junior doctors being influenced. The change in system behaviour in response to the change in microbiology laboratory turnaround time or senior doctors’ guideline compliance could be inferred using CLDs of the system. However, as discussed in Chapter 3, the inference of system behaviour sometimes can be erroneous due to the limitation of CLDs (Chapter 5, 5.3.1 Limitations of causal loop diagrams).
Based on the CLD below, one could always deduce that senior doctors’ guideline compliance level would be affected if the microbiology laboratory turnaround time changed (Figure 8.7).

**Figure 8.7 Causal relationships between microbiology laboratory turnaround time and senior doctors’ guideline compliance level at empiric stage**

![Diagram showing causal relationships]

However, the simulation under the scenarios of shortened microbiology laboratory turnaround time suggested that the increase in percentage of compliance empiric decisions was only significant (detectable) when the turnaround time was shortened to less than 24 hours. Hence, the causal relationship captured by the CLD above is not always necessarily true. Using CLDs only to infer system behaviour can result in fault deduction. The strength of simulation is highlighted here by showing that sometimes in the modelled system, certain causal relationships are only valid in a limited range.

Similarly, the CLD below captured the causal relationship between senior doctors’ guideline compliance level and the amount of compliant/non-compliant empiric decisions (Figure 8.8). Specialty registrars and consultants were grouped together for their similar
decision-making processes (perceived themselves as decision makers and taking more responsibilities when treating patients in more critical conditions, relied more on their own experiences, had a tendency to prescribe antibiotics with broader spectrum than the recommendations in prescribing guidelines).

**Figure 8.8 Causal relationships between senior doctors’ guideline compliance level and amount of at compliant/non-compliant empiric decisions**

![Causal diagram](image)

However, the CLD above could not suggest which variable had stronger influence on the overall causal effect. The strength of simulation is highlighted here by capturing difference in characters of variable with similar causal effect when CLDs lacked precision.

### 8.4.2 Arbitrary values of simulation population and period

The ‘what if’ scenario simulations were performed for a group of 1000 patients in a 100-day time period. The ‘1000 patients’ and ‘100 days’ were two arbitrary values selected to allow simulation. The system outcomes were measured by percentage of compliant empiric
decisions at empiric stage and percentage of empiric decisions reviewed by microbiologists at review stage. The values of the outcomes measured were not affected by the number of patients in the system and the length of time period simulated (as time delays were not included in the SD model).

An additional assumption was made to simplify the model in association with the arbitrary values of simulation population and simulation period. The number of patients entering the system per day was assumed to be constant, and the number of blood samples taken for the patients entering the system was assumed not to exceed the maximal capacity of microbiology laboratory. However, in real life, the number of patients admitted in medical wards changes seasonally and varies from region to region, from hospital to hospital, and from ward to ward (Mendel et al., 2014). The number of patients admitted might also influence microbiology laboratory turnaround time, as in real life, the turnaround time is associated with the workload of the laboratory. Time delay might occur if the workload exceeds the maximal capacity of the microbiology laboratory. Extra data, including the number of patients admitted in medical wards of interest during a selected time period, is required if the SD model is to be expanded successfully in future.

In this chapter, the SD model of doctors’ prescribing decision-making processes was used to provide estimates of prescribing outcomes under a series of ‘what if’ scenarios. At empiric stage, the percentage of compliant empiric decisions was increased from 92.9% to
99.3% in the scenario under which all specialty registrars and consultants followed prescribing guidelines and the microbiology laboratory time was shortened to less than 24 hours for all patients. At review stage, the percentage of empiric decisions reviewed by microbiologists was increased from 78.1% to 90.7%, when microbiology laboratory tests were performed for the all patients to allow specialty registrars and consultants to make empiric decisions based on pathogen information. The simulation results were interpreted using feedback loops which emerged in the system. The balancing feedback loop of senior and junior doctors’ practices at empiric stage, and the balancing feedback loop of performing laboratory test results for all patients, were dominating system behaviour. In the next chapter, all findings from this study are summarised. The limitations of the study and the scope of future work are also discussed.

Key points in Chapter 8:

- The SD model was simulated to predict prescribing outcomes measured in guideline compliance level under a various of scenarios. At empiric stage, the maximal increase in doctors’ guideline compliance could be achieved if microbiology laboratory turnaround time was reduced to less than 24 hours, and all senior doctors were following prescribing guidelines while influence doctors with lower seniority. At review stage, the maximal level of microbiology review could be achieved if blood test results were available for all patients.
Chapter 9 Discussion

In the previous chapter, the simulation results for a series of ‘what if’ policy scenarios were presented and interpreted. In this chapter, the major findings are summarised and discussed in relation to existing literature for convergence and divergence. The empirical and methodological contributions of this study are discussed, as well as the limitations, which help to define the scope for the future work.

9.1 Summary of major findings

9.1.1 Influence factors across healthcare systems

The series of factors influencing prescribing decision-making processes in secondary care were considered as facilitators and barriers. The facilitators to optimal antibiotic prescribing decision-making processes included:

- Using prescribing guidelines especially at empiric stage; adopting electronic prescribing systems and computer-based prescribing guidelines;

- Using care bundles to slow down the development of antimicrobial resistance;

- Sharing antibiotic usage data across healthcare systems;
• Delivering education and training programmes and obtaining feedback for all healthcare professionals involved in the prescribing processes;

• Increasing prescribers’ involvement in guideline development;

• Adopting rapid diagnostic tools to shorten microbiology laboratory turnaround time;

• Providing budget to regulate de-escalation practices in hospitals.

• Meanwhile, barriers existed within healthcare systems to prevent doctors’ making optimal prescribing decisions. The identified barriers included:

• The cultural rule of ‘non-interference’ with decisions made by other doctors; senior doctors’ influence on junior doctors overriding prescribing guidelines (‘prescribing etiquette’);

• The heterogeneous nature of staff involved in antibiotic prescribing practices as a barrier to the uptake of behaviour-altering single-mode interventions;

• Delayed delivery of microbiology test results and other pathogen information;

The barriers and facilitators above, synthesised from the literature have not been previously mapped to different levels of the health system in terms of their origin. The mapping here to micro, meso, macro’ levels, (individual level, organisational level, and healthcare system) is a useful output as it may be useful to mangers when trying to design interventions. This
mapping however bought to light the lack of exclusivity to any given level. Multiple influences could be assigned to more than one level and more importantly, this mapping was limited in ability to capture the ‘system’ aspects of antibiotic prescribing decision-making. The categorisation partly addressed the research question of where the influence factors were, but failed to say when or how they affect prescribing decision-making. Further the mapping did not clarify which relevant stakeholders to involve if these influence factors were to be adjusted. To enhance the understanding of how doctors’ prescribing behaviour was influenced, a powerful analytical tool was selected following exploration of systems thinking approaches.

9.1.2 A system thinking tool for prescribing management

While the ‘system’ aspects of antibiotic prescribing and AMS management were recognised, and the requirement of a whole-of-system approach to analyse prescribing behaviour was acknowledged, existing research did not provide methodological approaches that were strong enough to meet the requirement (Buising, 2015). System thinking analytical tools, such as SD modelling, help researchers gain insights in the underlying structure of a complex situation (Department of Health, 2014). They demonstrate how elements inside the modelled system interrelate and where the opportunities are to intervene the system and influence its behaviour. Such analytical tools
were urgently required to analyse prescribing decision-making processes within the context, involve stakeholders in different parts of health systems, and predict antibiotic prescribing behaviour systematically. Additionally, the development of analytical tools must consider the challenges of limited research resources/funding faced by UK health care systems.

### 9.1.3 Development of the System Dynamics model

In this study, a SD model was developed to help analyse behaviour of doctors with different prescribing habits over time inside a system with set boundaries equivalent to an NHS Trust teaching hospital. Doctors’ prescribing behaviours were predicted when facing changes in factors influencing their decision-making by performing a series of ‘what if’ scenario simulations using the SD model. The SD model was developed to:

- represent simplified processes of doctors prescribing antibiotics to treat patients admitted in medical wards with symptoms of bacterial infections in the context of English hospitals;
- capture casual relationships between key variables occurring in doctors’ antibiotic prescribing decision-making processes;
enable simulation and prediction of prescribing outcome measures under a series of ‘what if’ scenarios when the factors influencing doctors’ prescribing decision-making processes were altered;

incorporate qualitative and quantitative data collected from primary and secondary sources using multiple methods to enrich the textual database of prescribing decision-making processes and provide estimates of the parameters included in the SD model.

A schematic map was constructed to represent the processes of doctors prescribing antibiotics to treat hospital inpatients, based on the findings from the rapid literature review and the analysis of source data collected from NHS teaching hospitals across North West London. This schematic map provided the structural base of the SD model. The modelling activities following the construction of the schematic map were grouped into six stages, which are:

**Conceptualisation (Chapter 3):** the concepts of systems thinking and the fundamental principles of SD modelling were discussed in relation to the nature of health systems and health management. SD modelling has demonstrated its capability in solving problems in health management when it was employed to simulate population flows, predict health seeking behaviour, support health decision-making, test health policy alternatives, and evaluation effectiveness of health interventions in extant research. However, this systems thinking approach has not been previously applied to antibiotic prescribing management in
the UK. The research questions that needed to be answered and the purpose of the modelling practice were described to conceptualise the SD model. An SD model aiming to help understand the impact of doctors’ prescribing decision-making processes and predict doctors’ prescribing behaviour was to be built in the later stage of the study.

**SD modelling and source data processing (Chapter 4):** well-established guidance to develop an SD model was employed in this study. SD modelling activities included mapping the system modelled in terms of feedback loops and translating these maps into a rigorous quantitative simulation model that enabled analysing scenarios and consequences of actions on computer-based software platforms. Three data sources were chosen to provide qualitative and quantitative data required for model building, including 1) secondary data collected from a survey with Foundation Year doctors recruited from 5 NHS teaching hospitals across North West London, 2) secondary data collected from a series of in-depth interviews with specialty registrars and consultants recruited from 3 NHS teaching hospitals in West London, and 3) primary data collected from hospital inpatient notes of 150 patients admitted in 3 NHS teaching hospitals in West London who developed *E. coli* bloodstream infection at the time when they were admitted or during their hospital stay.

