Evaluating the sustainability of complex health system transformation in the context of population ageing: An empirical system dynamics study

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Abstract

Demographic changes, particularly population ageing, and rising morbidity from chronic conditions contribute to ever-increasing pressures on health and care systems in developed countries. Partly as a response, new models of care and service innovations are being piloted and introduced. However, the effectiveness and sustainability of these complex health system transformations are often not well understood and most modelling studies fail to capture both system configuration and populating dynamics. In this paper, we present a comprehensive system dynamics modelling approach to capture both population ageing and the organisation of the health and care services from a whole system perspective. The development of the model was directly informed by an ambitious care system transformation project designed to offer a different pathway for those patients deemed to be complex. The model input parameters were populated using estimates from empirical data. A series of simulation experiments were conducted to inform the design of the new service and its sustainability. We found that, subject to the model's limitations and assumptions, the new pathway could have a stabilising effect against increasing demand provided hospital readmission fractions and length of stay for complex patients can be managed effectively.

Keywords: OR in health services; Health system transformation; Population ageing; System Dynamics.

1. Introduction

Health and social care systems in developed countries are struggling to keep up with rising demand for their services. As a result of increasing life expectancies and lower birth rates, population structures in developed countries are changing in such a way that the proportion of elderly people is higher than ever before. Recent Global Burden of Disease (GBD) studies have highlighted increasing comorbidity levels and showed a strong association between age and multi-morbidity (Vos et al., 2015; Vos et al., 2016). It is not surprising that not only the number of such individuals are rising, but so is the complexity of caring for multi-morbidity patients as well as the requirement to organise integrated care services around such complex patients' needs (Prince et al., 2015). Current trends on population ageing and multi-morbidity clearly point that the care needs of populations will continue to evolve over time, creating additional pressures on health and social care systems.

The challenges of meeting increasing demand for care services is occurring against a backdrop of particularly tight budgets. This twofold setback has raised concerns in relation to the sustainability of existing care services and those services under design and evaluation aiming to meet the additional demands. The World Health Organization (WHO) defined sustainability as '*the ability to meet the needs of the present without compromising the ability to meet future needs*' (Roberts and WHO, 1998). Because of the possible mismatch between increasing demand and current levels of service provision, planners must consider options for care system transformation and assess the likely sustainability of such options (Maniatopoulos et al., 2020). By care system transformation we mean the large-scale changes (at local, regional or national level) aimed at coordinated, system wide change affecting multiple organisations and care providers (Best et al., 2012). Recent examples of large system transformations include the centralisation of stroke services in a number of metropolitan areas in England (Turner et al., 2016; Fulop et al., 2019), and the centralisation of specialist cancer surgery in London (Vindrola-Padros et al., 2020). The ultimate aim of these changes often is to improve the patient experience of care, the health of a population and reduce the per-capita cost of health care (IHI, The Triple Aim Initiative). However, care services are operating in a volatile environment (changing demographic structures, economic and political conditions, having to respond to influenza epidemics etc.), thereby potentially adding complexity to modelling attempts.

A number of modelling and simulation studies reported in the literature support care system transformation projects that offer alternative ways for patients to continue receiving high quality care (e.g. Abo-Hamad and Arisha, 2013; Ansah et al., 2013; Brailsford et al., 2004; Lane et al., 1998; Royston et al., 1999). A number of different modelling and simulation approaches are used to model the care system, including stochastic (Monte Carlo, discrete event simulation, and/or agent-based) and deterministic (e.g., system dynamics) methods (Pitt et al., 2016). Given that the choice of modelling methods depends on a range of factors, there are trade-offs to be considered within a particular project. Overall, the system dynamics approach appears to be more appropriate when decision-support needs are more strategic and long-term in nature, a situation which often necessitates a whole-system modelling perspective which spans across organisational boundaries (Brailsford and Hilton, 2001; Dangerfield, 2016; Ghaffarzadegan et al., 2011). Although the system dynamics method does not allow the user to capture individual patient level information, it does enable the analysis of the interactions between the system's components and an assessment of how these 'play out' over time under the effect of time delays and feedback mechanisms (Pitt et al., 2016; Sterman, 2000).

The system dynamics literature includes studies on the performance and sustainability evaluations of transformation of care systems (e.g., Esensoy and Carter, 2015; Lane and Husemann, 2008; Lyons and Duggan, 2015; Rashwan et al. 2015). However, the literature lacks a comprehensive approach which combines both population dynamics and patient flow in the organisation of health and care services. Partly with a view of addressing this knowledge gap, our study investigates the development of an integrated modelling approach as part of a study that explored the sustainability of an ambitious regional care system transformation project. To our knowledge, this is the first study to combine population dynamics and patient flow through the different parts of a regional care system.

In particular, we report on the construction of a system dynamics model which has a number of interacting components, including the dynamics of the local population, high-level aspects of elective (i.e. scheduled, planned patient arrival) and emergency care relating to all causes/conditions, and a care system transformation process designed for those patients who are heavy users of health care resources (defined in this study as complex cases). Having populated the model's input parameters with estimates from empirical data, including hospital patient activity records, we use the model to evaluate the likely impact of changes on system outcomes (e.g., number of admissions, readmissions, bed-day requirements) and to investigate the conditions under which the care system transformation can provide sustainable solutions within the local health economy. Our modelling aim was to provide the means to evaluate the initiative and test its sustainability from a systems perspective by capturing the influence of external dynamics and of the volatile environment of interacting factors.

The rest of this paper is organised as follows. Section 2 provides background information about the setting of this study (part of the National Health Service in England), while in section 3 we review the relevant literature and identify gaps in knowledge which inspired us to develop this study's modelling approach. In section 4, we detail the system dynamics model as well as the modelling process which was conducted in collaboration with healthcare partners. In sections 5 and 6, we first explain the model implementation process and present the results of our numerical experimentation. We conclude by highlighting the study's contribution to the literature, its practical implications, and its limitations. We also outline several directions for future research.

2. Background

Following this growing body of evidence on the rise of multi-morbidity and a renewed focus on those who are preventable (Newton et al. 2015), the National Health Service (NHS) in England has called for significant transformation in the way services are planned and delivered. As part of this effort, a nationwide transformation plan has been initiated with a number of hospital trusts chosen competitively to be the vanguards (see *New Care Models: Vanguards* (NHS, 2015)). Yeovil District Hospital NHS Foundation Trust (YDH), an NHS Trust providing acute care for a population of about 170,000 in the South West of England (Office of National Statistics, 2016), was one of the nine vanguard sites chosen to develop Primary and Acute Care Systems (PACS) with the aim of combining primary, secondary care and community and mental health services (NHS, 2015).

In particular, the South Somerset Symphony Programme (http://www.symphonyintegratedhealthcare.com/) was setup with the aim of developing a new service model for organising and delivering health and care services within the Trust's catchment area. This transformation programme is organised across a number of strands including designing a joint venture organisation between the local acute care hospital and local General Practitioners (GPs or family doctors) practices which will hold a single budget for the population and decide how to use local resources to deliver the best outcomes for patients.

Another strand of the programme aims to introduce and evaluate innovative ways of caring for those individuals in the community who are at high risk of hospitalisation. A study commissioned previously by the Trust, identified those as complex individuals with three or more conditions (or comorbidities) out of the following: diabetes, cardiac disease, chronic obstructive pulmonary disease (COPD), chronic kidney disease (CKD) or renal failure, depression or anxiety, dementia, stroke and cancer (Kasteridis et al., 2015). This group of individuals are also estimated to be the main cost generators in the care system (Kasteridis et al., 2015) due to their ongoing support need from multiple agencies in primary care. Following the study by Kasteridis et al. (2015) and before the commencement of our SD study, the partnering healthcare Trust had decided to use this definition of 'complex patient' as part of the health system transformation.

A number of interventions have been suggested for looking after those patients. These include the Enhanced Primary Care model, which incentivises GP practices to offer greater support for people with less complex conditions through health coaching; and Complex Care which offers intensive support for people with multiple conditions through a number of Complex Care Hubs. The patients registered with these Hubs benefit from senior medical support, care coordination, as well as a single personalised care plan and support to better manage their own conditions (Mears, 2015). Overall, the aim of the Complex Care team is to keep patients in their home, for as long as possible through integrating their care with all the agencies involved, and designing a plan for their care, that also takes into account patients' wishes. In this paper we focus on the latter hospital based intervention, the introduction of the of the Complex Care Hub as part of the whole care system.

From a broader perspective, the Complex Care Hub is a facilitator in a larger system and works interactively with the other departments of the hospital, where it is based, and the wider local health economy. It is also influenced by certain exogenous dynamics; namely, changes in the population structure, including ageing, and related changes in epidemiological conditions. Indicatively, the regional population's size in 2016 was 166,279, 25% of which comprised people over the age of 65, while people over 75 made up 11% of the total population (ONS, 2016). Compared with the national averages of such age groups, which are

18% and 8% respectively, the local population is thus relatively older. Projections for the upcoming years until 2037 also reveal that the annual compound growth rate of the over-65 populations is 1.95% compared with a 0.45% increase in total population in the county of South Somerset (Office of National Statistics, 2016). Thus, the proportion of over-65s will increase from 25% to 33% by the end of 2037. This situation raises a number of questions about the sustainability of current services under such dynamic circumstances.

3. Literature review

Demand for health and care services can be defined as a function of population dynamics and epidemiological trends (Soyiri and Reidpath, 2013). It is also influenced by the structure and capacity of the services on offer, one-off incidents such as epidemics and mass casualty events, and individuals' lifestyles and their awareness about their conditions (Forouzanfar et al., 2015). In addition, these factors evolve over time, making the problem of demand not only complex but also dynamic in nature. Thus, for the purpose of supporting policy development and intervention design and evaluation, the modelling approach should be able to capture these characteristics (Brailsford and Hilton, 2001; Pitt et al., 2016).

Over the last few decades, the system dynamics modelling approach has found fertile ground in the field of healthcare. It has been applied to a wide variety of study areas, ranging from the modelling of infectious diseases (Viana et al., 2014) to disease screening (Royston et al., 1999; Townshend and Turner, 2000) and the countrywide policy evaluation of long-term care options (Ansah et al., 2013). System dynamics was also used to conceptually explore the causes of emergency department congestion (Wong et al., 2012).

As part of this research project, we searched the literature for empirical healthcare system dynamics studies with the aim of supporting the reconfiguration of care systems and services through numerical experimentation. We also sought to identify whether the reported modelling studies include notions of sustainability in their analyses.

We found eight articles which meet our inclusion criteria. We have summarized these in Table 1 in accordance with three characteristics: a) whether population dynamics are captured by the model, b) the care system boundaries of the model (i.e. whether the model is designed for a regional hospital, a national health system and/or a specific specialty or disease group), and c) whether the study models any changes in the current patient pathway. The table illustrates the gap in the literature which our study addresses, thereby highlighting that our contribution presents the first system dynamics model to integrate population dynamics with the purpose of evaluating the likely impact of care system transformation at regional level.

