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System dynamics modelling to support policy analysis for sustainable health care

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System Dynamics Modelling to Support Policy Analysis for Sustainable Healthcare [1]

Abstract

System Dynamics (SD) is an established simulation methodology used to explore the behavior of social systems over time. The field has addressed challenging sustainability problems in fisheries, urban planning, and environmental resource management. It has also been successfully applied to healthcare, in chronic disease modelling and workforce planning. This paper presents system dynamics models of healthcare sustainability, and illustrates two complementary applications of SD: (i) continuous simulation of healthcare infrastructure adequacy; and (ii) conceptual modelling of the wider public policy context for healthcare sustainability. The infrastructure model provides a simulator for evaluating impacts of population growth and ageing, as well as assessing the likely effects of policy interventions on system sustainability. This model is validated using empirical data from Ireland's public health service, and its practical application for sustainability analysis is illustrated. Our conceptual endogenous SD model explores a wider system boundary and public policy interdependencies that impact sustainability outcomes.

Keywords: healthcare ecosystem, system dynamics simulation, socio-economic sustainability.

1. Introduction

The sustained global financial crisis of the past 5-6 years is a sharp reminder that high-cost models of healthcare delivery are not sustainable, in economic and social terms. Current publicly funded healthcare systems throughout the developed world are wedded to an underlying structural cost inflation cycle, with healthcare expenditure ratios already as high as 9.5% of GDP in the OECD, and up to 17.7% in the US (OECD 2013). This poses an immediate challenge for national governments. But a bigger challenge for policy makers is the un-sustainable healthcare system legacy we are likely to pass-on to the next generation, which will be faced with the additional socio-economic pressures of an ageing demographic profile, higher dependency ratios, increased prevalence of chronic diseases, multiple comorbidities of elderly patients, and higher unit cost diagnostic and treatment interventions (Boyd *et al.* 2008).

Sustainability in healthcare is defined by the WHO as "the ability to meet the needs of the present without compromising the ability to meet future needs" (Roberts 1998). Olsen provides further definition and a conceptual framework for healthcare sustainability analysis, based on understanding the balance between contextual factors, organisational capacity and delivery activities (Olsen 1998). Systems dynamics provides an effective simulation environment for exploring these complex social system environments.

The focus of this paper is on both the *economic* and *social sustainability*; so our simulation framework will examine these in terms of measurable changes in:

[1] The model and data can be obtained from the authors upon request

(i) **Economic sustainability**, expressed as a significant shift in the primary demand drivers for healthcare services; that is, overall system loading relative to economically available capacity.
(ii) **Social sustainability**. While social sustainability can involve many ethical and moral perspectives related to funding and provisioning policies (Eikemo *et al.* 2008; Olsen 1998), we use *access* to services (regardless of ability to pay) as a measurable proxy indicator of declining/improving performance for healthcare system social acceptability.

As a quantitative evidence-based approach to planning, simulation has three distinct communities of practice: discrete event simulation (Robinson 2005), agent-based modelling (Duggan 2008; Macal and North 2010), and system dynamics (Forrester 1961). The purpose of this paper is not to debate the relative merits of these different approaches to healthcare simulation. A number of comprehensive reviews of literature and available techniques have already been conducted where the strengths of each method are well articulated (Brailsford, Desai, and Viana 2010; Brailsford *et al.* 2009; Katsaliaki and Mustafee 2011; Mielczarek and Uziako-Mydlikowska 2012; Mustafee, Katsaliaki, and Taylor 2010; Royston *et al.* 1999).

The emphasis on system-wide sustainability analysis in this paper, rather than on detailed component simulation, predisposes our approach towards system dynamics. The key strength of system dynamics (SD) is its suitability to address long-term public policy problems that exhibit dynamic complexity (Sterman 1994), in terms of the significant time delays between cause and effect (Rahmandad, Repenning, and Sterman 2009; Yasarcan 2011). Further benefits of SD are its support for explaining learning in complex systems (Kopainsky, Pirnay-Dummer, and Alessi 2012), precise modeling for aging populations (Eberlein and Thompson 2013), connecting micro-dynamics with population distributions (Fallah-Fini *et al.* 2013), and capturing feedback characteristics that lead to unintended consequences (Wolstenholme 2003).