**Qualitative mapping (Chapter 5):** the scene of the SD model was set to be contextually and functionally equivalent to an NHS Trust teaching hospital in London. The boundaries of the system modelled were described in relation to the categorisation of excluded, exogenous, and endogenous variables. The causal relationships between the key variables
included in the SD model were captured using causal loop diagrams (CLDs) for the prescribing decision-making processes at empiric stage and review stage. The critical time point determining empiric and review stage was defined as the time when the microbiology laboratory test result was available for a patient. At empiric stage, 4 balancing feedback loops emerged in the system to dominate system behaviour assessed by the percentage of empiric decisions in compliance with prescribing guidelines. At review stage, 2 balancing feedback loops emerged in the system to dominate system behaviour assessed by the percentage of empiric decisions reviewed by microbiologists. The mapping techniques involved in qualitative stage included 1) a sub-system diagram, which helped visualise the components included in the system modelled and the connection between the components, 2) a model boundary chart, which presented the categorisation of excluded variables, exogenous variables, and endogenous variables based on the purpose of the model, 3) CLDs, which helped capture causal relationships between key variables and determine the polarities of feedback loops (balancing feedback loops and reinforcing feedback loops).

**Quantitative formulation (Chapter 6):** stock-and-flow structures were constructed for the SD model based on the causal relationships between key variables to allow differentiation of stock variables, flow variables, and converters and quantification of these variables. The CLDs of the SD model were translated into stock and flow diagrams (SFDs) to enable computer-based simulation in the later stage. A data triangulation protocol was employed to synthesize the qualitative findings from the analysis of each dataset. The
qualitative findings from the analysis of source data suggested that senior doctors (specialty registrars and consultants) had a tendency to prescribe broader than the recommendations provided in prescribing guidelines when treating elderly patients to cover all possible infections, especially when microbiology laboratory test results were not available. Foundation Year doctors, nurses, and microbiologists were found to be guideline driven. However, Foundation Year doctors, core trainees, and nurses were influenced by senior doctors in medical wards. Microbiology laboratory turnaround time and senior doctors’ decision-making had the strongest impact on all doctors’ prescribing habits assessed by guideline compliance. Hence, these two factors were selected as the focus when simulating the model. The quantitative findings from the analysis of the source data were combined to provide numerical estimates of the parameters included in the SD model, including the parameters describing senior doctors, junior doctors, and microbiologists’ guideline compliance level. Non-linear relationships were discovered between multiple variables, such as the guideline compliance level among senior doctors and junior doctors, which again confirmed that SD modelling was the ideal method because of its ability to analyse complex, non-linear systems. A ‘soft’ variable, ‘fear of under-treating infections’ when treating elderly patients, was included in the CLDs and SFDs to help describe the cause-effect relationship between patient’s age and senior doctors’ tendency of prescribing antibiotics with broader spectrum. Regression analysis was performed to confirm the existence of the correlation. However, the quantitative evidence obtained from the multiple
sources was not sufficient to establish algebraic equations to predict doctors’ prescribing decisions based on patient’s age. Hence, this ‘soft’ variable was eliminated from model simulation in the later stage. The lag time to doctors’ behaviour adjustment in response to the change in influence factors was considered at the qualitative mapping stage. The source data did not include evidence in whether this lag time existed, and how long it would be. Therefore, the time delays were not included in simulation either.

**Model validation (Chapter 7):** after the SD model was formulated, a series of tests were performed to verify the validity of model structure, model parameters, and the system behaviour simulated using the model. Multiple expert panel workshops were conducted to allow front-line staff in hospitals and researchers in infection prevention and control and SD modelling to provide expert opinion in the validation of model structure and model parameters. After addressing the comments obtained from the expert panel workshops and revising the model structures and parameters, the SD model passed all validation tests performed and was considered valid based on the purpose of the model by the expert panels. The SD model was simulated to predict the percentage of compliant empiric decisions and the percentage of patients who had microbiology laboratory test result available under baseline scenario to assess the model’s ability to reproduce the system behaviour in real life. Under baseline scenario, the SD model predicted that 92.9% empiric decisions made by all doctors were in line with prescribing guidelines, and 78.1% of patients admitted in medical wards had microbiology laboratory test results available. The simulation results
were considered a valid reflection of the system in real world by accurately estimating the statistics of 91.9% compliant empiric decisions and 79.7% of patients with laboratory test results available reported by the NHS Trust teaching hospitals. Statistical testing, used frequently to verify validation of other quantitative models, was considered to have little relevance to assessing the validity of an SD model due to the unique ‘white-box’ approach used to construct the model.

**Model simulation (Chapter 8):** after passing model validation tests, the SD model was simulated under various ‘what if’ scenarios to predict prescribing outcomes at empiric stage and review stage. Each defined ‘what if’ scenario was simulated singularly; some scenarios were simulated together to test the system behaviour with impact from multiple influence factors combined. The simulation results are discussed in detail in the next section.

### 9.1.4 Simulation of ‘what if’ scenarios

The simulation results of various ‘what if’ scenarios are presented in Table 9.1. Table 9.1 is a replica of Table 8.1 presented in Chapter 8 (Chapter 8, 8.3 Interpretation of simulation results). It is presented again here for ease of reference for the reader.
The SD model simulation results suggested that improvement of guideline compliance

<table>
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<tr>
<td>Increasing senior doctors’ guideline compliance level</td>
<td>Scenario 2(a): all specialty registrars following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 96.8%</td>
</tr>
<tr>
<td></td>
<td>Scenario 2(b): all consultants following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 95.3%</td>
</tr>
<tr>
<td></td>
<td>Scenario 2(c): all specialty registrars and consultants following the guidelines, while junior doctors not influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.0%</td>
</tr>
<tr>
<td></td>
<td>Scenario 3(a): all specialty registrars following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 96.9%</td>
</tr>
<tr>
<td></td>
<td>Scenario 3(b): all consultants following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 95.2%</td>
</tr>
<tr>
<td></td>
<td>Scenario 3(c): all specialty registrars and consultants following the guidelines, while junior doctors being influenced</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.3%</td>
</tr>
<tr>
<td></td>
<td>Scenario 4: combined scenario of shortening turnaround time to less than 24 hours and increasing specialty registrars and consultants’ guideline compliance level</td>
<td>Percentage of compliant empiric decisions increased from 92.9% to 99.4%</td>
</tr>
<tr>
<td>Review stage</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Improving microbiology test practices</td>
<td>Scenario 5(a): performing microbiology test for the patients who were not tested</td>
<td>Percentage of empiric decisions reviewed by microbiologists increased from 78.1% to 88.3%</td>
</tr>
<tr>
<td></td>
<td>Scenario 5(b): reporting results for the microbiology tests with no result</td>
<td>Percentage of empiric decisions reviewed by microbiologists increased from 78.1% to 78.7%</td>
</tr>
</tbody>
</table>
level at empiric stage could be achieved if microbiology laboratory turnaround time was shorted to less than 24 hours for all patients. The effect of shortening turnaround time to less than 3 days or to less than 2 days was insignificant. Doctors’ guideline compliance level measured by the percentage of compliant empiric decisions was increased from 92.9% under baseline scenario to 93.3% if microbiology laboratory test results became available in 24 hours for all patients. Specialty registrars’ behaviour had stronger impact on overall guideline compliance level of all doctors than consultants’ behaviour at empiric stage. Percentage of compliant empiric decisions was increased from 92.9% to 99.3% when all specialty registrars and consultants followed guideline compliance and junior doctors were influenced by senior doctors. The maximal improvement in guideline compliance level at empiric stage was achieved when all specialty registrars and consultants followed the guidelines and the microbiology laboratory turnaround time was shortened to less than 24 hours for all patients. In this case, the percentage of compliant empiric decisions increased from 92.9% to 99.4%.

At review stage, the level of microbiology review was improved by performing microbiology test for all patients. The percentage empiric decisions reviewed by the microbiologists increased from 78.1% to 88.3% when blood samples were taken and microbiology laboratory tests were performed for all patients admitted to medical wards. The results of ‘what if’ scenario simulations were interpreted using CLDs of the feedback loops to identify the most dominant feedback loops at empiric stage and review stage.
9.1.5 Comparing to existing literature

Earlier published studies which explored the factors influencing antibiotic prescribing decision-making processes, which were identified through the rapid literature review, can be divided into three main types based on the purpose the studies and the methodological approaches employed. The first type of the study used qualitative methods, including surveys, in-depth interviews, focus-groups, to report barriers and facilitators of antibiotic prescribing practices experienced by healthcare professionals. The second type of study aimed to evaluate antimicrobial stewardship interventions and measure the effectiveness/cost-effectiveness using health outcomes, including microbiological outcomes (number of infection cases) and patient clinical outcomes (morbidity, mortality), and/or health economic outcomes (length of hospital stay, medication expenditure). The third type of study was systematic literature reviews, which combined the first two types of the studies. Behavioural outcomes were neglected in all three types of studies. Compared with these earlier published studies, this study has a stronger focus on behaviour outcomes. When analysing the primary data collected from hospital inpatient notes, various behavioural patterns were recognised among doctors with different seniority. For example, Foundation Year doctors documented and followed decisions made by senior staff when initiating, switching and stopping antibiotic therapies rather than making decisions
themselves. At empiric stage, specialty registrars and consultants’ decisions were followed by Foundation Year doctors, despite the existence of prescribing guidelines, unless microbiologists were available to provide input. However, Foundation Year doctors’ practices in Accident and Emergency (A&E) department were guideline-driven considering the fact that empiric decisions must be made during a short period of time when senior staff were normally absent. These findings in prescribing behaviour correlate with the findings reported in studies conducted in other methods (Charani, Cooke & Holmes, 2010; Charani et al., 2013; Rawson, et al., 2016). The differences in the decision-making processes associated with doctors’ seniority were captured by the SD model.