Some of the studies are designed to carry out cost-benefit analysis: Homer et al. (2004), Maliapen and Dangerfield (2010). Those studies address monetary issues and they are not patient-centric.

Another major group of studies focus on supply-demand balance in healthcare systems. Lane et al. (1998) investigate the impact of operational level decisions such as bed-capacity and accident and emergency (A&E) staffing levels in a district hospital in London, whereas the rest of the studies listed in Table1 are more patient-centric and they address strategic level decisions. In particular, those studies explore the potential impacts of some new care models (i.e. service transfers: Taylor and Dangerfield, 2005; intermediary care services: Wolstenholme,1999) and other health care demand management policies, such as potential capacity expansions and flow rate interventions in acute and emergency care (Brailsford, 2004; Rashwan et al., 2015).

The study of Lyons and Duggan (2015) differs from the others by being the first to explicitly address notions of sustainability in a healthcare system. The authors present a system dynamics model of the Irish healthcare system in the face of increasing demand and an ageing population. The authors conclude that current resources are not sustainable for future demand over the time horizon of their study. They presented some options to achieve future sustainability goals, but introduced those by additional multipliers into the model; with no change in model flow structure.

A consensus seems to emerge from the literature that policies affecting patient flow rates constitute the most effective strategies, while capacity expansion is more typically associated with transient effects. The literature also highlights the risk of creating unexpected additional demand as a result of service transfer strategies. The studies we have mentioned so far have in common that they conducted empirical studies in either regional or national level, but the model structures have differed in terms of incorporating population dynamics and a change in patient pathway in the system (see Table 1). Thus, the literature contains little about comprehensive approaches which evaluate the sustainability of an intervention in secondary care while taking into account both population dynamics and changes in capacity, and patient flow through the care system. Our modelling study was designed to address this particular knowledge gap over a specific case in an NHS Trust.

<Table 1, near here>

4. Model conceptualisation and formulation

Under the auspices of a researchers-in-residence programme (Marshall et al., 2014) put in place between YDH and the University of Bath, a team of operational researchers worked in close collaboration with hospital managers and clinicians to support the implementation, improvement, and evaluation of the Complex Care Hub initiative. The aim was to provide the means to evaluate the initiative from a systems perspective by capturing the influence of external dynamics and of the volatile environment of interacting factors. For the reasons briefly explained in the Introduction, we chose to construct a system dynamics model that captures different components of the secondary care system.

To develop and refine the scope of the study, the modelling objectives and the structure of the model itself we held ~20 meetings with project stakeholders (board level directors and managers) over a period of 14 months (Jan 2016 – Feb 2017), including one-to-one and group meetings. During these meetings, we presented and solicited feedback on every aspect of the study, including the modelling assumptions and ensuring the face validity of the model. We supplemented the qualitative data collection with using anonymised routinely collected data on patient activity. This data was used to estimate some of the input parameter values used in the model.

As with any modelling study, several simplifying assumptions had to be made. The main assumptions are:

- Demand is generated solely from the regional population (in other words, any demand generated by neighbouring regions is disregarded).
- There is no specialty differentiation among hospital admissions, other than a separation of admission type: elective, non-elective, and readmissions.
- The hospital resource that determines the maximum number of inpatients is bed capacity; other resource limitations (e.g. levels of staffing or the availability of diagnostic machines) are not taken into account.
- Bed capacity is a bulk-sum resource unit for all types of admissions and is not disaggregated by wards or medical specialty.

Figure 1 presents a stock-flow diagram that, represents patient flow between the different components of the abstracted model of care which was used as the basis of the simulation experiments. The corresponding causal loop diagram is given in Appendix 1 (Supplementary Material) for integrity. <Figure 1, near here>

Patient flow in a secondary care system is characterized by five feedback loops: four balancing and one reinforcing. The modelled population is exogenous but dynamic, meaning that changes in population size and age structure over time are part of the model and influence its interacting variables. The demand rates for elective care (EC, also known as scheduled care) and non-elective care (NON-EC, also known as emergency care) are proportional to the regional population. However, the number of inpatients admitted to hospital is restricted by the available bed capacity, which is a function of the number of patients already admitted to hospital, length of stay and maximum bed capacity (i.e., number of beds) (B2, B3). Discharges from hospital (elective/non-elective) give room for new elective/non-elective admissions (B1, B4). Hospital admission rules stipulate that admissions of non-elective patients have priority over elective patients. The proportion of the demand that has not been met is recorded as "Unmet Demand". In the model, part of the non-elective demand is comprised of readmissions which, for the purposes of this study, are defined as non-elective admissions occurring within 30 days of hospital discharge (from either elective or non-elective care) (R1). The time delay for readmissions is depicted by two short parallel lines across the arrow stem in the diagrams (Figure 1 & Appendix 1, Supplementary).

As stated previously, we aimed to test the sustainability of a newly introduced care unit for complex patients with three or more comorbidities. A stock-flow diagram that represents patient flow in a secondary care setting with the Complex Care Hub incorporated are depicted in Figure 2. The corresponding causal loop diagram is included in Appendix 2 (Supplementary).

<Figure 2, near here>

In this model, the demand for elective and non-elective care arising from the Complex Care Hub patients is handled separately from the demand generated by the regional population, providing a new pathway through secondary care in line with the intervention. Moreover, patient flow within the model is disaggregated by patient group, age and sex. Patient group disaggregation is necessary for internal logic purposes, while age and sex disaggregation of patient flow allows us to capture the relevant population dynamics in the region in a meaningful way. Technically, this has an impact on how stock variables Complex Care Hub Patients and Regional Population as well as the auxiliary variables that these stock variables are linked with through a first order differential equation are implemented, see Figure 2 and Appendix 2 (Supplementary).

The main feedback structure of the patient flow in the secondary care setting is mainly preserved (i.e., loops B1, B2, B3, B4 and R1). Some additional feedback mechanisms characterizing the dynamic structure of Complex Care Hub (i.e., loops B5 and B6) are introduced along with a higher level of detail arising from the patient group and age/sex disaggregation.

Below, we first explain the disaggregation of population according to patient groups in the secondary care setting with Complex Care Hub. We then give details of the demand generation and admission process in such a healthcare system. We also explain how the dynamic nature of the Complex Care Hub is modelled via an ageing chain.

4.1 Patient groups

The main patient groups are defined as ‘Regular Population’, ‘Complex Care Hub Candidates’ and ‘Complex Care Hub Patients’. Those in the regional population who have three or more comorbidities among the qualifying conditions (Kasteridis et al., 2015) are potential candidates for the Complex Care Hub. However, not all such patients are clinically, or otherwise, deemed suitable candidates for admission to the hub. Those who are indeed deemed suitable are admitted to and have their care managed by the Complex Care Hub provided its capacity permits with the remaining eligible patients counted in the subcategory ‘Complex Care Hub Candidates’.

The disaggregation of population according to patient groups can be explained by the difference equations as follows:

Note that the unit of measurement for each variable is given in brackets, “< >”, to ensure the dimensional consistency.

$$\begin{aligned}
&People\ with\ 3^{+}\ Comorbidities\ [age, sex](t) < people > \\
&= (Regional\ Population\ [age, sex](t) < people \\
&> * \ 3^{+}\ Comorbidity\ Prevalence\ [age]) < dimensionless \\
&> -(Regional\ Population[age, sex](t) < people \\
&> * \ Proportion\ of\ 3^{+}\ Comorbidity\ People\ with\ No\ Need\ for\ Complex\ Care) \\
&< dimensionless >
\end{aligned} \tag{1}$$

$$\begin{aligned}
Complex\ Care\ Hub\ Candidates[age, sex](t) < people > \\
&= People\ with\ 3^{+}\ Comorbidities\ [age, sex](t) < people \\
&> -People\ Admitted\ to\ Complex\ Care\ Hub[age, sex](t) \\
&< people >
\end{aligned} \tag{2}$$

$$Regular\ Population\ (t) < people > = \sum_{sex}\sum_{age}(Regional\ Population\ [age, sex](t) < people > - Complex\ Care\ Hub\ Patients[age, sex](t) < people > - Complex\ Care\ Hub\ Candidates[age, sex](t) < people >) \quad (3)$$

4.2 Demand generation and admissions

The demand for elective care is determined by the linear combination of demand fractions and population sizes of a particular patient group.

$$Elective\ Demand[patient\ group](t) < people > = Population\ Size\ of\ Patient\ Group(t) < people > * Elective\ Demand\ Fraction[patient\ group] < dimensionless > \quad (4)$$

Where $Population\ Size\ of\ \ Patient\ Group(t)$ in equation (4) stands for number of patients in one of the tree patient groups: Regular Population, Complex Care Hub Candidates or Complex Care Hub Patients as illustrated in Figure 2 and Appendix 2 (Supplementary).

Demand for non-elective care is also calculated in the same fashion with an additional consideration for readmissions which are a function of patient group specific readmission fractions and number of patients discharged from either elective or non-elective care in the last 30 days.

$$Non\_Elective\ Demand[patient\ group](t) < people > \quad (5)$$

$$= Population\ Size\ of\ Patient\ Group(t) < people >* (Non\_Elective\ Demand\ Fraction[patient\ group]) < dimensionless > + \int_{t-30}^{t} \big((Discharge\ of\ Elective\ Inpatients[patient\ group] < people/time > + Discharge\ of\ Non\_Elective\ Inpatients[patient\ group] < people/time >) * Readmission\ Fraction[patient\ group] < dimensionless >\big)dt$$

Bed capacity is a common resource depleted by all admitted inpatients, so that different patient groups use up the same resource according to the priority rules that are defined for different patient groups and admission types (e.g., admitting non-elective patients before admitting elective patients if the capacity allows, or admitting 3+ comorbidity patients before admitting regular population). An illustrative example of the admission procedure in discrete time steps is formulated with the pseudo code presented in Appendix 3 (Supplementary).

Note that bed capacity is calculated in terms of bed-days. In other words, if there are *n* hospital beds available it will result in 30*n* bed-days of bed capacity per month (given that a month is 30 days long). For instance, a hospital with 100 beds can accommodate monthly 600 inpatients with 5 days of average length of stay using the following equation.

$$Maximum\ number\ of\ inpatients\ in\ a\ month < people > \quad (6)$$

$$= \frac{(Number\ of\ Beds\ x\ Number\ of\ Days\ in\ a\ Month) < bed - days >}{(Average\ Length\ of\ Stay) < days/people >}$$

Also note that non-elective patients are the emergency cases who need urgent treatment and in ideal scenario they have priority over all other patients.