Healthcare applications of system dynamics described in the literature cover three different levels of analysis: (1) disease models of the body; (2) operational models of healthcare delivery units; and (3) strategic whole-system models. Earlier reported work on whole-system SD modelling provides a robust foundation for applications to sustainability analysis of national public health systems. Taylor and Dangerfield (2004) explore the consequences of shifting the balance of healthcare delivery away from centralised facilities and "closer to home", illustrating dynamic feedback mechanisms through a number of case studies. Homer, Hirsch, and Milstein (2007), study chronic illness, and show the impact of up-stream policy intervention and targeting of behaviours that impact disease risk factors. Lane, Monefeldt, and Rosenhead (2000) perform a simulation analysis of an accident and emergency department, and highlight the problem of basing policy decisions on narrowly bounded models, rather than on whole-system simulations. Wolstenholme (1999), through a study of patient flows in the UK Health Service, demonstrates that policy adjustments to throughput (flow) variables can provide significantly greater leverage than adjustments to capacity (stock) variables.

One of the main advantages of SD in the analysis of healthcare is that it provides a structured enquiry framework for whole-system identification, analysis and implementation. This allows the modeller to develop both *quantitative simulations* of system structures, as well as more conceptual abstract models for *qualitative analysis* and problem description (Wolstenholme and Coyle 1983). The quantitative SD approach to simulation is viable where the model can be validated against a real-world foundation of data and measurable relationships or processes. Several recent examples of quantitative and qualitative applications in specific healthcare domains are available in the literature (Vanderby and Carter 2009; Wong *et al.* 2012).

This paper describes a whole-systems SD approach to modelling and evaluation of healthcare sustainability, at the macro level of a public healthcare system. The contributiuon draws on the authors' past experience in public healthcare system design, upon previous modelling projects, as well as on the SD literature. It illustrates the strengths of SD as a planning and research methodology for both:

(i) long-term quantitative analysis of sustainability, in terms of provider capacity and patient access adequacy, in the core public health provider infrastructure;
(ii) conceptual modelling for exploration of the wider public policy context for healthcare sustainability, as SD facilitates structural model alterations as well as parameter changes.

Sustainability is initially explored in terms of a population level SD demand/capacity model and simulates the dynamic interdependencies of the different care provision constituencies (or care *capacities*): primary care, outpatient day-case and acute in-patient services. The *capacity* model components are disaggregated to allow for the evaluation of various national or local policy decisions on both the total system equilibrium or on individual provider sector performance. For instance, in the primary care model (general practitioner – GP) a *stock management structure* takes account of recruitment and training policies, as well as the gender and age demographic of the GP population. In acute care, disaggregation allows for bed-day capacities, and so captures Average Length of Stay (ALOS) variance in terms of different patient and disease cohorts. Finally, the entire *demand* model is fully disaggregated by patient age cohort, and uses the most recent national population projections in our case study. This model is validated using published data and planning assumptions for the Irish public health system, and a set of scenarios is developed to illustrate the application of SD for sustainability analysis over prolonged planning periods.

Expanding on this validated model of healthcare infrastructure, we then develop a qualitative feedback model to illustrate the application of SD as a conceptual framework for exploring the wider public policy context, and interdependencies likely to impact healthcare sustainability. This whole-systems feedback model highlights the potential dynamics at the interface of healthcare, social, and economic systems. Its stock and flow structure also provides the basis for future quantification and empirical validation of causal relationships.

2. Characterising sustainability of public healthcare infrastructure

Sustainability of the healthcare system is influenced by a multitude of inter-dependent and dynamic causal elements. These include: (i) a range of exogenous, pre-determined factors, mainly associated with underlying population dynamics; and (ii) internal decision variables, which allow for a range of policy and management responses to externally imposed sustainability threats. The policy options available include: public health interventions, system-wide organisation design and funding choices, as well as provider-level management and productivity changes. Long-term sustainability management of the whole healthcare system is thus based upon:

- Comprehension of the likely impacts of exogenous factors at an early enough stage in the planning cycle in order to allow appropriate policy and system configuration responses;
- Implementation of policy measures to mitigate the effects of exogenous factors; and
- Development of the healthcare delivery ecosystem to cope with the new and different demands created by exogenous factors, such as the increased prevalence of chronic diseases, and multiple comorbidities amongst a greater portion of the population.

Our high-level characterisation of the public healthcare ecosystem allows us to focus on the essential modelling variables required for an evaluation of healthcare sustainability. This also provides a valuable context for building an effective SD simulation. Figure 1 details a high-level $IDEF_0$ (Feldmann and Tieso 1998) representation of public healthcare, showing the Exogenous (Demand Drivers) and Decision (Policies and Organisation) variables, as well as the downstream consequences for sustainability of changes in any of these influencing factors.