Adoption of rapid diagnostic tools and other procedural initiatives to allow timely delivery of microbiology test results were recognised as factors facilitating prudent antibiotic prescribing practices in hospitals in the UK. However, earlier published studies only suggested why timeliness was a facilitator but failed to reveal how prescribing decision-making was influenced. The SD model in this study quantitatively estimated the relationship between microbiology laboratory turnaround time and prescribing outcomes assessed by doctors’ guideline compliance level. Also, other factors associated with microbiology laboratory tests were also included when simulating the model. The results suggested that the improvement in prescribing practices can not only be achieved by shortening turnaround time, but also by performing tests on all patients and making sure all tests done were processed properly to provide results. Shortening microbiology
laboratory turnaround time, regulating blood sampling practices in medical wards, and preventing sample loss and contamination were all considered to be facilitators in improving guideline compliance level. The simulation results provided guidance for future policy intervention. Earlier published studies only suggested that shortening microbiology laboratory turnaround time and increasing the speed of test result delivery would facilitate doctors to make optimal prescribing decisions. However, in real life, shortening turnaround and sample delivery time was sometimes not achievable due to limit of resources and technology. Rather than narrowly focusing on shortening turnaround time, procedural initiatives, such as regulating blood-sampling practices to perform microbiology laboratory tests for all patients at, can also help achieve the goal of optimising prescribing practices.

9.2 How the research questions were addressed and the aims met

This study aimed to answer the following over-arching research question:

*How can the multiple and concurrent influences on prescribing decision-making processes in secondary care be captured to provide a model for prediction of intervention effects?*

An SD model was developed to meet this aim by addressing the following sub questions:

* Which stakeholders are involved in prescribing decisions?
• Which influence factors affect prescribing behaviours?
• From where in the health system to these arise? And when during prescribing decision-making processes?

The findings from the rapid literature review and analysis of source data, and the results from SD model simulation can be summarised to answer the research questions above:

Doctors, nurses, and microbiologists are the most dominating decision-makers in antibiotic prescribing in hospitals, while pharmacists and other healthcare professionals, and patients are less involved. Doctors’ decision-making processes are influenced by a series of factors occurring on multiple levels across healthcare systems. Timeliness and availability of microbiology diagnostic information, and senior doctors’ prescribing habits have shown the strongest impact on overall guideline compliance level among all doctors. SD has been successfully employed to develop a model for prediction of intervention effects by simulating doctors’ prescribing habits assessed by guideline compliance level and capturing the complex, non-linear nature of prescribing behaviour.

9.3 Contributions

9.3.1 Empirical knowledge of antibiotic prescribing

The two main contributions to the empirical knowledge of prescribing behaviour in secondary care are as follows.
First, this study demonstrates that the ‘system’ aspects of prescribing behaviour must be considered if effective behaviour-altering interventions are to be implemented. The factors influencing prescribing decision-making processes arise on different levels across healthcare systems with interconnection and interaction among them. The study shows that prescribing decision-making processes in secondary care were influenced by different factors occurring on multiple levels across healthcare systems. When analysing the impact of these influence factors, the ‘system’ aspects, which are the interconnection among these factors and the interaction between the factors and the context these factors act within, must be considered if effective behaviour-altering interventions are to be implemented.

Second, by using SD modelling and simulation, the study captures the impact of behavioural influence factors quantitatively in order to inform future policy-making. By shortening microbiology laboratory turnaround time to less than 24 hours for all patients, and improving specialty registrars and consultants’ guideline compliance, overall guideline compliance among all doctors can be improved at empiric stage. At review stage, by increasing the availability of microbiology test results for as many patients as possible, microbiologists can be engaged at review stage to the greatest extent to ensure timely adjustment of empiric decisions.

Though previous research in AMR management has reported the impact on prescribing practices of structural determinants (difference in prescribing pattern in acute care, medical wards and surgical theatres), procedural determinants (microbiology laboratory turnaround
time), and cultural determinants (“prescribing etiquette”). All of these studies provide further insights to what researchers describe as context. There are two research questions needed to be answered in relation to context: 1) how to study interactions between contexts and interventions to develop more effective interventions, and 2) how to deal with contextual factors in implementing interventions (Mary Dixon-Woods, 2016). Many studies conclude with the inability to generalise because results would be different in different cultural and structural contexts. “How we should structure thinking about context remains a stubborn puzzle”, according to Professor Mary Dixon-Woods, Professor in Medical Sociology and Wellcome Trust Senior Investigator. She suggested that no account of context can be decoupled from a broader understanding of causation. The unanswered questions in spite of the studies in context are ‘what are the causal mechanisms’ and ‘how can the causal mechanisms be captured’. No previous study provides information on the causal mechanisms between the identified influence factors and individual doctors’ decision-making processes, or consider the multiple factors in one given setting, but instead treats different parts of the system in each study. For instance, the findings conclude that the same determinant might influence different individuals in different ways, depends on their experience and posts (Laws et al., 2009). These studies acknowledge that the management of prescribing practices is a complex issue and influenced by multiple determinants at the same time, however, none of these studies could predict quantitative outcome measures in doctors’ behaviours with either single or multiple influence
considered. In this thesis, by using a systems thinking analytical tool, the causal relationships between the identified influence factors and doctors’ decision-making were captured, and impact of these influence factors on doctors’ prescribing behaviour was predicted collectively, which provides information for future intervention design and evaluation. For example, it is indeed “common sense” in AMR management that by shortening microbiology laboratory turnaround time, the empiric prescribing decisions could be improved. However, microbiology laboratory turnaround time sometimes cannot be shortened due to limitation in technology. Moreover, hospital managers need to know the effect size and if investment in new technologies here is the best option.

### 9.3.2 Methodology of antimicrobial resistance management and health management

In addition to the two empirical contributions, the study also makes two methodological contributions.

First, a contribution to literature on public health and health management through the implementation of SD.

Second, the implementation of SD modelling extends the emergent literature on integrating qualitative and quantitative data to address public health issues and specifically to the crucial area of addressing AMR. This is achieved through multiple data analysis methods
during the process of SD model development, including regression analysis and mixed-method data triangulation. The full capabilities of SD modelling have been exploited in this study, including the controversial topics and unresolved debates surrounding the use of qualitative and quantitative data.

This study is a successful attempt in the employment of SD modelling in the research field of antibiotic prescribing behaviour management, and health management more widely. The first fully parameterised and validated SD model was constructed to provide quantitative estimates of doctors’ prescribing behaviour in the context of secondary care in the UK. Other simulation and modelling methods, including regression analysis and mixed-method data triangulation, were employed during the SD model development process. Quantitative and qualitative evidence, and primary and secondary data collected using different methods were integrated organically to support model construction.

Cause-effect relationships between doctors’ prescribing behaviour and influence factors were captured by CLDs. Non-linear relationships between senior and junior doctors’ guideline compliance level and overall prescribing outcomes were discovered by performing sensitivity analysis of the model. A table function was generated to capture the impact on junior doctors’ decision-making from senior doctors’ prescribing habits. Feedback loops and computer-based simulation enabled the quantitative prediction of prescribing outcomes systematically when the factors influencing doctors’ decision-making changed. The comprehensiveness of the SD approach as implemented here is a
strength of the study. SD modelling demonstrated its ability to analyse behaviour when facing policy alternatives and inform intervention design. It can be used in other AMR management and health management research topics in future.

9.3.3 Methodology of System Dynamics

The full capabilities of SD modelling have been exploited in this study, including the controversial topics and unresolved debates surrounding the use of qualitative and quantitative data. Qualitative data from multiple sources was synthesized together to support the construction of CLDs of the SD model and interpretation of quantitative simulation results.

Additionally, the debate about the relative credibility of ‘white-box’ approaches compared to ‘black-box’ approaches. In this study, the SD model was constructed based on well-defined causal relationships between key variables in prescribing decision-making processes. The causal relationships included were validated thoroughly to produce a sound, defensible, and well-grounded model. Although SD modelling is a ‘white-box’ approach, ‘black-box’ approaches, such as regression analysis, building table function to connect senior doctors and junior doctors’ guideline compliance level at empiric stage, and building graph function to generate random integers based on the distribution of microbiology laboratory turnaround time measured in days, were incorporated in the process of SD
model development when the relationship between variables could not be captured using mathematical equations or the cause-effect relationships remained unclear. The practices of integrating black-box data analysis methods in the process of building a white-box simulation model suggested that the two types of modelling approaches did not conflict with each other. Black-box approaches and white-box approaches offered complementary quantitative information to help formulate the SD model completely.

In this study, four of the five major concepts of SD modelling were employed in the simulatable SD model, including feedback loops, stock-and-flow structures, non-linearity, and table functions. Balancing feedback loops emerged in the system connected all key variables in antibiotic prescribing decision-making processes at different stages based on the causal relationships between these variables. Stock-and-flow structures were constructed using SFDs to translate qualitative CLDs to rigorous computer-based model. Non-linear relationships between senior doctors and junior doctors’ guideline compliance level, and between senior doctors’ compliance level and prescribing outcomes of the system were discovered and analysed. A table function was generated to simulate the impact from senior doctors on junior doctors’ decision-making processes at empiric stage.

The fifth major element, which is time delays, was not incorporated in the quantitative SD model at current stage. However, the recommendations for areas of future research were discussed. In future, time delays caused by doctors reporting, measuring, and perceiving risks of inappropriate prescribing practices, healthcare professionals deciding to take
actions, and doctors adjusting their prescribing habits in response to the actions taken should be included in the SD model.

9.3.4 Methodology of operational research

In operational research, various techniques have been proposed to model the complexity and dynamics of human behaviour and interaction between human beings (Scholl & Phelan, 2004). SD modelling has been classified as a ‘top-down’ approach, whereas other traditional agent-based modelling methods are referred to ‘bottom-up’ approaches. When building an SD model, researchers model a static structure of feedback loops based on causal relationships between key variables and observe the dynamic behaviour at an aggregate level over time simulated by the model. The behaviour is simulated on a system level to identify the most dominant feedback loops and variables to inform implementation of policy interventions and initiation of structural changes. The behaviour of individual agents in the system modelled is not focused on by the model. In contrast, the bottom-up methods rely on modelling behaviour of individual agents, whose interactions are governed through a set of simple rules. Historically, operational researchers have often used discrete-event simulation approach to healthcare modelling (Huang, Jennings & Fox, 1995; Elabi, Paul & Young, 2007).