In short, the structure of the model enables us to track the flows of different patient groups through the secondary care setting with their own fractions for elective care, non-elective care, readmissions, and length of stay (LOS). Moreover, it gives the opportunity to define different admission priority rules that are specific to admission type and patient groups.

4.3 Stock disaggregation and the ageing chain for complex care hub

The stock variable representing those who are treated under the Complex Care Hub is taken to be dynamic, with inflows and outflows, and is modelled as an 'ageing chain'. A representative visualization is given in Figure 3. The ageing chain is the system dynamics sub-model in which the total hub population is disaggregated into multiple categories (age groups) with external inflows and outflows from/to all age groups. In our case, the hub population is disaggregated into 1-year age groups and a younger age group 'graduates' (in terms of survival) to an older age group in accordance with age-specific survival fractions determined by life expectancy estimates in the corresponding ONS life tables. The external inflows to each age group are the new entrants by age (i.e., new patients who get under the control of the Complex Care Hub); the external outflows represent deaths by age group.

<Figure 3, near here>

As the model has been implemented with discrete time steps, the stock variable of an intermediate age group is given by the following difference equation:

$$Complex\ Care\ Hub\ Patients[age, sex](t+1) < people > \quad (7)$$
$$= Complex\ Care\ Hub\ Patients[age, sex](t) < people$$
$$> +Survival[age-1, sex](t) < people$$
$$> +People\ Admitted\ to\ Complex\ Care\ Hub[age, sex](t)$$
$$< people > -Survival[age, sex](t) < people$$
$$> -Death[age, sex](t) < people >$$

Inflows to an intermediary age group consist of new entrants to that age group together with those of the hub patients who have aged and come from the immediately prior age group. Outflows, on the other hand, are deaths and those of the hub patients who survive to the next age group.

Each age group's death and survival numbers are calculated by the population size and the predetermined death fractions which are derived from corresponding life tables (https://www.ons.gov.uk – National Life Tables):

$$Death[age, sex](t) < people > \quad (8)$$
$$= Complex\ Care\ Hub\ Patients[age, sex](t)$$
$$< people > * Death\ Fraction[age, sex]$$
$$< dimensionless >$$
$$Survival[age, sex](t) < people > \quad (9)$$
$$= Complex\ Care\ Hub\ Patients[age, sex](t)$$
$$< people > * (1 - Death\ Fraction[age, sex]$$
$$< dimensionless >)$$

where $Survival[age, sex](t)$ stands for the survival of one age group (i) to an older age group $(i+1)$ at time $t+1$.

Note under limited hub capacity the capacity allocation in the real care system is done in accordance with some priority rule; for example, older people first, younger people first, and people with higher patient activation measures (PAMs) first. Thus:

$$\sum_{sex}\sum_{age} People\ Admitted\ to\ Complex\ Care\ Hub[age, sex](t) < people > \tag{10}$$
$$= \min\left(\begin{array}{c} Available\ Capacity\ for\ New\ Entrants\ to\ the\ Complex\ Care\ Hub(t) < people >, \\ \sum_{sex}\sum_{age} People\ with\ 3^{+} Comorbidities[age, sex](t) < people > \end{array}\right)$$

Where

$$Available\ Capacity\ for\ New\ Entrants\ to\ the\ Complex\ Care\ Hub(t) < people >= Complex\ Care\ Hub\ Capacity < people > - \sum_{sex}\sum_{age} Complex\ Care\ Hub\ Patients[age, sex](t) < people > \tag{11}$$

Complex Care Hub capacity is denoted by the maximum number of people that can be managed by the hub. It is a strategic decision that is based on budget constraints and the number of health practitioners who are specialised in the care of complex patients.

Flows are different for the first and last age groups:

$$Complex\ Care\ Hub\ Patients[0, sex](t+1) < people > = Complex\ Care\ Hub\ Patients[0, sex](t) < people > + People\ Admitted\ to\ Complex\ Care\ Hub[0, sex](t) < people > - Death[0, sex](t) < people > - Survival[0, sex](t) < people > \tag{12}$$

$$Complex\ Care\ Hub\ Patients[90, sex](t+1) < people > = Complex\ Care\ Hub\ Patients[90, sex](t) < people > + Survival[89, sex](t) < people > + People\ Admitted\ to\ Complex\ Care\ Hub[90, sex](t) < people > - Death[90, sex](t) < people > \tag{13}$$

Overall, we have set out the model dynamics in such a generic way so as to provide a flexible environment for the users to implement different priority rules among different patient groups under the effect of population ageing on the system. In our implementation, admissions to non-elective and elective care services are prioritised as follows: Complex Care Hub patients first, followed by patients Complex Care Hub candidates, and then regular population.

5. Model implementation

5.1 Model coding

The model we present in this study is complex in nature and it becomes ever more so when details of age, sex, and patient groups are introduced. Capturing such detail requires extensive stock disaggregation which increases the number of variables in the model, which in return creates a computationally challenging situation. For that reason, we have found it more efficient to implement the model and conduct the numerical experimentations on a programming language platform, which in this case is Python 2.7.11. Although the common practice is to use purpose specific software, the use of programming languages has been recently introduced in the field of system dynamics (Duggan, 2018; Duggan, 2019; Dural-Selcuk et al., 2019). Our choice of implementation platform provided us with the flexibility to work with a higher level of granularity and the opportunity to demonstrate that it is feasible to work with a large number of stock disaggregation within the SD modelling paradigm.

While the model was coded in Python (available on https://github.com/gozdemds/Complex-Care-Hub.git), we used Vensim (https://vensim.com/) to produce the diagrams shown in Figures 1, 2 and 3 and in Appendices 1 and 2 (Supplementary).

5.2 Model validation

Model validation is a sequential procedure, starting with structure tests and followed by structure-oriented behaviour tests and finally behaviour reproduction tests (Barlas, 1996). Our study was designed to support a transformation project by evaluating potential impacts of service transformation which had just been introduced (or, were about to be introduced). As a result, it was not feasible to validate model output against historical data or even compare the resemblance of model behaviour against historical trends. Despite these challenges, we were able to increase confidence in the results by conducting conventional structural validity tests (e.g., structure/parameter confirmation, extreme condition test, dimensional consistency, boundary adequacy, etc.). In complex whole-system models as is the case with our study, working in close collaboration with problem owners and policy implementers is a common practice to increase confidence in model validity (Esensoy and Carter, 2018). In this project, we had the opportunity to do just this, revising and finalising the model design as part of an iterative process through a number of meetings with managers and clinicians. As a result, they were involved both in designing the conceptual model and the numerical experimentation phases. We consulted with and informed them about the model's scope, boundaries, assumptions and limitations. We also consulted with them in relation to the scenarios.

5.3 Model calibration

In order to calibrate the baseline version of the model, we derived a number of estimates using a combination of publicly available sources and secondary, routinely collected data obtained from the hospital partner, Appendix 4 (Supplementary).

The simulation time window was between January 2014 and December 2037 in line with the available official population statistics. It is a common practice to conduct sustainability studies over long periods of time in order to evaluate the effectiveness of the interventions for the following generations (Shediac-Rizkallah and Bone, 1998; Nilsen et al., 2005 and Pammolli et al., 2012). The smallest time step in the simulation was one month providing a good compromise between the fidelity of modelling results and computational demands. The choice of a month as the smallest time step also provided the required granularity to observe seasonality within a year while making it easier, from an end user perspective, to populate it with input parameter values that are typically reported on a monthly basis. On the other hand, age structures in the model were modelled on yearly basis, as life tables used in calibration provide death fractions in one-year age brackets. In similar fashion, we coded the capacity allocation in relation to the hub to be revised yearly. Given that length of stay of inpatients is recorded in days, the method we used to convert lengths of stay (in days) to monthly bed-day requirements and monthly admissions is provided in section 4.2.

In summary, the following time units were used in the model:

- Bed capacity use and inpatient admissions (monthly);
- Ageing of Complex Care Hub patients (yearly);
- Complex Care Hub capacity allocation (yearly).

6. Numerical results

We conducted a series of numerical experiments to explore the likely impact of the transformation and its likely effects on the wider system. Four of these scenarios are presented here for illustrative purposes. We quantified the impact in terms of the number of admissions and bed-day requirements. Different scenarios were constructed with the main goal of undertaking a comparative analysis between scenarios with and without the Complex Care Hub, and with different Hub capacities (i.e., variable over time and fixed capacity through the planning horizon) (see Table 2). Note that all input parameters are used as it has been reported in Appendix 4 (Supplementary) unless otherwise is stated in scenario analysis.

<Table 2, near here>

In the first three scenarios, we used the total number and types of admission as the performance metric. In the fourth scenario, we used bed-day requirements to understand the likely effect of the Hub on hospital-wide resource use (i.e., bed requirements). We conceptualised the theoretical bed capacity as unlimited and aimed to observe how far demand goes beyond the limits. We also conducted a sensitivity analysis to gain further insights about the sustainability of the Hub in the medium and long term.

6.1 Baseline scenarios

Population ageing is one of the main factors that drive the increase in demand for healthcare services. Accordingly, we first observed the effect of changes in the population's age structure on the prevalence of people with 3+ comorbidities who need complex care treatment. The number of people in need of complex care treatment increases to more than 8000 patients by 2037 from a baseline of approximately 5400 patients in 2014. This increase corresponds to a 1.2% absolute increase in the 3+ comorbidity prevalence rate from 3.3% to 4.5%. In this sense, the need to evaluate the sustainability of the current and proposed care system transformation in a volatile environment is again identified.

Assuming that there are no capacity constraints and no Complex Care Hub, we calculated future theoretical (unfettered) demand in terms of monthly hospital admissions and monthly bed-day requirements, given the changing population dynamics. We then ran the same experiment with the Complex Care Hub in place, again assuming no capacity constraints (i.e., unlimited capacity for the Hub). We also looked at the case where Complex Care Hub is in charge with variable capacity over time with incremental increases of 500 patients per year, starting from 500 to 4500. The comparative results of these three experiments are illustrated in Tables 3 and 4.

The average number of hospital admissions per month in the model increased by **39%** from 2014 to 2037 (i.e., from **2147** patients per month to **2980**) (see Table 3) in the scenario of no Complex Care Hub in place. In addition to the headline increase in demand, the composition of patients changed dramatically, with a higher percentage of admissions for those with 3+ comorbidities (see Table 4). Specifically, in 2014, approximately two in every three hospital admissions were patients with 3+ comorbidities; by 2037, this figure was three in every four. There is no significant change observed in the elective vs. non-elective distribution.

<Table 3, near here>
<Table 4, near here>

When we introduced the Complex Care Hub with unlimited capacity to the baseline scenario with unfettered demand (Scenario 2), the total number of admissions decreased. However, the balance between non-elective and elective patients changed too with a higher proportion of non-elective patients reaching up to 83% in 2037 (see Table 3). This counterintuitive outcome was due to the very high readmission rates of hub patients (see Appendix 4, Supplementary). Recall there is a reinforcing loop between discharges and readmission, that is, readmissions feed into the non-elective demand and discharge of non-elective cases again results in higher number of patients coming back to hospital with a high chance of readmission.