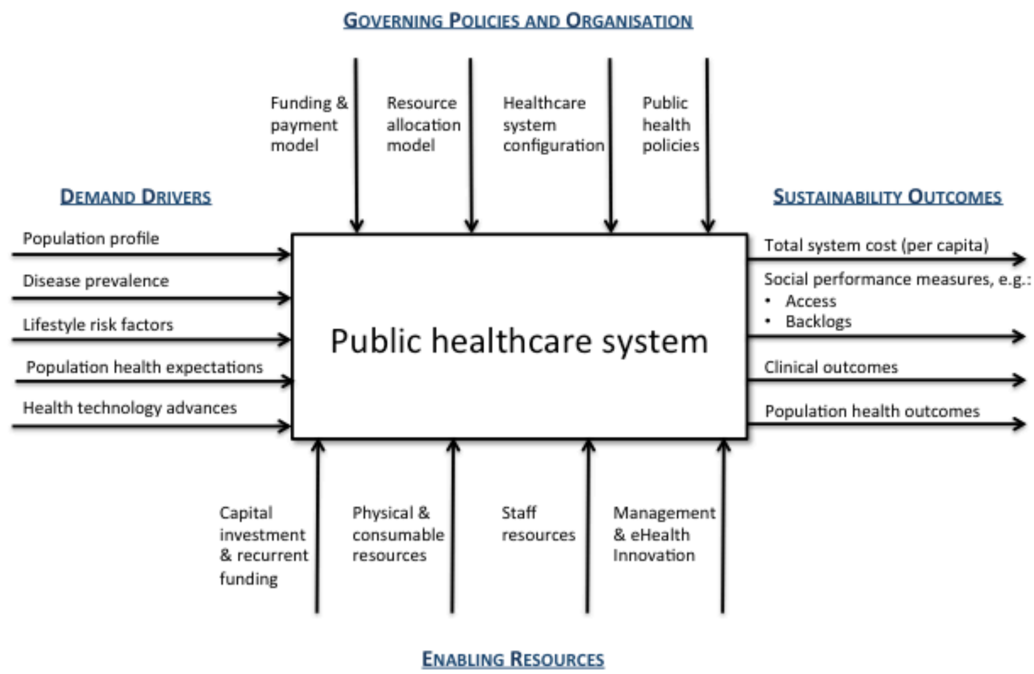

Figure 1: Top-level characterisation of a national public health system

Exogenous threats to sustainability:
Demographic, lifestyle and environmental changes are at the root of healthcare sustainability, as they determine the aggregate system burden in operational demand and overall cost terms. In Europe and North America, the underlying demographic profile reveals an ageing population structure, with greater life expectancies; this results in extended periods of healthcare dependency as elderly people with chronic and multiple disease conditions now live considerably longer.

A supplementary escalation in healthcare demand can be expected from increased prevalence of many chronic disease conditions. Some of these are related to lifestyle risk factors, and may apply to sub-cohorts of the overall population. These include: Type 2 Diabetes, as well as a number of Cancers involving high lifestyle risk associations with tobacco and alcohol consumption. However, higher expected prevalence levels are also associated with earlier and more effective diagnoses of disease, regardless of risk source – lifestyle or genetic. Together, we can think of these lifestyle and prevalence factors as an *overlay* on the basic demographic healthcare demand driver.

Finally, advances in healthcare technologies drive an escalation in both unit treatment costs and demand volume, as clinicians prescribe more sophisticated remedies. These technologies currently include: new diagnostic procedures, medical and surgical treatments and pharmacological products. But we can expect a further expansion in health technology based demand and cost, as advances in genomics and personalised medicine create opportunities for even higher levels of individual care, with a corresponding rise in overall healthcare expectation levels of the population. Whether these can be accommodated in a sustainable public healthcare ecosystem remains to be determined.

Policy levers to enhance sustainability:
While policy makers can exercise little direct control over these exogenous demand drivers, the long-term sustainability of the healthcare system is ultimately determined by the policy, investment and management choices made by healthcare leaders. Amongst the portfolio of design responses available are:

(i) **Development of chronic disease management structures** to reduce dependency upon highest-acuity in-patient care settings. Several opportunities are available to rebalance the provision model, and these can lead to improvements in long-term overall sustainability. These include: development of the primary care setting for greater community based management of patients with chronic disease and older persons with multiple comorbidities; avoidance of acute admissions through appropriate provision in primary care or outpatient clinics; and increased use of day-case procedures to reduce the reliance on limited in-patient capacity.