Antimicrobial resistance is a healthcare systems level problem which affects the population
on a large scale (Kapadia et al., 2018). Top-down modelling methods such as SD modelling, combined with national level surveillance, help evaluate population health outcomes. SD modelling offers other benefits such as supporting debate on how the underlying system structure might influence system behaviour over time, while traditional modelling methods in operational research tend to focus on localised decisions for individual patients (Taylor & Lane, 1998). This study demonstrated the role of SD modelling in probing operation in health systems.

### 9.3.5 Theory of prescribing behaviour

This thesis made a theoretical contribution by interpreting doctors’ antibiotic prescribing decision-making processes using ‘bounded rationality’. Unlike previous research in prescribing behaviour, which assumed that doctors were perfectly rational when making prescribing decisions, my research evidence in literature and primary and secondary source data to demonstrate that antibiotic prescribing decisions were acceptable, rather than optimal, due to doctors’ bounded rationality. Prescribing behaviours are the outcome of bounded rationality. The factors influencing individual doctors’ antibiotic prescribing behaviour are the timeliness and availability of microbiology laboratory test results, and senior doctors’ decision-making. Using the idea of bounded rationality, the doctors’ prescribing decision-making is bounded by the cognitive limitations in both knowledge
(knowledge in pathogens that caused the infections, patient’s co-morbidities and infection history, etc) and computational capacity (to calculate an optimal solution to treat potential infections, cause minimal adverse clinical outcomes and/or the development of AMR, and consider other factors such as stocking, financial incentives, etc), and the limitation in the time available to make a decision (an empiric prescription must be made as soon as possible even without diagnostic information). The existence of ‘prescribing etiquette’, the principle of non-interference, and the situation when senior doctors’ decision-making overriding prescribing guidelines and influencing junior doctors’ guideline compliance, all suggest that decision-makers act like ‘satisficers’, searching through available alternatives until an acceptability threshold is met. Doctors were seeking a satisfactory solution rather than an optimal one when prescribing antibiotics.

The contribution to theory development is hence clarified. In this thesis, the theory of “bounded rationality” is acknowledged, tested in the research topic of doctors prescribing antibiotics in the hospitals, and a systems thinking analytical tool was selected for its ability to address the limitations of bounded rationality.
9.4 Limitations and future research

9.4.1 Variables excluded before simulation stage

This study has three major limitations caused by the elimination of certain variables before simulation stage. First, patients’ influence on decision-making processes was not included in the rapid literature review nor the SD model. Second, the ‘soft’ variable ‘fear of under-treating’ was identified as a key variable in prescribing decision-making processes of senior doctors, however, the analysis of this variable stopped after the construction of CLDs and SFDs of the SD model. Third, the time delays in doctors’ decision-making processes were only briefly discussed using CLDs, and not included in the SD model. Extra data is required to expand the model in future to include patients’ influence on doctors’ decision-making, the parameters measuring fear, and the time delays in doctors’ behaviour change.

9.4.1.1 Patients’ influence on prescribing decision-making

When constructing the SD model, an assumption was made to simplify the model structure. It was assumed that patients were only to passively accept treatment and not be involved in the decision-making processes.

Earlier published studies have reported that patients were involved in antibiotic prescribing mainly in general practice (Cadieux et al., 2007). Perceived patient demand was reported
as a factor with strong impact on doctors’ antibiotic prescribing decisions in primary care (Coenen et al., 2006). Limited evidence existed in patients’ expectation and request influencing doctors’ prescribing decision-making processes in secondary care. A study of physicians’ prescribing behaviour conducted in a university hospital reported that when physicians thought a parent wanted an antimicrobial drug, they prescribed them 62% of the time versus 7% of the time when they did not think the parent wanted antimicrobials when treating paediatric patients with age between 2 to 10 years old (Mangione-Smith et al., 1999). Patients were not involved in the prescribing decision-making processes in secondary care partially because of the reason that the patients admitted in medical wards were normally in more critical conditions and less able to state their requirement in prescription compared to the patients visited general practitioners (GPs). However, when reviewing the hospital inpatient notes in the model formulation stage, the documentation of the communication between the doctors who made empiric decisions and the patients or the patients’ relatives was found on several occasions. The conclusion of whether the communication with the patients and the patients’ relatives influenced doctors’ prescribing practices at empiric stage cannot be made yet, solely based on the qualitative information extracted from the source data. Further investigation must be conducted to establish the causal relationship, if there is any, between patients’ demand and doctors’ prescribing habits. If the SD model is to be modified to simulate doctors’ prescribing decision-making processes in primary care, influences associated with patients’ demand should be
9.4.1.2 The ‘soft’ variable: fear

When analysing the secondary data collected from interviews with senior doctors, the reason behind low guideline compliance level among senior doctors was revealed. When senior doctors in medical wards were making empiric decisions, they perceived themselves the decision makers that take full responsibility of patients’ well-being. When treating elderly patients, who were normally in worse critical conditions compared to patients in younger age groups, senior doctors tended to prescribe broader than the recommendations in prescribing guidelines to cover all possible infections due to the ‘fear of under-treating’, especially when microbiologist’s input was not available at empiric stage. A causality pathway of patients’ age – ‘fear of under-treating’ – guideline compliance at empiric stage among senior doctors was established and captured by the CLD in Chapter 5 (5.2.2.2 Causal loop diagram of prescribing decision-making at review stage). In the qualitative mapping stage, the variable ‘fear’ was categorised into the group of exogenous variables and considered to remain constant in the system to maintain the completeness of the feedback loops. This exogenous variable is determined by the auxiliary variable ‘patients’ age’. However, after the source data was analysed to formulate the model, the quantitative data was not sufficient to establish mathematic equations to describe the relationship
between patient’s age and senior doctor’s guideline compliance level. No adjustment can be made directly on ‘fear’ to simulate the system behaviour in relation to this variable. Hence, this variable was eliminated from the SD model in simulation stage. Future approaches for quantitatively measuring ‘fear’ as well as other factors associated with the cultural atmosphere of the prescribing environment will allow the integration of these ‘soft’ variables in the SD model.

In future, ‘fear of under-treating’ can be defined as an endogenous variable which can be measured and altered quantitatively by creating an ‘indexed variable’. To do this, the value of the variable is set to ‘1’ at some given point in time, usually at the beginning of simulation. The factors that affect the indexed variable are then identified to establish mathematical or graphical relationships that caused the indexed variable to change over time. If an indexed variable is created for ‘fear of under-treating infections’ and set a value equal to 1 outside simulation, assuming that doctors did not experience fear at this point. A survey then can be conducted with doctors to ask how this measure of fear they experienced would be increased (due to patient’s age, co-morbidity, or any other factors associated with fear). An arbitrary number can be chosen to set a maximal limit of the scale, for example, the scale of ‘fear’ can be from 1 to 10, or 1 to 100. A graphical plot can be drawn to visualise the behaviour of the indexed variable ‘fear’ against the independent factor (e.g. patient’s age) and its value relative to 1. The relationship can also be mathematically represented using a statistical approach, such as calculating the correlation
coefficient between the level of fear and patient’s age. Formulating an explicit equation or graphical relationship between a qualitative ‘soft’ variable and its drivers provides opportunity to share mental models about the research topic. It helps explain doctors’ thought process about how prescribing decisions are made in the real world.

In addition, economic approaches to the measurement of risk aversion can be adopted to quantify the intangibles in SD. Risk aversion is a measure of the feeling guiding the person who faces a decision with uncertain outcomes (Thomas, 2015). Though risk aversion is widely considered a concept in economics, previous studies have demonstrated that it also played a role in antibiotic prescribing behaviour management (Krockow, 2018). Risk-aversion intuition is a key driver in decision-making, including doctors’ antibiotic prescribing decision-making. To produce quantitative measure of risk aversion, the standard approach in economics has been to utilise the model of expected utility (Thomas, 2013). When individuals make decisions under uncertainty, they will choose the act that will result in the highest expected utility, being this the sum of the products of probability and utility over all possible outcomes. The decision made will also depend on the agent’s risk aversion and the utility of other agents. The expected utility theory consists of two components: diminishing marginal utility and utility maximization. There is no complete agreement in the past on the behaviour of risk aversion, nor universally accepted standard way to measure risk aversion (Thomas, 2016). In some behavioural models, person’s risk-aversion is assumed to be constant during the decision process (it rationalised the
assumption made for the SD model built in this thesis, which is the doctors’ behaviour was assumed to be constant, it only changed when their perceived risk of prescribing inappropriately changed); risk aversion varies between individuals with different starting wealth and may also vary between individuals possessing the same starting wealth. While in other models, risk aversion is assumed to be changed dependent on time or the importance of the event (Boyle, 2015).

The concept of risk aversion has only briefly touched in the research field of prescribing decision-making. The risk of AMR was generally perceived to be serious, but the abstract and long-term nature of its consequences led doctors to doubt personal susceptibility (Krockow, 2018). Prescribing behaviour is heavily (and rationally) weighted towards the avoidance of tangible, immediate and short-term risks, at the cost of the potentially catastrophic, but abstract and uncertain, future outcome of widespread AMR. The salience of individual patient risks was a key barrier to more conservative prescribing. Prescribing broad-spectrum antibiotic involved low cognitive demand and enabled doctors to manage patient expectations (Eggleston, 2010). This prioritizing of short-term, concrete risks, and discounting of abstract future risks has long been recognized as a core feature of human psychology (Krockow, 2018). Individual risk attitudes influenced doctors’ practices. In a cross-sectional survey of a nationwide sample of doctors conducted in France, risk aversion and uncertainty avoidance have been tested for their impact on antibiotic prescribing behaviour (Michel-Lepage, 2010). The study results suggested that uncertainty avoidance
can be used to explain non-compliance with prescribing guidelines as a national-level cultural determinant. Absence or delayed delivery of diagnostic information is associated with inappropriate use of antibiotics. At individual level, risk-aversion has showed a stronger impact. Risk-averse doctors prescribed more antibiotics when diagnostic results were not available, compared to risk-tolerant doctors.