When we look at the case where Complex Care Hub is in charge with a variable capacity that increases from 500 to 4500 with yearly increments of 500, which is a realistic scenario indeed, we observe slight declines in number of admissions and almost no change in elective-care and non-elective care proportions compared to Scenario 1.

In the scenario 2, the results also highlight that most admissions are complex patients regardless of admission type, i.e. elective, non-elective, readmissions (see Table 4). High proportions of complex and non-elective patients act as a driving force for higher demand for hospital resources. The effect of this likely change in patient case mix results in the mean monthly bed-day requirement to set around the theoretical hospital capacity (**10584**) in year 2014, but increase up to **16358** by 2037. Despite a lower number of admissions, a high proportion of non-elective and complex patients generated more demand for hospital resources. That said, the introduction of the complex care hub seems to inflate the use of hospital resources by a particular group of patients, namely the complex care hub patients. However, in scenario3, the results display a moderate level of mean monthly bed-day requirements, e.g. **9386** in 2014 and **12738** in 2037 (Table 3). In that case, the outcomes are significantly different in terms of the contribution of patients with 3+ comorbidities, such that the inflation effect of the hub is suppressed by its capacity limitation. By this means, the complex care hub seems to work as a facilitator in the whole system in the setting of Scenario 3.

In order to examine the incremental influence of changing demand composition on the wider system in the context of the Complex Care Hub, we also experimented with different capacity levels for the Hub, i.e. 500, 1000, 1500, 2000, 3000, ..., 10000 (i.e. Scenario 4).

In scenarios 3 and 4, we assumed a priority rule of ‘oldest first’ to calculate the number of 3+ comorbidity patients who are admitted to the Complex Care Hub (as long as capacity permits). For those patients eligible for but unable to be admitted to the Hub, they are added to patient group Complex Care Hub Candidates. That limiting assumption gives way to underrepresentation of younger age groups in the special care offered by the Complex Care Hub (Figure 4, Scenario3).

<Figure 4, near here>

In scenario 4, we quantified likely impact in terms of monthly bed-days required to meet the entire demand (Figure 5). We hereby present maximum, mean and minimum monthly bed-day requirements observations throughout the entire simulation horizon . We found that all three quantities have a non-decreasing trend with increasing hub capacity. That is, the higher the capacity of the Hub the higher use of hospital resources by complex care patients, leaving increasingly less available resource for the needs of regular population. We scrutinised this finding by observing unmet demand proportions under the assumption of limited bed capacity and displayed the monthly mean values over years with a heat map for three levels of hub capacity 500, 1000 and 1500 respectively (Figure 6). In the short term, the current capacity is not able to meet the elective demand arising from the regular population, even in the case where hub capacity is restricted to 500 patients. As the hub capacity increases unmet demand proportions gets higher and starts to lag behind the needs of the complex care elective patients as well. The simulation results highlight the strategic value to test the circumstances under which the introduction of the hub could help the whole system work within certain capacity limits and against a backdrop of increasing demand.

<Figure 5, near here>

<Figure 6, near here>

6.2 Sensitivity analysis

We conducted a series of sensitivity analysis experiments using the baseline model with Hub (capacitated) and unfettered demand in terms of monthly hospital admissions and monthly bed-day requirements. Sensitivity analysis can be performed using various methods depending on the complexity of the model and study objectives (Robinson, 2004). We opted for a one-way (univariate) sensitivity analysis where the value of only one parameter is systematically varied (through increases and/or decreases in its original value) and all other parameter values remained unchanged. Following discussions with the healthcare collaborators and the preliminary results presented in the preceding section, we focused the sensitivity analysis around Complex Care Hub patients' readmission fractions, LOS values and different levels of Hub capacity. As output measures, we used the mean and maximum monthly bed-day requirements. The study design for sensitivity analysis is reported in Table 5. The results are summarized in Figure 7 and Tables 6-7.

<Table 5, near here>

Note that for the sensitivity analyses with respect to Hub patient readmission fraction, we studied within the range between 10 and 38% with 2 percent point increments. We assumed that the hub's capacity is limited to 1500 patients, which was the initial target capacity in the ongoing pilot (Case 1 in Table 5).

The mean bed-days required per month decreased in line with decreases in the readmission fractions for hub patients. However, we found that the number of bed-days required per month is not very sensitive to changes in readmission fractions. When the fraction decreased from 38% to 10%, the bed-day requirement declined by a maximum of 7%, although this still exceeded the nominal target for a fixed capacity of 10500. In addition, as the non-linear nature of the two curves in Figure 7 shows, the marginal rate of change in max and mean number of bed-days is declining as the readmission fraction drops.

<Figure 7, near here>

The preliminary results showed that the number of bed-days per month increases against declining number of admissions, which is the result of a higher proportion of complex, i.e. resource consuming, patients in the system. Thus, we expect the bed-day requirement would be more sensitive to LOS for hub patients. If LOS is decreased from eight days to four, the percentage decline in the monthly bed-day requirement is approximately 11.5%, resulting in a lever of capacity provision which is close to the nominal target of 10500 bed-days, Table 6 (Case 2 in Table 5).

<Table 6, near here>

Lastly, we constructed a sensitivity design to evaluate Hub capacity when the mean LOS is fixed at four days and the readmission fraction for hub patients is 20% (instead of eight days and 38% respectively) (Case 2 in Table 5). These values were set after consulting with project partners. The main underlying criteria were that it is a reasonable target to achieve and substantially improves the resource needs. Accordingly, we observed the bed-day requirements with respect to different hub capacities ranging between 500 and 4500, which are the initial and the possible long-term targets associated with this project, Table 7.

<Table 7, near here>

Hub capacity and the bed-days required per month have an inverse relationship under the ideal conditions of lower LOS (i.e., four days) and lower readmission fractions (i.e., 20%). When the hub capacity is set at 4500 patients, the mean bed-day requirement per month is below the current capacity level, whereas the maximum number of bed-days required per month is still above the current capacity level. These results support our insight that the Complex Care Hub could be a viable facilitator of the whole care system if and only if it is operating within certain target ranges of parameter values.

7. Discussion and conclusions

In this study, we developed a system dynamics model which takes into account the changing regional population structure to help evaluate the sustainability of suggested transformations in the way care services are organised and delivered. Employing a system dynamics approach enabled us to explore the likely spill over effects from a systems perspective rather than evaluate the impact of suggested changes in isolation.

We chose to use an off-the-shelf systems dynamics software package (Vensim) for the diagrammatic component of the modelling process. The user-friendly interface of the software package eased our communication with project partners, especially at the early and intermediate stages of the project. At the same time, the use of ageing chains and disaggregation of stock variables by patient, age and sex groups increased the computational complexity and the number of variables in the model. For these reasons, we opted for a programming language platform (Python) to implement the model and run the computer simulation experiments. Using Python provided us with the flexibility to accommodate age-specific flows and carry out the repetitive calculations in a computational efficient manner.

Most healthcare systems in the developed world operate increasingly in areas where the population is ageing. Because there is a positive relationship between the number of comorbidities and age, we observed that changes in the age structure inevitably lead to increases in the prevalence of individuals with a number of significant comorbidities. Given that this population subgroup is known to be a key driver of demand for health and care services (Kasteridis et al., 2015), it is unsurprising that we also observed an increase in the number of related admissions. Partly as a response, a different patient pathway and service for those with 3+ comorbidities, the Complex Care Hub, was designed by healthcare planners and modelled in this study. However, preliminary empirical data suggested that although current hospital admission rates are low for such patients, the ratio of non-elective vs. elective care and hospital readmission rates are somewhat higher than those for other patient groups. Moreover, patients who are served by the Complex Care Hub appear to have the longest LOS among all the patient groups. In contrast, our modelling results show that the introduction of the Complex Care Hub in the care system resulted in fewer hospital admissions over time but a higher proportion of non-elective cases. When we investigated the effect of the change in demand composition on general bed-capacity use, we found very high levels of bed requirements beyond the current capacity and a non-decreasing trend with respect to higher levels of hub capacity.

Computer simulation results also revealed that the introduction of a Complex Care Hub may overemphasise the needs of Complex Care Hub patients, leaving less or no room for the other groups of patients. The Complex Care Hub, however, was designed with the aim of having a stabilising effect on increasing demand and limited resources. Limiting the capacity of Complex Care Hub equalises the aforementioned inflation effect on hospital needs of a certain group of patients, however, with a restriction of letting only elderly patients to have the specialised service, leaving the other patients with 3+ comorbidities outside the new care pathway, which may create relatively poor health conditions that we cannot account in the scope of this study.

In general, experimenting with the model showed that the critical parameters which are likely to influence the Complex Care Hub's effectiveness and sustainability in the long run are hospital readmission fractions and length of stay for those complex patients who are treated in the hub. This insight has practical implications, insofar that healthcare managers should invest effort in collecting quality data related to these performance indicators, actively monitor any changes over time and consider intervening if certain limits were to be exceeded.

As with any modelling study, the reported results and insights are subject to a number of assumptions, simplifications, and limitations. The assumptions and simplifications which were used in the modelling process have been reported extensively throughout the study (see section 4 for example). In terms of limitations, the lack of performance data regarding the new care system was one of the challenges we faced. For example, we did not know how much of an impact the Complex Care Hub may have on hospital admissions when it is fully operational as it had only been in place for a short period of time and operating with a small number of patients. However, given that this is often the raison d'être of modelling exercises, we believe this limitation is not particularly restrictive. The lack of an operational system at the time of the study also meant that it was not feasible to validate model output against actual historical data. This is a challenge faced often by modellers, which we overcame by frequent engagement with the healthcare partners with the aim of communicating and discussing the various assumptions used in the model as well its interim and final results. By having the assumptions of the model explained, interrogated and confirmed throughout the modelling process, we ensured the model’s face validity (whether the model appears to be a plausible representation of reality) was tested not only by the modelling team but also the healthcare collaborators.

We also make the implicit assumption that there will be no other major changes over the long time horizon of our simulation experiments. Although this will, in all certainty, not be the case in real life, nevertheless, our results can still be used to inform decisions about the sustainability of different transformation options on the basis of ‘current trends. Should underlying trends change in the future, the model’s input parameter values and/or structure can be adjusted accordingly and the simulation experiments run again. Such model re-use is further facilitated by the fact that our modelling is open source and has been made widely available.