(ii) **Improvements in management and productivity** in various provider constituencies (especially acute care) can yield substantial gains in effective capacity and throughput (with lower average length-of-stay, ALOS) over the planning horizon. Process improvements include development of: discharge planning, electronic patient record systems, diagnostic support and patient monitoring systems, e-prescribing and care pathway management.

(iii) **Public health policy interventions** to improve the population health, especially related to lifestyle risk factors. The net beneficial effect of such policy measures would be to reduce the demand at source, by improving the population health status, either for the whole community or for segmented cohorts targeted by individual policy interventions.

Based upon this characterisation, we now present a system dynamics representation of the underlying demography, demand drivers and capacity formulations of the healthcare system. Apart from simulating the overall primary impact of demographic change, the model allows the planner to activate/deactivate these three policy responses, to explore their impact on system sustainability. The model also allows for variation of different underlying planning assumptions, using a number of *demand modifiers*, relating to such factors as disease prevalence trends, chronic disease levels, health technology advances, healthcare expectation levels and the impact of targeted public health campaigns.

3. Healthcare systems dynamics demand-capacity model

Our overall model structure is designed as a *powerful small model* that is sufficient to explain system-wide dynamics, illustrate component interdependencies, and build intuition regarding appropriate policy responses (Ghaffarzadegan, Lyneis, and Richardson 2011). The model captures key stocks, a small number of feedback loops, and important rate equations, including capacity constraint formulations. It also allows for detailed policy experimentation, including analysis of permutations for decision variables such as health service configuration, public health interventions and productivity improvements.

The top-level SD model (Figure 2) captures the *demand-capacity* health system dynamics, and summarises the system's high-level *stocks* and *flows*.

The main health system *stocks* are:

- **Population Being Treated and Waiting for Treatment**. Based upon the underlying demographic forecasts from the exogenous **Population** variable, this represents patient demand in the system, being treated or awaiting treatment. The stock also models any backlog in the system, which is an indicator of unmet presenting demand and/or access delays.

- **Resources.** This represents the disaggregated health care capacities for the different provider constituencies. This includes the number (and processing capacity) of primary care practitioners (general practitioners - GPs), the quantity of available beds in the acute setting, and the bed capacity for daycare settings.