In line with the dominant economic doctrine that only revealed preferences can be taken as reliable and stable, only few attempts have been made to obtain direct measurement (Hartog, Ferrer-i-Carbonell & Jonker, 2000). In this thesis, economic approaches to measure risk aversion have been considered as an addition to the standard ‘index scaling’ technique to measure the intangibles when formulating an SD model (‘index scaling’ is the technique to obtain direct measure by letting decision-makers to reveal their preferences).

The major challenge comes from the lack of a clear definition of utility from the decision-makers’ (doctors’) perspective, which includes patients’ well-being, doctors’ experience, knowledge, and professional satisfaction gained from successful treatment, and other financial incentives – it is almost like producing a function for an intangible variable from more intangibles. The soft variables identified to have impact on doctors’ decision-making processes will definitely be investigated further and incorporated in the immediate future.
9.4.1.3 Time delays in behaviour change

SD is an approach to understanding the non-linear behaviour of complex systems over time. In SD modelling, there are five important concepts: feedback loops, stock-and-flow structures, non-linearity, table functions, and time delays (Sterman, 2002). So far, the first four concepts have been employed in the simulation model. When constructing the CLDs for the SD model of antibiotic prescribing decision-making processes, 6 feedback loops emerged and dominated doctors’ prescribing behaviour at empiric and review stage in response to the perceived changes in the factors influencing doctors’ decision-making processes (5.2.2 Causal loop diagrams). The CLDs were translated into SFDs to allow parameter estimation and quantitative simulation of the SD model (6.2.1 Stock and flow diagram of prescribing decision-making at empiric stage). Non-linear relationships were detected between the parameters describing doctors’ guideline compliance level (senior doctors’ rate of complying, junior doctors’ rate of complying) and the outcome measure of the system at empiric stage assessed by the percentage of compliant empiric decisions made by the doctors when sensitivity analysis was performed to validate the model behaviour (7.2.3.2 Behaviour sensitivity analysis). When estimating the influence on system behaviour from senior doctors’ decision-making, a table function was generated to establish the interconnection between junior doctors and senior doctors’ prescribing habits at empiric stage (6.3.4.3 Estimation of senior doctors’ influence: table function).

However, the fifth concept of SD modelling, which is time delays, was not adopted in the
study. The example of time delays in a decision process was discussed in Chapter 5, the CLDs were constructed for the SD model without including time delays (Chapter 5, 5.3.3 Modelling time delays, Figure 5.13, Figure 5.14).

The SD model at this stage only focused on the probability of doctors making certain decisions under varies scenarios, but not ‘how fast’ the decisions were made. The ‘what if’ scenario tests only simulated the magnitude of the change in outcome measures (level of guideline compliance at empiric stage, and level of microbiology review at review stage), which is a snapshot of the final status of the evolved system. If a discrepancy was perceived by doctors within the system between the prescribing outcomes at the current stage and the optimal prescribing practices, then the simulation results suggested the status of the system after certain corrective actions were taken. For example, by shortening microbiology laboratory turnaround time towards less than 24 hours for all systems, eventually the doctors within the system would achieve a guideline compliance level of 93.3% at empiric stage. However, the model did not incorporate the time element of behaviour change. In real life, delays occur between the change in factors influencing decision-making and the change in system behaviour. A gradual change in outcome measures is expected in response to the change in system environment through the process to build awareness, perceive and assess the risk, decide to take actions, for the actions to affect, and to change outcome measures as a result of collective behaviour change.

In future, time delays can be introduced in the model (Figure 9.1). Delays occur
in doctors’ prescribing decision-making processes at empiric stage. Delay 1 occurred in the process of assessing and reporting prescribing practices and determining whether the ‘discrepancy’ existed in the current state. Delay 2 occurred in the process of making decisions to change prescribing habits if a discrepancy was perceived by healthcare professionals within the system. Delay 3 occurred due to the time consumed from initiating behaviour adjustment among doctors until the prescribing outcomes started to improve. The desired state of the system can be quantitatively represented by an auxiliary variable ‘the ideal percentage of compliant empiric decisions’. The difference between the percentage of compliant empiric decisions and the ideal percentage creates another auxiliary variable representing the ‘gap’, which quantifies how big the discrepancy is between reality and expectation.

**Figure 9.1 Stock and flow structure of the delays in adjusting prescribing behaviour**

If the discrepancy emerges, the parameters of the model can be adjusted to simulate
‘corrective actions’ taken within the system to minimise the discrepancy. The initiation of corrective actions is triggered if the discrepancy reaches a certain level. A flow variable can be defined as ‘rate of taking corrective actions’ to represent the rate of the discrepancy being reduced. This flow variable is dependent on the magnitude of the ‘gap’. The bigger the gap is, the faster the corrective actions will be taken to push the change in system behaviour until the ideal percentage of compliant empiric decisions is achieved.

9.4.2 Single type of outcome measures

Another major limitation of this study is that only prescribing behavioural outcome measures were estimated by the SD model. Earlier published studies in the undesired consequences caused by sub-optimal antibiotic prescribing practices mainly focused on emergence and spread of antimicrobial resistance following exposure to antibiotics (Cantón & Morosini, 2011). Limited evidence was found in literature to connect prescribing behavioural outcomes with immediate patient outcomes. A study conducted in a tertiary care centre in the UK reported that the physician group led by an infectious diseases acute physician used 30% less antibiotic therapy with no adverse clinical outcome, suggesting antibiotic use can be reduced safely in the acute setting (Fawcett et al., 2016). This result may be achieved in part by holding antibiotic drugs and admitting the patient for observation rather than prescribing immediately after admission, which has
implications for costs and hospital occupancy. However, more information is needed to indicate whether any such longer admission will increase or decrease risk of antibiotic-resistant infections. The primary data collected from reviewing hospital inpatient data can be utilised to investigate whether immediate patient health outcomes were associated with the antibiotic prescribing decisions made to treat them. Moreover, if the association is detected, further investigation is required to establish correlations between prescribing outcomes and health/health economic measures to allow expansion of the SD model to provide multiple outcome measures.

9.4.3 Assumptions made to simply the model

A model is a simplified representation of a real-life situation. Like applying any other modelling approach, a series of assumptions were made at the beginning stage of model construction. At current stage, the number of doctors in the system was assumed to be constant. Patients were assumed to enter the system at a steady pace. The patient flow never exceeded the maximal capacity of the hospital and the microbiology laboratory modelled. Each patient was assumed as being treated by only one doctor at empiric stage, and this doctor was assumed to make only one decision on prescribing antibiotics. Microbiologists were assumed to be involved in prescribing decision-making processes only when the laboratory test results were available, and they always followed prescribing guidelines.
These assumptions must be addressed in future to modify the SD model to reflect the
dystem in the real world more accurately.

This thesis demonstrated the feasibility to employ a systems thinking analytical tool in
antibiotic prescribing behaviour management. SD modelling enabled quantitative
prediction of doctors’ decision-making processes and provided a methodological protocol
for future researchers to develop similar models to simulate health professionals’ decision-
making processes in different settings. For example, if such model needs to be generalised
to evaluate doctors’ behaviour along a complete patient pathway in secondary care, sub-
system models can be built for A&E, surgical theatres, and medical wards with the adequate
support in data collection. In future, the SD model constructed in this thesis can be
expanded to help examine prescribing behaviour and other issues in antimicrobial
stewardship (AMS) across the health economy systematically through the One Health
approach. The One Health approach has been explained in Chapter 2 (Chapter 2, 2.4 The
need for a systems thinking approach to explore prescribing behaviour). It is defined as a
whole-of-system, collaborative effort of multiple disciplines – working locally, nationally,
and globally – to attain optimal health (Robinson, 2017). Developing a One Health service
delivery model – Integrated Care System (ICS) – which brings together local organisations
(coversing both primary and secondary care) to re-design care and improve population
health is the core component of NHS long term plan (The NHS Long Term Plan; Ahmad
9.5 Reflections as a doctoral researcher

The process of conducting research in any setting involves learning about the researcher’s own strength and limitations. At the beginning stage of professional training as a biomedical engineer and a modeller, I was used to evaluating everything in real world through numbers and equations. I refused to accept the messiness in human behaviour, and always naively hoped to establish a clean, tidy, perfectly quantified model when facing issues in behaviour management and health management. Later on, I realised that a good model does not necessarily have to eliminate uncertainty, instead, a good model only has to be able to tolerate uncertainty and still serve the purpose. My understanding of ‘modelling’, and furthermore, my understanding of the world, was shaken by my first encounter with SD modelling when I conducted research for my Master of Public Health degree. Chaos was considered by me as the biggest enemy of a modeller. System Dynamics does not eliminate or ignore chaos, it does not tolerate chaos, it does not even ‘accept’ chaos, but System Dynamics acknowledges that chaos is the fundamental concept of the world (Sterman, 1994). I quickly moved to the other extreme, thinking SD modelling was the ultimate solution for everything - anything can be modelled, and any problem can be
solved by SD modelling.

My journey became more logistically challenging when I started my doctoral research. I was challenged on daily basis by doctors, and modelling experts using other methodological approaches. The former's resistant to any external interference aimed at changing their behaviour, even though behaviour might be problematic, while the latter questioned the credibility of the method. It forced me to develop a broad knowledge base not only about SD modelling, and also about the context within which a SD model is to be built. I spent more time interacting with people, observing and interpreting their behaviour, instead of sitting with my laptop all day trying to save the world with a magic equation. Through this process, I gradually understand how difficult it was to change people’s belief, let alone their behaviour. Perception, motivation, fear, these are the factors dominating doctors’ behaviour rather than any hi-tech electronic system. At the initial stage of this study, the cultural determinants and unspoken rules inside hospitals were considered negligible ‘errors’. At the end they became the most important influence factors in the system modelled.