Another limitation is related to the age-specific survival fractions that are used for the aging-chain modelling of complex care hub patients. The assumption that survival fractions are age-dependent rather than number of comorbidities is necessitated by the kind of data that is available and the ability to realistically capture the risk of death at such a granular level with one-year age brackets. However, a further study may focus on applying different survival fractions to different patient groups by taking into account their health conditions. Finally, we did not capture the consequences of unmet elective demand and its potential impact on patient outcomes, including quality of life and mortality, and system parameters such as increased emergency admissions.

A number of practical implications and opportunities for further research have arisen from our modelling study and the results. First, the hospital readmission fraction is critical in the successful operation of the care system with a hub managing the care of those patients with complex care needs. Planners, healthcare managers and clinicians need to be conscious of this, actively and purposely collect the necessary data, and continuously monitor any fluctuations in practice. Second, early empirical analysis suggests that hospital length of stay of those complex care hub patients who are admitted either on an elective or non-elective (emergency) basis is long. Our results suggest that longer lengths of hospital stay could impact on any efficiency gains made by the introduction of the hub. More empirical research is needed to confirm whether these patients indeed experience longer lengths of stay as compared to other patients with increased needs and the reasons behind this phenomenon. Finally, our modelling results also suggest that any increase in the capacity to admit patients to the complex care hub when not associated with a low readmission fraction and hospital length of stay once these patients need to be admitted to hospital (keeping within range), will negate any gains arising from the operation of the complex care hub.

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Table 1 Summary of the empirical system dynamics literature on the reconfiguration of care systems and services

Article	**Are population dynamics included?**	**Care system boundaries**	**Does the model represent a change in a patient pathway?**
Lane et al. (1998)	No	A regional hospital	No
Wolstenholme (1999)	No	National health-care system	Yes
Brailsford et al. (2004)	No	A regional health-care system	No
Homer et al. (2004)	Yes	A regional hospital/specific specialities	No
Taylor and Dangerfield (2005)	No	A regional hospital	Yes
Maliapen and Dangerfield (2010)	No	A regional hospital	Yes
Lyons and Duggan (2015)	Yes	National health-care system	No
Rashwan et al. (2015)	No	National health-care system	No

Table 2 Experimental scenarios

Scenario no.	Complex Care Hub	Hub capacity	Bed capacity	Observed metrics
1	No	N/A	Unlimited	Admissions & Bed-days per month
2	Yes	Unlimited	Unlimited	Admissions & Bed-days per month
3	Yes	Variable with incremental increases (Initially 500 and increases up to 4500 with yearly increments of 500)	Unlimited	Admissions & Bed-days per month
4	Yes	Fixed at different values (i.e. 500, 1000, 1500, 2000, 3000, .., 10000)	Unlimited	Bed-days per month

Table 3 Mean monthly hospital admissions and mean monthly bed-day requirements (unfettered demand) without (Scenario 1) , with Complex Care Hub (Scenario 2) and Complex Care Hub – Variable Capacity

	Without the Complex Care Hub (Scenario 1)		**With the Complex Care Hub - Unlimited Hub Capacity (Scenario 2)**		**With the Complex Care Hub – Variable Hub Capacity (Scenario 3)**	
	2014	**2037**	**2014**	**2037**	**2014**	**2037**
Mean monthly admissions	2147	2980	1891	2629	2094	2481
Elective-Care proportion in admissions	24%	23%	19%	17%	24%	22%
Non-Elective care proportion in admissions	76%	77%	81%	83%	76%	78%
Mean monthly bed-day requirements	9462	14045	10584	16358	9386	12738

Table 4 The proportion of hospital admissions for patients with 3+ comorbidities without (Scenario 1), with Complex Care Hub– Unlimited Hub Capacity (Scenario 2) and with Complex Care Hub – Variable Hub Capacity (Scenario 3)

Years	**Total Admissions**			**Elective Care**			**Non-Elective Care**			**Readmissions**		
	With out	**With**	**With – Var. Cap.**	**With out**	**With**	**With – Var. Cap.**	**With out**	**With**	**With – Var. Cap.**	**With out**	**With**	**With – Var. Cap.**
2014	68%	64%	63%	51%	30%	47%	74%	72%	68%	72%	84%	68%
2037	74%	71%	40%	59%	37%	33%	79%	78%	42%	78%	89%	46%

Table 5 Univariate Sensitivity Analysis Design

Case no.	**Complex Care Hub Capacity**	**Parameter changed**	**Range of change**	**Increment of change**	**Bed capacity**	**Observed metrics**
1	Fixed - 1500	Readmission Fraction for Hub Patients	10%-38%	2 percent points	Unlimited	Bed-days per month
2	Fixed - 1500	Length of Stay for Hub Patients	4-8	1 day	Unlimited	Bed-days per month
3	Variable	Hub Capacity	500-4500	500 patients	Unlimited	Bed-days per month

Table 6 Summary table for sensitivity analysis on LOS for patient in the Complex Care Hub (figures rounded to the nearest ten)

Readmission fraction(hub patients)=38%; **LOS(hub patients) ∈ [8-4 days]**; Hub capacity= 1500 patients (Case 2 in Table 5)					
LOS(hub patients) in days	**8**	**7**	**6**	**5**	**4**
Max bed-days	15660	15230	14810	14380	13960
Mean Bed-days	12180	11820	11470	11120	10770

Table 7 Summary table for sensitivity analysis on Hub Capacity (figures rounded to the nearest ten)

Readmission fraction(hub patients)=20%; LOS(hub patients)=4; **Hub capacity ∈ [500-4500 patients]** (Case 3 in Table 5)									
Hub Capacity	**500**	**1000**	**1500**	**2000**	**2500**	**3000**	**3500**	**4000**	**4500**
Max bed-days	14380	14020	13650	13280	12920	12550	12180	11830	11450
Mean Bed-days	11310	10880	10450	10020	9600	9170	8740	8310	7880