My journey is blessed with the guidance from my supervisors. Prof. Atun, who introduced SD to me, has been leading the way since. Dr. Ahmad, who has been monitoring the whole process with her watchful eyes, also grew up with me as SD modellers. If my passion in SD modelling is the driver in initiating the work. Their faith in this method, and in me, is what supported me to complete this study. I became more mature as an SD modeller, and
as a researcher in general. I acknowledge the limitation of SD modelling while appreciate its capability. It provides a lens for me through which the most complex issues can be analysed. However, there is still a long way to go before the deliverables of my research can be translated into anything practical. It is my responsibility now to share the findings and continue the research.

In this chapter, the major findings of the study were discussed in relation to existing evidence for convergence and divergence. This study made contributions to the empirical knowledge of antibiotic prescribing behaviour, AMR management, and health management. The limitations and the recommendations for future research were included. In the next chapter, the implications of the simulation results in policy making are discussed.

Key points in Chapter 9:

- This thesis made empirical, methodological, and theoretical contributions.
- The limitations of the SD model provided the direction of future research to expand the model to include intangible variables, such as ‘soft’ variables measuring emotional determinants. The model can also be modified, with the support of adequate source data, to simulate prescribing decision-making processes in different settings.
Chapter 10  Translation and Potential Impact

In the previous chapter, the major findings of the study were discussed in relation to existing evidence for convergence and divergence in how prescribing decision-making was influenced by factors. The contributions of the study, the major limitations and the recommendations for future research were also described. In this chapter, the potential impact of this study and the implications for future policy design are discussed.

10.1 Potential impact of this study

10.1.1 For doctors and other prescribers

AMS interventions aimed at altering doctors’ prescribing behaviour have been implemented in English hospitals. However, policy resistance has been observed at individual and organisational level (Charani et al., 2011; Ashiru-Oredope et al., 2013; Holmes et al., 2016; Ahmad & Holmes, 2018). Feedback on healthcare systems level performance indicators had limited impact on individual doctors’ prescribing decision-making processes. Extant research has demonstrated that by presenting individual feedback on prescribing practices, especially the feedback on their individual practices in
comparison to prescribing guidelines, provided a foundation for improvement of process
(Lagerløv et al. 2009).

The SD model developed in this study provided a tool to predict prescribing outcomes
measured by guideline compliance and microbiology review at a sub-organisational level
(i.e. prescribing outcomes within medical wards in a hospital). Prescribing outcomes can
be simulated using the model for different groups of doctors (i.e. senior doctors, junior
doctors, and microbiologists), which would help doctors develop better understanding of
the consequences caused by their own prescribing behaviour. So the model itself could
serve as a feedback and learning tool for doctors.

10.1.2 For researchers in antibiotic prescribing management

Antibiotic prescribing management is complex, dynamic, and systemic. Inadequate
management of prescribing practices results in undesired individual impact and public
health consequences. Problems in antibiotic prescribing decision-making are caused by a
web of elements and the unpredictable interactions among these elements. Doctors’
prescribing behaviour is influenced by a collection of interlinked structural and cultural
factors that are interacting with each other and with the contexts they arise from. The
tendency of health systems to defeat the policies that have been designed to improve them,
sometimes referred to as ‘policy resistance’, is associated with the inadequate policies and
managerial decisions made using traditional analytical methods which lack the ability to capture the multi-level, nonlinear and sophisticated nature of prescribing decision-making processes. In this study, SD modelling demonstrated its ability to simulate doctors’ behaviour under various ‘what if’ scenarios. It is a successful novel attempt to apply this modelling method into the research area of antibiotic prescribing management. However, the SD model delivered at the end of this study still has major limitations. Further data collection, mapping practices, and exploration for robust, powerful research methodologies are required if full understanding of prescribing decision-making processes is to be developed. In addition, researchers would benefit from employing multi-disciplinary and mixed-method study strategies. Implied by the evidence in literature and the results of SD model simulations, ‘soft’ variables, such as cultural determinants, had a strong impact on doctors’ decision-making processes and furthermore on prescribing outcomes. However, current research methods cannot explain the exact mechanistic cause-effect relationships between these ‘soft’ influence variables and doctors’ prescribing behaviour. Qualitative methods adopted in sociology, psychology and behaviour science must be utilised in health management to enrich the textual database of research in prescribing and help construct mental models to represent and explain prescribing decision-making processes.
10.1.3 Organisational learning

Organisational learning is the process of creating, retaining, and transferring knowledge within an organisation. An organisation improves its performance over time as it gains experience and creates knowledge (Argote, 2012). Organisational change is seen as the result of a basic learning process resulting in the updating of routines based on the interpretations of experience (Lant & Mezias, 1990). A systematic review conducted in 2006 suggested that clinical guideline compliance was associated with the learning environment in hospitals (Dijkstra et al. 2006). Organisational learning theory was used to explain the findings. In hospitals with better learning environment, information gathering and sharing perception of performance gaps caused higher clinical guideline compliance level observed. The concept of organisational learning was involved in this research. The feedback loops within the modelled system emerged when the doctors were assumed to be intelligent agents who would adjust their behaviours in response to the changes in system environment. When the performance gap (e.g. prescribing decisions not in compliance with prescribing guidelines) was perceived by the healthcare professionals within the system, behaviour change was then initiated as the consequence of the learning process. The SD model can be used as a tool to demonstrate the importance of creating a better learning environment to initiate and accelerate the organisational learning process to achieve better system performance (e.g. guideline compliance).

Historically, adoptive models were developed to explain the process of organisational
learning. In adoptive models, organisation learning is the process where organisations gradually adopt routines that lead to favourable outcomes, which are typically based on the notion of ‘bounded rationality’ (i.e. individual agents have limited ability to process information in uncertain and rapidly changing environments) (Chapter 3, 3.3.2 ‘Bounded rationality’; Chapter 6, 6.1.1 Overcome ‘bounded rationality’). As a result, the traditional methods involved in organisational learning were concerned with the search and selection of desired alternatives. When multiple alternatives existed, an analytical tool was needed to support the decision-making of selection. Computer-based simulations have been used as a tool to examine the consequences of learning processes in organisations (Lounama & March, 1987; Lant, 1992). Traditional computer-based simulation for adoptive learning failed to assess whether the consequences were caused by the learning processes or by random changes in causal structure of the inner organisational environment. A systems thinking modelling method was required to concentrate explicitly on the link between individual decisions and system level consequences. SD modelling has been previously used to evaluate the consequences of organisational learning in business firms (Lant, 1992; Lomi, Larsen, & Ginsberg, 1997). Some of the consequences which were considered to be caused by random components confounding the causal structures within the systems were proven to be the results of the learning processes, and vice versa, as SD modelling has the ability to assess system behaviour including the impact from multiple influence factors. In the case of learning processes for senior doctors, a possible scenario maybe that when
senior doctors perceive higher risk of inappropriate practices (caused by the increased amount of non-compliant decisions), they would respond by changing their own behaviour. Meanwhile, an external interference introduced into the system, such as an intervention implementation, adoption of a new rapid diagnostic tool, or faster microbiology laboratory turnaround time; these factors must also be included in analysis. The overall guideline compliance has now been improved as a collective consequence of the learning process and the implemented interventions. SD modelling has the ability to assess which ‘portion’ of this improvement was caused by organisational learning and which ‘portion’ was caused by the intervention, which can be considered as a random component confounding causal structures inside the system. Also, SD modelling takes into account the impact of non-linearities and time delays, which are commonly involved in the process of adoptive learning.

10.2 Policy implications of findings

The findings of this study have implications for policy makers and hospital managers who wish to improve prescribing behaviours in order to more effectively treat patients to improve their outcomes and also reduce the risk of emergence of AMR.
10.2.1 For policy makers and managers

Both evidence in literature and findings from this study suggested that senior doctors relied more on their own experience rather than following prescribing guidelines, despite such a behavioural pattern having a negative influence on junior doctors’ guideline compliance. Lack of compliance with prescribing guidelines among senior doctors was acknowledged by doctors and other healthcare professionals involved in the data collection and model validation activities (expert opinion) for this study. However, the association between guideline compliance and other behaviours and doctor’s seniority has not been studied. Limited evidence in literature was found to report and analyse the association between doctors’ behaviour and doctors’ seniority. Few interventions have explicitly been designed to target senior doctors. One intervention has been implemented to target all doctors, including senior doctors, by using mobile application to support decision making (Charani et al., 2017). Existing education and feedback programmes in the NHS teaching hospitals, where the doctors were recruited to collect the source data used in this study, were designed to target primarily junior doctors to improve their prescribing practices. However, these interventions had limited effectiveness considering senior doctors’ prescribing habits may override prescribing guidelines. The mismatch between the requirement and provision of interventions needs to be addressed urgently.

Doctors’ guideline compliance assessed by percentage of compliant empiric decisions made by doctors in medical wards was simulated using the SD model in this study. Under
baseline scenario, 92.9% empiric decisions were in line with prescribing guidelines (Chapter 7, 7.2.3.1 Behaviour reproduction test). A guideline compliance level of 92.9% under might seem high. However, non-adherence to prescribing guideline compliance was reported to be associated with adverse patient outcomes caused by inappropriate prescribing practices (Mol et al., 2005). Evidence in literature suggested that it was critical to improve guideline compliance to 100% despite a relatively high compliance level had already been achieved. The simulation results of this study suggested that overall guideline compliance level can still be improved despite the baseline level being already relatively high. When looking more widely at infection prevention and control practices which also can help address antimicrobial resistance through reducing healthcare associated infections, the compliance levels of doctors for prescribing guidelines are high. For example, hand hygiene compliance is only of 42.6% among health worker in English hospitals (Dai et al., 2015. The approach used in this study is a valuable framework to enable the evaluation of future interventions in this wider field too.

The findings of this study suggested that guideline compliance among all doctors could be improved by shortening microbiology laboratory turnaround time, which correlated with evidence in the literature. Earlier published studies have suggested that shortening microbiology laboratory turnaround time and increasing the speed of test result delivery would facilitate doctors to make optimal prescribing decisions. But this has been
considered in isolation to other factors. Shortening turnaround and sample delivery time is sometimes achievable in real life due to limitations of resources and technology. Staff shortages have been reported to be a major cause of prolonged turnaround time and impacting on timelines of test ordering, sample collection, and the analytical phases. These factors within the laboratory pathway may need to be modelled in finer detail as simply identifying the delays does not improve practice (Hawkins, 2007). Advances in diagnostic technologies together with regulating blood sampling practices to ensure that microbiology laboratory tests are performed for all patients, can also help achieve the goal of optimising prescribing practices. From a cost perspective this would increase short-term laboratory and diagnostic expenditure, but the medium and long-term economic benefits need to be considered for patients, hospitals and the health system.

10.3 Potential ways in which the research findings could be disseminated and translated

This research has already been disseminated at one international conference with feedback being incorporated into the model construction in the later stage. Future presentations in local, national, and international academic and non-academic events will increase the awareness in AMR, prescribing decision-making, and the methodology of SD modelling. Further publication and lay articles can help translate this research into policies and
interventions as well as materials to involve and engage public in AMR management.

A user friendly graphical interface can be developed for the SD model built in this study to convert this model into a decision support tool for healthcare professionals and researchers.

Key points in Chapter 10:

- The findings of research have implications for policy makers and managers.
Chapter 11  Conclusion

In the previous chapter, the policy implications of this research were discussed for policy makers, hospital managers, and future researchers in antibiotic prescribing management and AMR management. This chapter concludes this thesis.

This study demonstrated the ‘system’ aspects of prescribing behaviour management. The factors influencing doctors prescribing decision-making processes arise on different levels across healthcare systems with interconnection and interaction among and between them and the environment in which they exist. The system nature must be considered if effective behaviour-altering interventions are to be implemented. Systems thinking research tools were required to analyse prescribing decision-making processes in a dynamic and systemic fashion without extra requirement in research funding and other resources. By using the method of SD modelling and simulation, previously reported influence factors were investigated quantitatively to enhance the understanding of doctors’ prescribing behaviour and inform future policymaking. Impact and threshold effect were estimated for various policy alternatives. Doctors’ guideline compliance can be improved at empiric stage by shortening microbiology laboratory turnaround time to less than 24 hours for all patients, or by increasing specialty registrars and consultants’ guideline compliance level, considering their influence on doctors with lower seniority. At review stage, the level of microbiology review can be maximised if microbiology tests were performed for all patients.
patients and every test performed had results available. The SD model constructed in this study is the first fully parameterised and validated model to measure prescribing decision-making processes in the context of English hospitals. The findings from the literature review and SD model simulation empirically contributed to the knowledge of antibiotic prescribing decision-making and AMR management. The implementation of SD modelling contributed methodologically to AMR management and health management. This study also makes contributions to the methodologies of SD modelling and operational research.

An aphorism can be used as the closure of this study.

“All models are wrong, but some are useful.”

--- Box and Draper 1987
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Appendices

Appendix 1. Antimicrobial Prescribing Education for Doctors (APED) Study Questionnaire

You have been invited to take part in this study because you are a foundation, core or registrar doctor working within a clinical setting in the North West London Deanery, and at some point in your rotation you will have worked at Imperial College Healthcare NHS Trust. It is your choice to decide if you would like to volunteer to complete this questionnaire. You may discontinue the questionnaire at any time.

Background

The Centre for Infection Prevention and Management, Imperial College London is conducting this research study to develop a better understanding of issues that doctors face with respect to antimicrobial prescribing and the training that doctors have received, or would like to receive, in antimicrobial prescribing.

Our plan is to use the responses from this questionnaire to determine the need for and develop a short course on antimicrobial prescribing for doctors.

Anonymity

Your responses will be anonymous. No answers will be attributable to you; all responses will be aggregated. No one apart from the study team will ever see the anonymous individual responses.
**Prize**

If you would like to be entered into a raffle to win one of twenty £25 vouchers from Amazon please fill in the relevant form at the end of the questionnaire.

**Next stage of the project**

If you would be interested in participating in the next stage of the project as part of the study please fill in the relevant form at the end of the questionnaire.

This questionnaire will take approximately 15 minutes to complete

Would you like to volunteer to complete this questionnaire?

a) Yes

b) No

c) Already completed questionnaire

To start we would like to ask you some questions about your current prescribing experiences and practices, your thoughts on prescribing and antimicrobial resistance, and how you use policy on prescribing in your Trust.

1) Do you currently prescribe antimicrobials in your post? (Please select one)

   a) Yes Skip to question 3a

   b) No

   c) Decline to answer
2) **Do you currently prescribe antimicrobials on your own or with a more senior doctor?**

(Please select one and if prescribing with another doctor please specify their level of seniority)

a) Not at all confident  
Skip to question 9

b) Not very confident  
Skip to question 9

c) Fairly confident  
Skip to question 9

d) Very confident  
Skip to question 9

e) Decline to answer  
Skip to question 9

3) (a) **Do you currently prescribe antimicrobials on your own or with a more senior doctor?** (Please select one and if prescribing with another doctor please specify their level of seniority)

a) Primarily on my own

b) Sometimes with a more senior doctor  
**Please circle** FY2 / ST / SpR / Consultant

a) Most often with a more senior doctor  
**Please circle** FY2 / ST / SpR / Consultant

c) Other  
**Please specify** _______________________

d) Decline to answer

3) (b) **In your current post, on average, how often do you prescribe antimicrobials?**

(Please select one)
a) \( \leq \) than once per week

b) 2-4 times per week

c) Once a day

d) \( \geq \)2 times a day

e) Other Please specify______________________________

f) Decline to answer

4) **How confident would you be that you are prescribing the appropriate antimicrobial each and every time that you write a prescription?** (Please select one)

a) Not at all confident **Skip to question 9**

b) Not very confident **Skip to question 9**

c) Fairly confident **Skip to question 9**

d) Very confident **Skip to question 9**

e) Decline to answer **Skip to question 9**

4) **(a) What makes you feel less confidence in antimicrobial prescribing?** (Please select all that apply)

a) I am always confident in antimicrobial prescribing

b) I do not have sufficient experience in antimicrobial prescribing

c) I do not have sufficient knowledge in antimicrobial prescribing
d) I do not receive much help with antimicrobial prescribing

e) I am not always confident that the more senior doctor that I prescribe with is knowledgeable in antimicrobial prescribing

f) I do not always have confidence that the diagnosis is correct and therefore that antimicrobial prescribing is correct

g) Other. Please specify________________________

h) I do not know

i) Decline to answer

4) (b) What makes you feel more confident when prescribing antimicrobials? (Please select all that apply)

a) I am rarely ever confident in antimicrobial prescribing

b) I have sufficient experience in antimicrobial prescribing

c) I have sufficient knowledge in antimicrobial prescribing

d) I have confidence that the diagnosis is correct and therefore that antimicrobial prescribing is correct

e) I am confident that the more senior doctor that I prescribe with is knowledgeable in antimicrobial prescribing

f) Other. Please specify________________________

g) I do not know
5) When did you first begin to feel confident about your antimicrobial prescribing decisions? (Please select one)

a) I am not yet confident

b) I have always felt confident (i.e. from day one of foundation training)

c) During my first foundation training year

d) After my first foundation training year

e) During my second foundation training year

f) After my second foundation training year

g) During my core training year 1 or 2

h) After my core training year 1 or 2

i) During my first specialty/registrar training

j) With guidelines/ confidence in knowing condition

k) I do not know

l) Decline to answer

6) When prescribing antimicrobials, do you consider the wider implications of antimicrobial resistance for each and every prescription that you write? (Please select one)
a) Yes
b) No
c) Sometimes
d) I do not know
e) Decline to answer

7) In practice, when you review a patient who is on intravenous (IV) antibiotics, how often do you consider de-escalation (IV to oral switch)? (Please select one)

a) Every 24 hours for every patient
b) Every 48 hours for every patient
c) Every 72 hours for every patient
d) It is different case by case
e) When the patient begins to respond to therapy
f) When told how to prescribe
g) I do not know
h) Decline to answer

8) Do you find deciding to de-escalate (IV to oral switch) easy? (Please select one)

a) Yes
b) No
c) Sometimes

d) I do not know

e) Decline to answer

9) Have you read the antimicrobial policy at Imperial College Healthcare NHS Trust?

(Please select one)

a) Yes, all of it

b) Yes, part of it

c) No

d) Unsure if a policy exists

e) Decline to answer

10) Do you think that the policy helps you make better prescribing decisions? (Please select one)

a) Yes

b) No

c) Sometimes

d) I do not know

e) Decline to answer
11) Has this policy helped you learn to prescribe antimicrobials better? (Please select one)
   a) Yes
   b) No
   c) No, but a previous policy did
   d) I do not know
   e) Decline to answer

12) Why do you believe the policy has not helped you to learn to become better at prescribing antimicrobials? (Please select all that apply)
   a) It is not applicable to my specialty
   b) It is not laid out to enable learning  Skip to question 14
   c) The doctors whom I work with do not follow policy Skip to question 14
   d) I disagree with the policy  Skip to question 14
   e) The policy is not well grounded in evidence  Skip to question 14
   f) It is a prescribing tool not an educational resource  Skip to question 14
   g) Optimal prescribing relies on experience and practice  Skip to question 14
   h) Other. Please specify__________________  Skip to question 14
   i) I do not know  Skip to question 14
   j) Decline to answer  Skip to question 14
13) How has this policy helped you to learn to become better at prescribing antimicrobials? (Please select all that apply)

a) I can check my decisions against it

b) It helps to remind me to assess drug resistance and Healthcare Associated Infections

c) It reminds me of what I should not prescribe

d) It lets me know which current prescribing related issues I should review

e) Other. Please specify________________________

f) I do not know

g) Decline to answer

14) Which format, if any, of the policy do you use? (Please select all that apply)

a) Paper copy of policy on the ward

b) Poster of the policy on the ward

c) Personal booklet

d) Policy on the intranet

e) Mobile/Tablet application

f) Anything accessible on the ward

g) Anything accessible at home

h) Anything accessible at home or on the ward
i) Other. *Please specify* __________________

j) I don't know

k) I don’t use it

l) Decline to answer

15) If you were unsure about an antimicrobial prescribing decision, from whom would you ask for help?  *(Please rank the following people in order of which you would contact first starting with 1, if you would not ask them cross off the answer)*

   a) FY1 __________
   b) FY2 __________
   c) CT1 or 2 __________
   d) SpR / ST 3+ __________
   e) Consultant (in your specialty) __________
   f) Pharmacist __________
   g) Nurse __________
   h) Infection specialist / Microbiologist __________
   i) Other. *Please specify* __________________________
   j) Decline to answer