List of figures

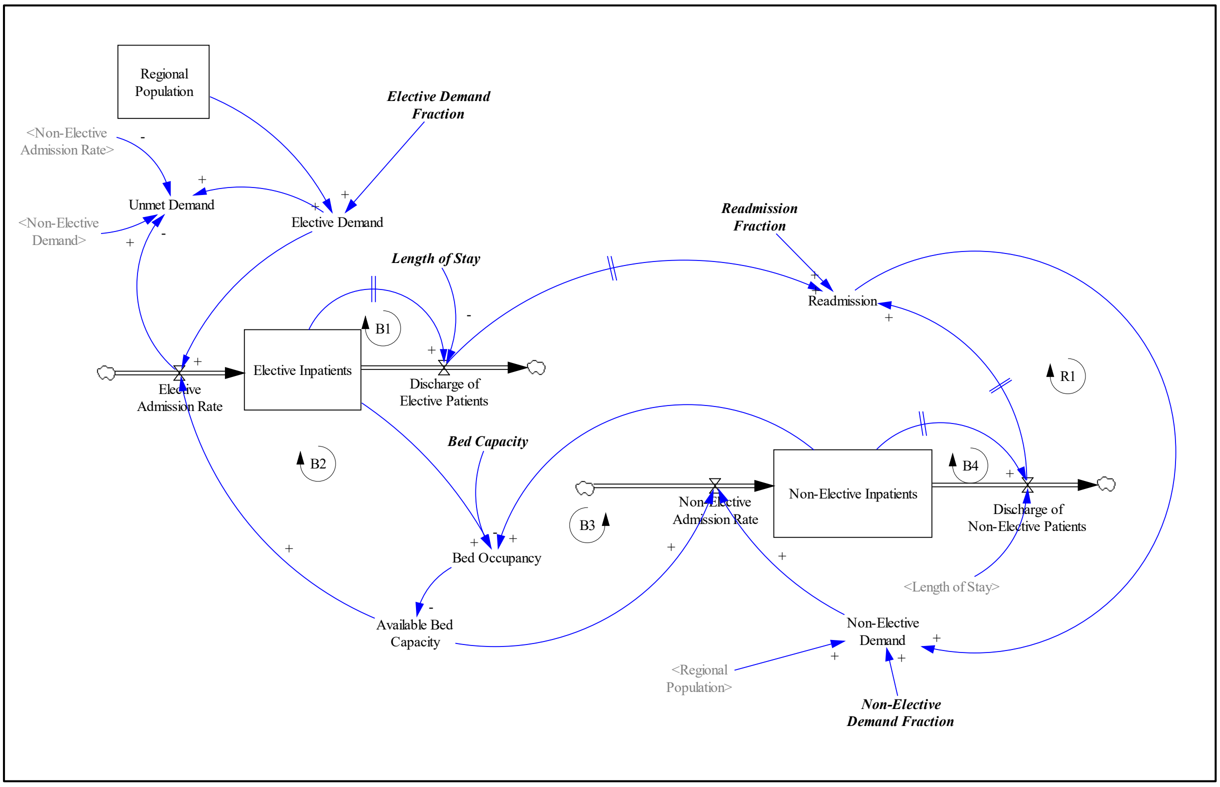


Figure 1 Stock-flow diagram of patient flow in a secondary care setting

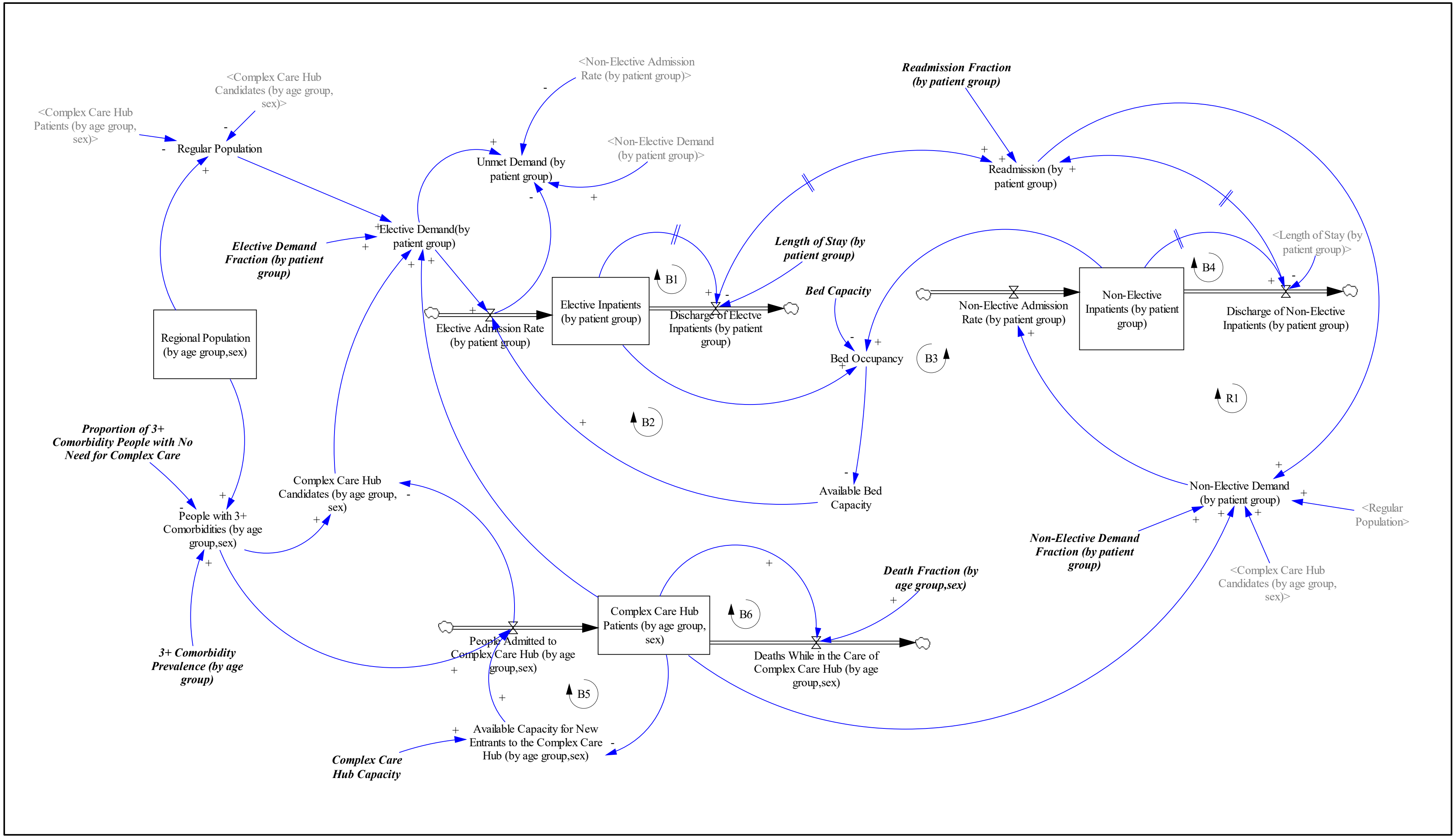


Figure 2 Stock-flow diagram of patient flow in a secondary care setting with Complex Care Hub

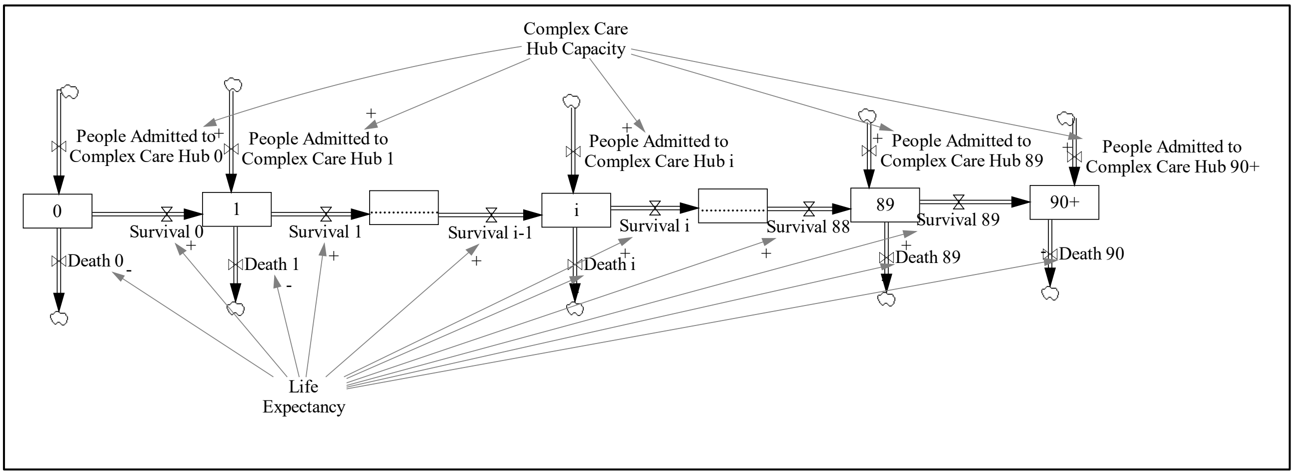


Figure 3 Stock-flow diagram of the hub population's ageing chain

Each rectangle in the figure represents Complex Care Hub Patients by age group i, where $i \in \{1,2,3, \dots, 89, 90^{+}\}$

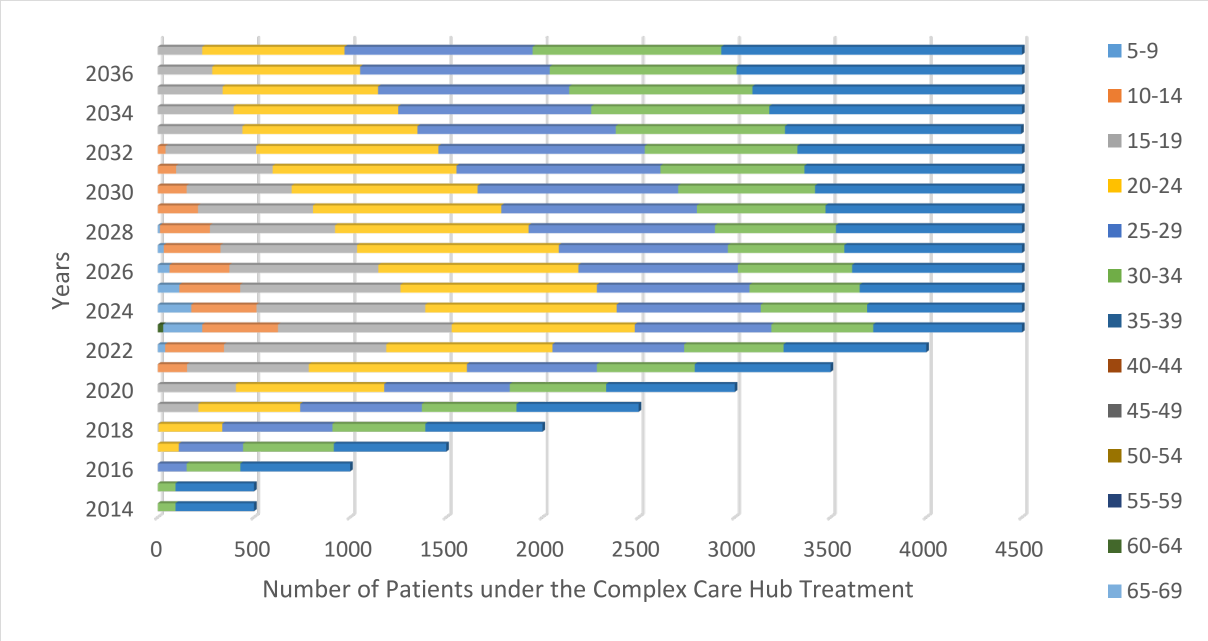


Figure 4 Age Distribution of Patients under the Complex Care Hub Treatment with Variable Hub Capacity with incremental increases of 500 patients per year, starting from 500 to 4500 (Scenario 3)

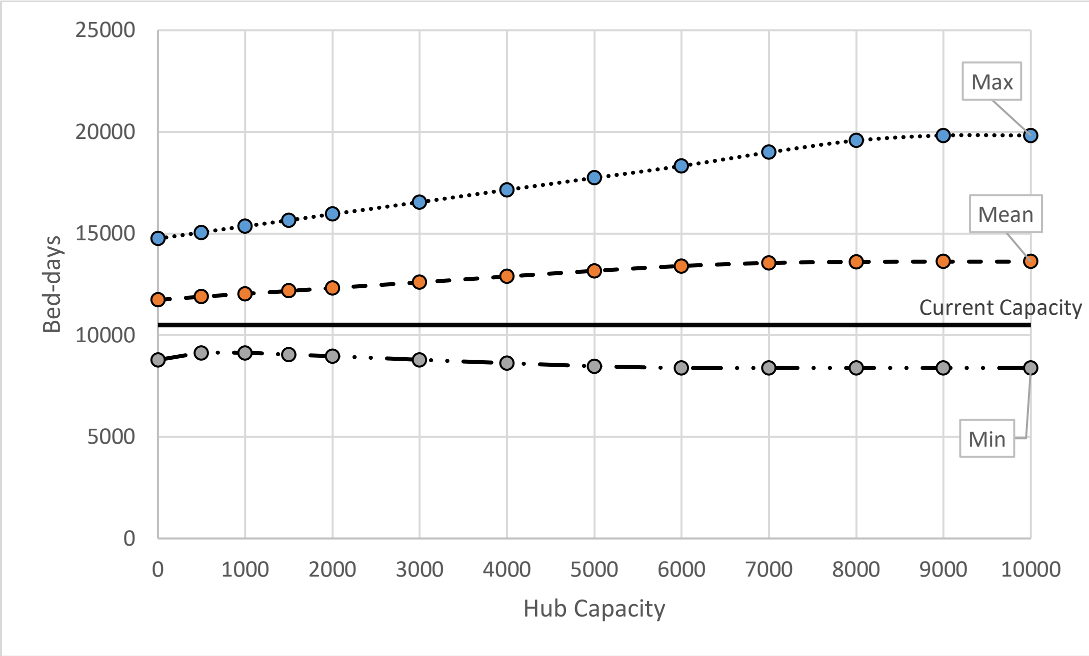


Figure 5 Mean, maximum and minimum number of bed-days per month with respect to changing Complex Care Hub capacities