16) Are there times of the day or week when it is more difficult to find someone to help
you make a prescribing decision? (Please select all that apply)

a) No
b) Mornings
c) Lunchtimes
d) Afternoons
e) Evenings
f) Nights
g) Weekends
h) Holidays
i) Other Please specify ___________________________

j) I do not know
k) Decline to answer

17) In your current rotation, how would a non-optimal antimicrobial prescription for a patient get corrected? (Please select all that apply)

(For example if a broad spectrum antibiotic was prescribed when a more specialised antibiotic could have been used)

a) Another doctor on the following shift would probably notice and correct it
b) Someone would pick it up on patient rounds
c) A more senior doctor would check the junior doctors work
d) The ward pharmacist would point it out

e) The administering nurse would mention it

f) The prescribing doctor would have to notice

g) It probably would go unnoticed

h) Other. Please specify ________________________________

i) I am not sure

j) Decline to answer

18) In your current rotation, if a non-optimal antimicrobial prescription was noticed by another clinician, would it be reported back to the prescribing doctor? (Please select one)

a) 100% of the time

b) 67-99% of the time

c) 34-66% of the time

d) 1-33% of the time

e) 0% of the time

f) I do not know

g) Decline to answer

19) In your current rotation, how would an unsafe antimicrobial prescription for a
patient get corrected? (Please select all that apply)

(For example if there was potential for a dangerous drug interaction)

a) Another doctor on the following shift would probably notice and correct it

b) It would be picked up on patient rounds

c) A more senior doctor would check the junior doctors work

d) The ward pharmacist would point it out

e) The prescribing nurse would mention it

f) The prescribing doctor would have to notice

g) It probably would go unnoticed

h) Other. Please specify ____________________________________________

i) I am not sure

j) Decline to answer

20) In your current rotation, if an unsafe antimicrobial prescription was noticed by another clinician, would it be reported back to the prescribing doctor? (Please select one)

a) 100% of the time

b) 67-99% of the time

c) 34-66% of the time

d) 1-33% of the time
Now we would like to ask you about the training that you have received in antimicrobial prescribing and your future training interests.

21) Would you have liked more training in treatment of infection and antimicrobial prescribing at medical school? (Please select one)

a) Yes
b) No
c) I do not know
d) Decline to answer

22) Thinking about all of your antimicrobial prescribing training, what proportion or percent do you feel that you learned from medical school, in post prescribing, in post training session, and self study? (Please ensure the total of the percentages adds up to 100%)

a) Medical school _______%
b) In-post prescribing _______%
c) In-post training sessions ________% 

d) Self-study ________% 

e) Other. Please specify ________________ ________% 

f) Decline to answer 

23) From whom did you learn the most about antimicrobial prescribing in medical school? (Please select one) 

a) Myself during self-study 

b) My classmates 

c) My professors and lecturers 

d) Other. Please specify ________________ 

e) Decline to answer 

24) Thinking about your training from first foundation year until now, what was the most effective training you received with respect to antimicrobial training? (Please select one) 

a) On the job prescribing alone 

b) On the job prescribing with a senior colleague 

c) Ward rounds 

d) Teaching sessions
25) From whom did you learn the most about antimicrobial prescribing since you started your first foundation year? (Please select one)

a) Myself

b) Other doctors at the same level (in my specialty)

c) Other doctors in training at a higher level (in my specialty)

d) Consultants

e) Infection specialists / microbiologists

f) Nurses

g) Pharmacists

h) Other. Please specify ____________________________

i) Decline to answer

26) When learning about prescribing on the job (i.e. foundation, specialist and registrar training), what per cent of your learning comes from each of the following?
(Please ensure the total of the percentages adds up to 100%)

a) seeing another doctor’s prescriptions in a patient’s notes / drug chart

b) working directly with another doctor to decide how to prescribe

c) making a prescribing decision and then discussing with another doctor

d) attending rounds

e) attending structured study time

f) self-study

g) other Please specify_______________________________

h) Decline to answer

27) Would you like additional training, resources, or courses on any aspect of antimicrobial prescribing now? (e.g., prescribing in general, prescribing for specific patient groups, mechanisms) (Please select one)

a) Yes

b) No

c) I do not know

d) Decline to answer

28) If you were to receive a short course in antimicrobial prescribing, which of the following topics would you like included? (Please select all that apply)
a) Diagnosis of infections

b) Principles of antimicrobial prescribing

c) Mechanisms of emergence of antimicrobial resistance

d) Epidemiology of antimicrobial resistance and patterns of spread

e) Principles of clinical review of infections and antimicrobial therapy

f) The role of the microbiology laboratory testing in disease management

g) Other. Please specify __________________________________________

h) All of the above

i) I am not sure

j) Decline to answer

29) Which of the following formats would you find most useful for a short course on antimicrobial prescribing? (Please select all that apply)

a) Full day course

b) Half day course

c) Series of 1 hour seminars

d) Online learning (computer based)

e) Mobile learning (phone/tablet based)

f) Didactic teaching (mainly lecture based)

g) Interactive problem-based learning
h) Problem based learning (no interaction, but answers provided)

i) Other. Please specify_________________________________________

j) Decline to answer

30) How would you describe the ideal short course for enhancing your skills in antimicrobial prescribing? (Please write ‘decline’ if you wish to decline to answer)

For the last section, we would now like to ask you some questions about yourself, your current post, and previous training. These questions will be used to determine if tailoring additional training to specific groups would be useful and/or welcomed.

31) If you are a Specialist Registrar or Specialist Trainee, please tell us which deanery you completed your foundation training in. (Please write ‘decline’ if you wish to decline to answer)

___________________________________________________________________

32) How old are you? (Please select one)

   a) 22-25 years       d) 34-37 years
   b) 26-29 years       e) 38+ years
   c) 30-33 years       f) Decline to answer
33) **Are you male or female?**  (Please select one)
   
   a) Male
   
   b) Female
   
   c) Decline to answer

34) **What stage of medical training are you currently in?** (Please select one)
   
   a) FY1
   
   b) FY2
   
   c) ST1 or 2
   
   d) ST3+
   
   e) SpR
   
   f) Other  
   Please specify ________________________________
   
   g) Decline to answer

35) **What is or was your first FY1 rotation?** (Please select one)
   
   a) Medicine
   
   b) Surgery
   
   c) Both
   
   d) Decline to answer
36) Where did you attend medical school?
   a) In the United Kingdom
   b) Outside of the United Kingdom Please specify country __________________
   c) Decline to answer

37) What is the name of the medical school you attended?

38) Which of the following best describes your medical degree training? (Please select one)
   a) 5 year course starting as an undergraduate
   b) 5 year plus intercalation year starting as an undergraduate
   c) 6 year access to medicine course starting as an undergraduate
   d) 6 years including an undergraduate
   e) 4 year graduate course
   f) Other. Please specify ________________________________
   g) Decline to answer

39) In what year did you complete medical school? (Please write ‘decline’ if you wish to decline to answer)
40) **Which specialty are you currently working in?** (Please write ‘decline’ if you wish to decline to answer)

41) **What area of medicine/surgery are you specialising in for your training?** (Please write ‘decline’ if you wish to decline to answer)

42) **Which Trusts have you worked in during your training in the North West Thames Deanery?** (Please select all that apply)

   a) Chelsea & Westminster NHS Foundation Trust
   b) Ealing Hospital NHS Trust
   c) The Hillingdon Hospitals NHS Trust
   d) Imperial College Healthcare NHS Trust
   e) North West London Hospitals NHS Trust
   f) West Hertfordshire Hospitals NHS Trust
   g) West Middlesex University Hospital NHS Trust
   h) Decline to answer

Thank you for taking the time to complete this questionnaire!

We are most appreciative of your help with our research and we hope that our work will benefit new doctors.
Appendix 2. Additional information in statistical significance and its relevance in System Dynamics

To understand the technical reasons why statistical significance testing had little relevance in verifying the validity of SD models, the fundamental assumptions held for statistical tests to be valid must be explained first.

Most statistical tests hold three fundamental assumptions:

1) Serial independence: a series of variables are considered to be serially independent if a variable is unrelated to any other variable in any way. The level of relativeness is described by the term ‘serial correlation’ and when the serial correlation of a group of variables is zero, these variables are serially independent. Most statistical tests assume that the data of observation included in the tested sample is serially independent. For example, the age of all patients included in a study sample is serial independent, if all patients were selected randomly across all age groups. If a group of variables are not serially independent, they are auto-correlated.

2) No cross correlation: similar to serial correlation which describes one variable of all observations in the tested sample, cross correlation describes the correlation between multiple variables. In most statistical tests, different variables of study samples are normally assumed not to be cross-correlated. Using the example of patients’ age again, cross correlation might be assumed to be void between patients’ age and patients’
demographic location.

3) Normal distribution: when performing statistical tests, data is assumed to be normally distributed, or at least symmetric. The plot of a normal distribution is symmetric. The probabilities of occurrence of a certain event (or data value) are drawn to produce a bell-shaped curve. If the size of a study sample is large enough to include many randomly selected patients, the patients’ age should be normally distributed.

The three assumptions described above are fundamental for many statistical tests to be valid. When these assumptions are violated, the test results of the analysis can be misleading or completely erroneous. However, the data involved in SD modelling are almost never appropriate for these assumptions to be held.