Patient, Admission Type	Complex Care Hub Capacity = 500						Complex Care Hub Capacity =1000						Complex Care Hub Capacity =1500					
	Non-Elective Hub Patients	Non-Elective Hub Candidates	Non-Elective Regular Patients	Elective Hub Patients	Elective Hub Candidates	Elective Regular Patients	Non-Elective Hub Patients	Non-Elective Hub Candidates	Non-Elective Regular Patients	Elective Hub Patients	Elective Hub Candidates	Elective Regular Patients	Non-Elective Hub Patients	Non-Elective Hub Candidates	Non-Elective Regular Patients	Elective Hub Patients	Elective Hub Candidates	Elective Regular Patients
2014	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2015	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	6.14%	0.00%	0.00%	0.00%	0.00%	0.00%	2.88%
2016	0.00%	0.00%	0.00%	0.00%	0.00%	3.62%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	6.42%
2017	0.00%	0.00%	0.00%	0.00%	0.00%	7.36%	0.00%	0.00%	0.00%	0.00%	0.00%	5.01%	0.00%	0.00%	0.00%	0.00%	0.00%	3.06%
2018	0.00%	0.00%	0.00%	0.00%	0.00%	8.03%	0.00%	0.00%	0.00%	0.00%	0.00%	5.27%	0.00%	0.00%	0.00%	0.00%	0.00%	27.11%
2019	0.00%	0.00%	0.00%	0.00%	0.00%	15.18%	0.00%	0.00%	0.00%	0.00%	0.00%	22.75%	0.00%	0.00%	0.00%	0.00%	0.00%	28.79%
2020	0.00%	0.00%	0.00%	0.00%	0.00%	36.62%	0.00%	0.00%	0.00%	0.00%	0.00%	49.22%	0.00%	0.00%	0.00%	0.00%	0.00%	38.85%
2021	0.00%	0.00%	0.00%	0.00%	0.00%	21.51%	0.00%	0.00%	0.00%	0.00%	0.00%	82.95%	0.00%	0.00%	0.00%	0.00%	7.40%	40.96%
2022	0.00%	0.00%	0.00%	0.00%	0.00%	78.29%	0.00%	0.00%	0.00%	0.00%	0.00%	63.10%	0.00%	0.00%	0.00%	0.00%	8.23%	94.87%
2023	0.00%	0.00%	0.00%	0.00%	0.00%	95.92%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
2024	0.00%	0.00%	0.00%	0.00%	0.00%	99.56%	0.00%	0.00%	0.00%	0.00%	7.52%	100.00%	0.00%	0.00%	0.00%	0.00%	7.64%	100.00%
2025	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	8.22%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
2026	0.00%	0.00%	0.00%	0.00%	6.90%	100.00%	0.00%	0.00%	0.00%	0.00%	7.22%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
2027	0.00%	0.00%	0.00%	0.00%	7.58%	100.00%	0.00%	0.00%	0.00%	0.00%	7.91%	100.00%	0.00%	0.00%	4.38%	7.91%	28.81%	100.00%
2028	0.00%	0.00%	0.00%	0.00%	15.20%	100.00%	0.00%	0.00%	0.00%	0.00%	7.35%	100.00%	0.00%	0.00%	6.16%	0.00%	54.96%	100.00%
2029	0.00%	0.00%	0.00%	0.00%	14.79%	100.00%	0.00%	0.00%	3.99%	8.01%	30.78%	100.00%	0.00%	0.00%	11.40%	0.00%	56.58%	100.00%
2030	0.00%	0.00%	0.00%	0.00%	16.06%	100.00%	0.00%	0.00%	5.78%	0.00%	46.23%	100.00%	0.00%	0.00%	5.19%	0.00%	57.84%	100.00%
2031	0.00%	0.00%	3.34%	7.69%	52.98%	100.00%	0.00%	0.00%	10.57%	0.00%	63.01%	100.00%	0.00%	0.00%	6.71%	0.00%	80.86%	100.00%
2032	0.00%	0.00%	5.11%	0.00%	54.77%	100.00%	0.00%	0.00%	5.00%	7.94%	96.32%	100.00%	0.00%	0.00%	15.28%	0.00%	97.55%	100.00%
2033	0.00%	0.00%	10.10%	0.00%	88.56%	100.00%	0.00%	0.00%	10.75%	0.00%	98.62%	100.00%	0.00%	0.00%	14.35%	0.00%	99.56%	100.00%
2034	0.00%	0.00%	9.66%	0.00%	90.29%	100.00%	0.00%	0.00%	24.91%	0.00%	99.90%	100.00%	0.00%	0.00%	44.88%	0.00%	100.00%	100.00%
2035	0.00%	0.00%	33.61%	0.00%	98.63%	100.00%	0.00%	0.00%	35.10%	0.00%	100.00%	100.00%	0.00%	0.00%	47.00%	57.61%	100.00%	100.00%
2036	0.00%	0.00%	47.16%	39.81%	99.36%	100.00%	0.00%	0.00%	41.41%	0.00%	100.00%	100.00%	0.00%	0.00%	58.12%	100.00%	100.00%	100.00%
2037	0.00%	0.00%	56.17%	8.33%	100.00%	100.00%	0.00%	0.00%	82.69%	0.00%	100.00%	100.00%	0.00%	0.00%	89.46%	100.00%	100.00%	100.00%

Figure 6 Heat map for unmet demand over time (years), for different types of patient and capacities associated with the Complex Care Hub

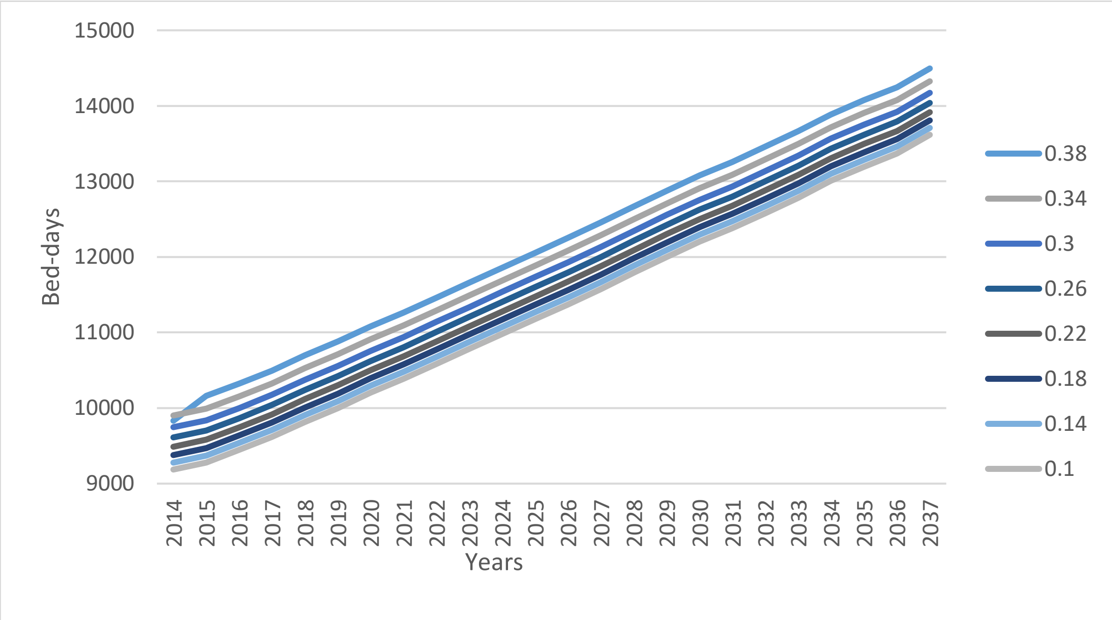
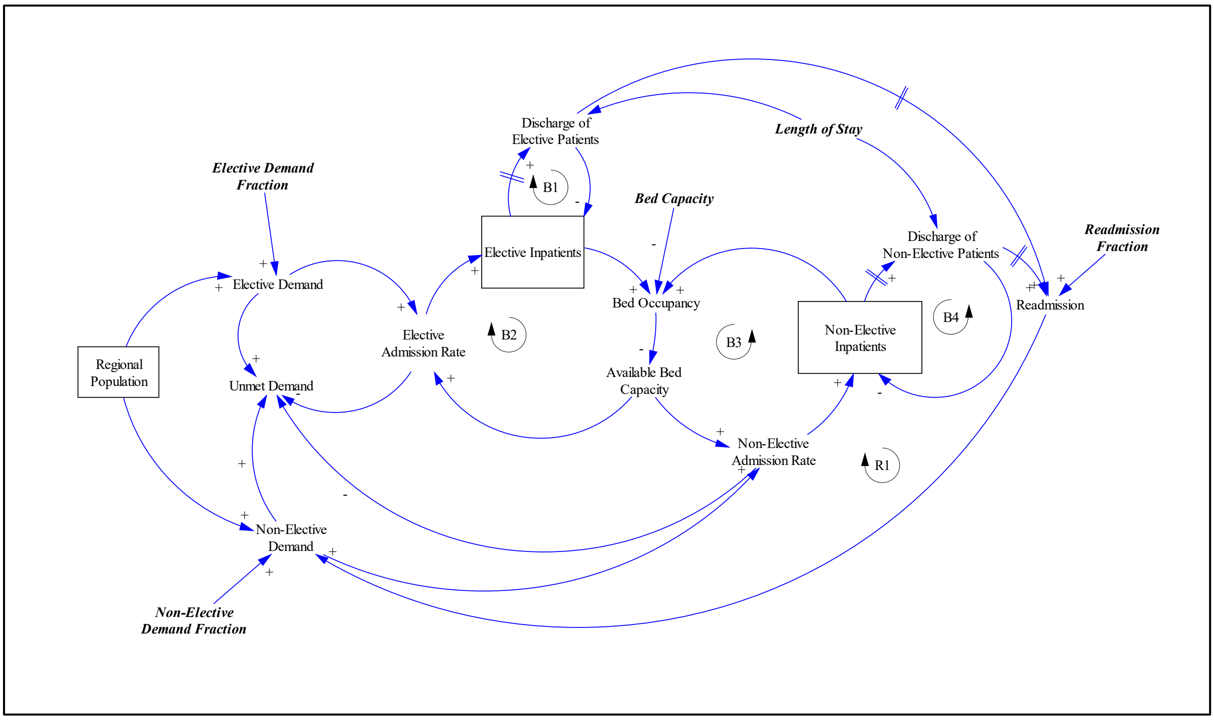


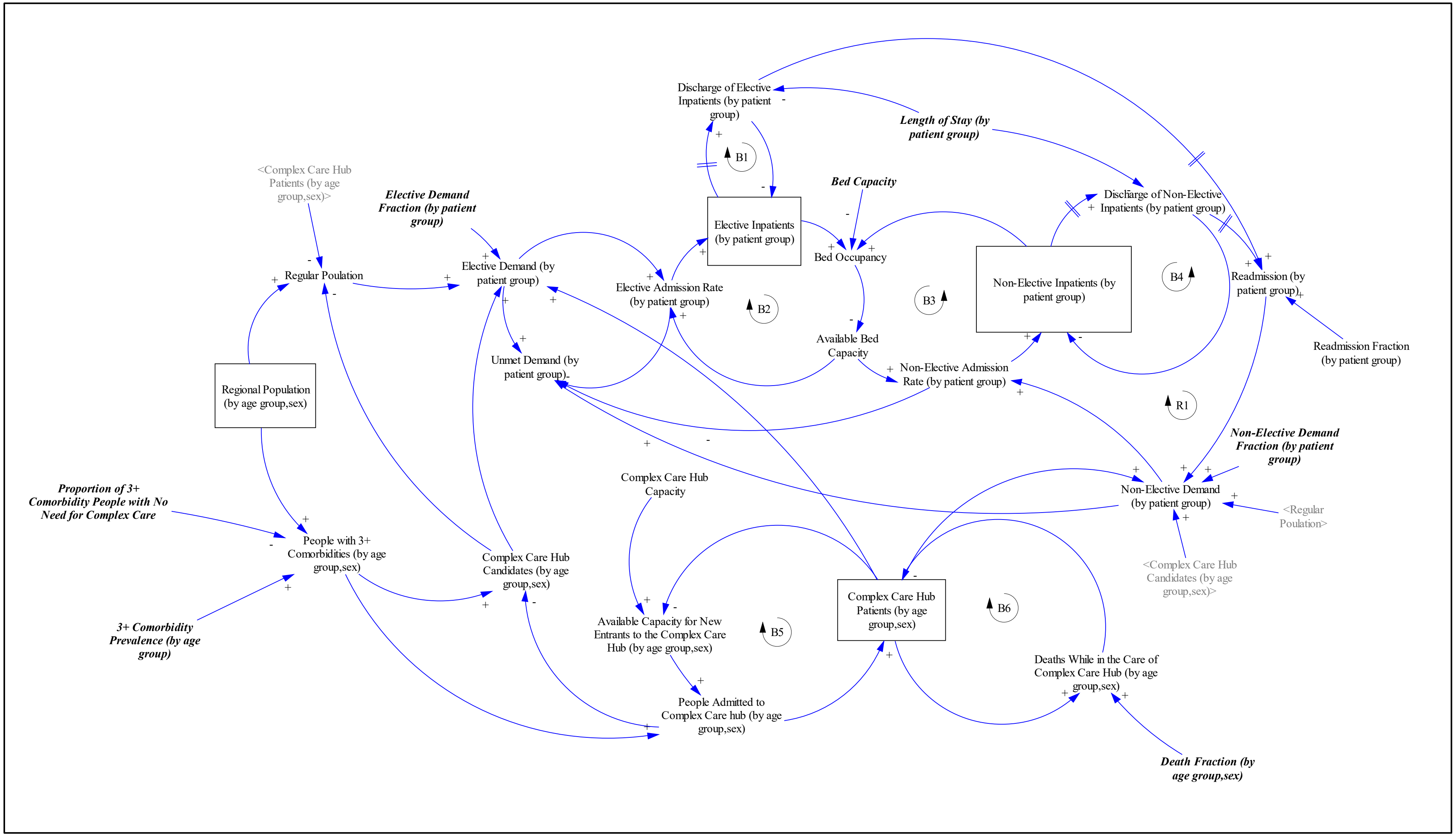
Figure 7 Mean bed-days per month with respect to changing readmission fractions for hub patients

Readmission fraction(hub patients) ∈ [38%-10%]; LOS(hub patients)=8 days; Hub capacity=1500 patients (Case 1 in Table 5)

Appendix 1: Causal loop diagram of patient flow in a secondary care setting



Appendix 2: Causal loop diagram of patient flow in a secondary care setting with Complex Care Hub



Appendix 3: Pseudo code of the admission procedure

$Initialize$ $\boldsymbol{Available\ Bed\ Capacity}$**=Bed Capacity**

$For\ Each\ Time\ Step$ [t]:

$For\ Non\_Elective\ Patients$:

$For\ each\ patient\ type\ from\ 1\ to\ n\ (given\ that\ a\ hierarchy\ is\ set\ among\ the\ groups\ and\ the\ first$

$group\ denotes\ the\ number\ 1\ priority)$:

$$\boldsymbol{Non\_Elective\ Admission\ Rate}\ [\boldsymbol{patient\ group}][\boldsymbol{t}] = MIN(\boldsymbol{Available\ Bed\ Capacity}[\boldsymbol{t}], \boldsymbol{Non - Elective\ Demand}[\boldsymbol{patient\ group}][\boldsymbol{t}] * \boldsymbol{Length\ of\ Stay}[\boldsymbol{patient\ group}])/\boldsymbol{Length\ of\ Stay}[\boldsymbol{patient\ group}]$$

$Update$ $\boldsymbol{Available\ Bed\ Capacity}[\boldsymbol{t}]$

$For\ Elective\ Patients$:

$For\ each\ patient\ type\ from\ 1\ to\ n\ (given\ that\ a\ hierarchy\ is\ set\ among\ the\ groups\ and\ the\ first$

$group\ denotes\ the\ number\ 1\ priority)$:

$$\boldsymbol{Elective\ Admission\ Rate}[\boldsymbol{patient\ group}][\boldsymbol{t}] = MIN(\boldsymbol{Available\ Bed\ Capacity}[\boldsymbol{t}], \boldsymbol{Elective\ Demand}[\boldsymbol{patient\ group}][\boldsymbol{t}] * \boldsymbol{Length\ of\ Stay}[\boldsymbol{patient\ group}])/\boldsymbol{Length\ of\ Stay}[\boldsymbol{patient\ group}][\boldsymbol{t}]$$

$Update$ $\boldsymbol{Available\ Bed\ Capacity}[\boldsymbol{t}]$

IF $\boldsymbol{Elective\ Admission\ Rate}[\boldsymbol{patient\ group}][\boldsymbol{t}] < \boldsymbol{Elective\ Demand}\ [\boldsymbol{patient\ group}][\boldsymbol{t}] THEN$:

$$\boldsymbol{Unmet\ Demand}[\boldsymbol{patient\ group}][\boldsymbol{t}] = (\boldsymbol{Elective\ Demand}\ [\boldsymbol{patient\ group}][\boldsymbol{t}] - \boldsymbol{Elective\ Admission\ Rate}[\boldsymbol{patient\ group}][\boldsymbol{t}])/\ \boldsymbol{Elective\ Demand}\ [\boldsymbol{patient\ group}][\boldsymbol{t}]$$

IF $\boldsymbol{Non\_Elective\ Admission\ Rate}[\boldsymbol{patient\ group}][\boldsymbol{t}] < \boldsymbol{Non\_Elective\ Demand}\ [\boldsymbol{patient\ group}][\boldsymbol{t}] THEN$:

$$\boldsymbol{Unmet\ Demand}[\boldsymbol{patient\ group}][\boldsymbol{t}] = \boldsymbol{Unmet\ Demand}[\boldsymbol{patient\ group}][\boldsymbol{t}] + (\boldsymbol{Non\_Elective\ Demand}\ [\boldsymbol{patient\ group}][\boldsymbol{t}] - \boldsymbol{Non\_Elective\ Admission\ Rate}[\boldsymbol{patient\ group}][\boldsymbol{t}]) /\boldsymbol{Non\_Elective\ Demand}\ [\boldsymbol{patient\ group}][\boldsymbol{t}]$$

Appendix 4: Input Parameters

<table>
<tr><th>Input parameter</th><th colspan="19">Explanation/Input Data/Initialisation</th><th>Data source</th><th>Unit/Dimension</th></tr>
<tr><td>Regional population (by age group, sex)</td><td colspan="19">Official statistics for population projection for years between 2014-2037 is taken as exogenous. The population projections are disaggregated by sex and 1-year age groups starting from 0 to 90+.</td><td>Office for National Statistics (ONS)</td><td>Number of people</td></tr>
<tr><td>Death fractions (by age group, sex)</td><td colspan="19">Used for ageing chain calculations of the hub patients.</td><td>ONS Life Tables Years:2012-2014</td><td>Dimensionless</td></tr>
<tr><td rowspan="2">3+ prevalence (by age group)</td><td>0-4</td><td>5-9</td><td>10-14</td><td>15-19</td><td>20-24</td><td>25-29</td><td>30-34</td><td>35-39</td><td>40-44</td><td>45-49</td><td>50-54</td><td>55-59</td><td>60-64</td><td>65-69</td><td>70-74</td><td>75-79</td><td>80-84</td><td>85-90</td><td>90+</td><td rowspan="2">Kasteridis et al., 2015, Figure 2</td><td rowspan="2">Dimensionless</td></tr>
<tr><td>0.004</td><td>0.004</td><td>0.008</td><td>0.010</td><td>0.012</td><td>0.012</td><td>0.012</td><td>0.012</td><td>0.016</td><td>0.016</td><td>0.027</td><td>0.033</td><td>0.043</td><td>0.070</td><td>0.097</td><td>0.117</td><td>0.136</td><td>0.156</td><td>0.312</td></tr>
<tr><td rowspan="4">Elective/Non-Elective demand fractions (by patient group)</td><td colspan="19">The proportion of population that will generate elective/non-elective demand per month.</td><td rowspan="4">Patient activity data *</td><td rowspan="4">Dimensionless</td></tr>
<tr><td colspan="4">Admission Type</td><td colspan="5">Regular Population</td><td colspan="5">Complex Care Candidates</td><td colspan="5">Complex Care Patients</td></tr>
<tr><td colspan="4">Non-Elective</td><td colspan="5">0.22%</td><td colspan="5">18.45%</td><td colspan="5">12.47%</td></tr>
<tr><td colspan="4">Elective</td><td colspan="5">0.16%</td><td colspan="5">4.90%</td><td colspan="5">2.03%</td></tr>
<tr><td rowspan="3">Readmission fraction (by patient group)</td><td colspan="19">This is the proportion of discharged patients who will end up being readmitted within 30 days.</td><td rowspan="3">Patient activity data</td><td rowspan="3">Dimensionless</td></tr>
<tr><td colspan="6">Regular Population</td><td colspan="7">Complex Care Candidates</td><td colspan="6">Complex Care Patients</td></tr>
<tr><td colspan="6">7.57%</td><td colspan="7">14.25%</td><td colspan="6">37.90%</td></tr>
<tr><td rowspan="3">Length of stay (by patient group)</td><td colspan="19">This is the mean value that an inpatient spends in the hospital occupying a bed.</td><td rowspan="3">Patient activity data</td><td rowspan="3">Number of days/person</td></tr>
<tr><td colspan="6">Regular Population</td><td colspan="7">Complex Care Candidates</td><td colspan="6">Complex Care Patients</td></tr>
<tr><td colspan="6">1.5</td><td colspan="7">5.81</td><td colspan="6">8</td></tr>
</table>

<table>
<tr><td rowspan="3">Initial number of readmitted inpatients (by patient group)</td><td colspan="3">Initial values used for the initialization of the model when simulating.</td><td rowspan="3">Patient activity data</td><td rowspan="3">Number of people</td></tr>
<tr><td>Regular Population</td><td>Complex Care Candidates</td><td>Complex Care Hub Patients</td></tr>
<tr><td>46</td><td>169</td><td>11</td></tr>
<tr><td>Initial number of Complex Care Hub patients</td><td colspan="3">It is assumed that simulation starts with 200 patients under the control of the Complex Care Hub.</td><td>Patient Activity Data (YDH)</td><td>Number of people</td></tr>
<tr><td>Proportion of 3+ comorbidity people with no need for complex care</td><td colspan="3">It is assumed that 20% of people with 3+ comorbidities can manage their health conditions and do not need to get complex care service.</td><td>Expert Judgement</td><td>Dimensionless</td></tr>
<tr><td>Bed capacity</td><td colspan="3">The physical capacity of Yeovil District Hospital is 350 beds, which makes up 10,500 bed-days per month.</td><td>Physical limits of the hospital</td><td>Number of bed-days per month</td></tr>
</table>

**Note that hospital patient activity data covers three financial years between 2013 and 2016.*