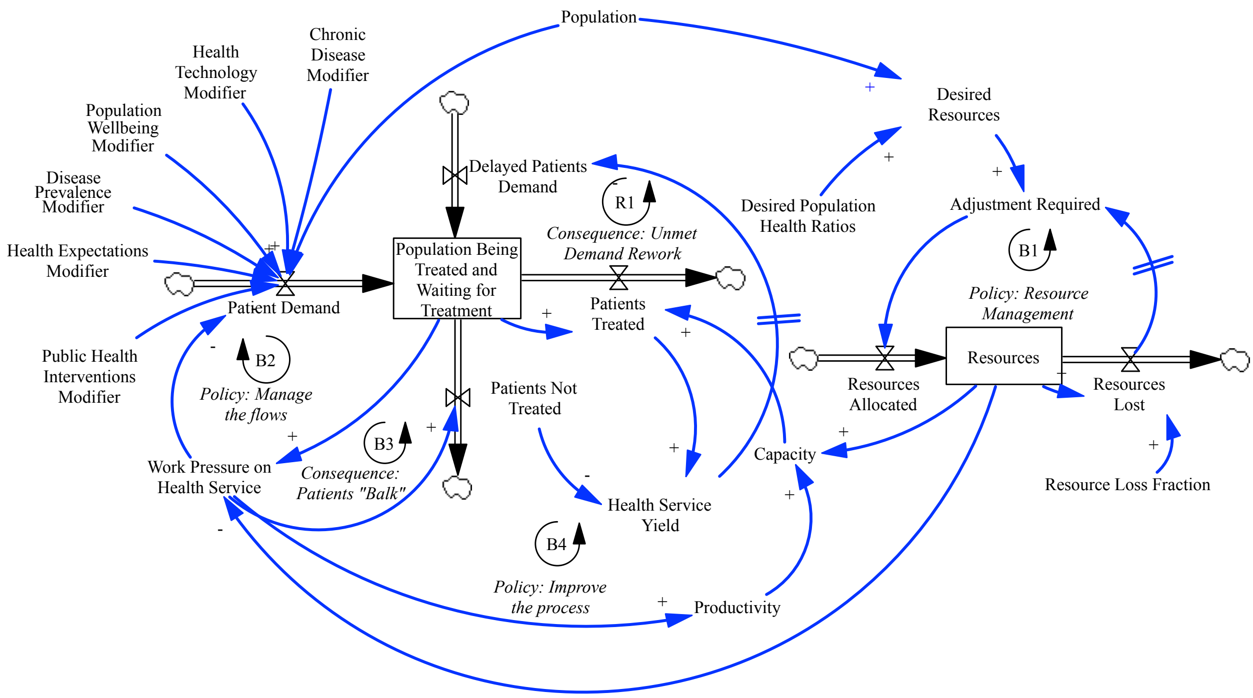

Figure 2: Aggregate SD demand-capacity model for healthcare sustainability

The stock's behaviours are determined through their *flows*. For the Resource stock these values are straightforward, whereas the stock for Population Being Treated has multiple inflows and outflows, namely:

- *Patient Demand* – The normal demand on the healthcare system, in terms of number of episodes per annum, by patient age cohort. This demand can be adjusted by Demand Modifiers to take account of macro level dynamics such as changes in overall population health, health technology, or health expectation levels.

- *Patients Treated* – The effective capacity of the system, and the number of patients treated each year. Factors that influence capacity include productivity, resource numbers (people and infrastructure), and the average length of stay (ALOS) for acute care episodes.

- *Patients Not Treated* – A measure of how many patients do not get treated within any given year.

- *Delayed Patients Demand* – where patients not treated due to capacity limitations re-enter the system after a time delay.

Un-met demand or delayed processing (resulting in backlogs) reflects poor social acceptability of the healthcare system as they imply a reduction in system access, a clear indicator of declining social sustainability. In addition to these flows, there are a number of important *feedback loops* that capture responses to changes in stock values. These are:

- *B1 (resource management),* which is a stock management structure balancing control loop (Sterman 1989) that regulates resources according to (1) the expected loss rate, (2) the desired value and (3) the adjustment time – i.e. the time taken to close the gap between desired and current resource levels.

- *B2 (manage the flows),* a balancing loop that captures health service reconfiguration policies, such as acute sector avoidance through the development of primary or day-case capacities.

- *B3 (patients "balk"),* an undesirable balancing loop that reduces pressure on the system because patients may be discouraged from entering the system at all, due to poor quality of service and expectations of long delays.

- *B4 (improve the process),* where targeted productivity improvements are captured at an aggregate level, and result in additional capacity, which in turn reduces the overall backlog. For example, this might include efforts in the acute sector to reduce average length of stay (ALOS).

- *R1 (unmet demand rework),* a reinforcing loop to take account of the build-up of patients in queues for diagnostic or treatment services.

A number of *demand modifier* parameters influence the total system demand (and ultimately cost) by increasing/decreasing the volume of attendances at various care settings (Figure 2). These can be independently set by the analyst, taking account of local evidence for these variables, or can be modelled as a parameter sweep over a range of values where reliable data is not available. These include:

(i) changes in prevalence levels for many common diseases;
(ii) changes in the expected wellbeing status of the population over time;
(iii) level of chronic disease in the population;
(iv) the impact of public health interventions on improving health status;
(v) increasing health expectations of the population over time; and
(vi) an increased demand expectation for diagnostic and treatment services created by advances in health technologies.

As detailed independent demographic forecasts are available, **Population** (which is the primary driver of healthcare demand) is treated as an exogenous variable in the model. For the case-study presented in this paper, the most recent long-range forecasts of population were provided by Ireland's Central Statistics Office (CSO 2013). The overall model is disaggregated by both patient gender and age cohort, to take account of the reported differences in GP visit rates, acute admission rates and average length of stay (PA Consulting 2007). As might be expected visit rates and admissions increase exponentially with patient age.

The total capacity for primary care is a product of the total number of GPs (full-time equivalents, FTE), the hours worked and patient throughput. GPs are modeled as an aging chain (Sterman 2000) in seven five year cohorts over a 35 year career span, disaggregated by gender, and replenished by a stock management structure. The total FTE per GP takes account of empirically based studies estimating the aggregate impact of the overall female percentage in the GP workforce. These highlight the impact of an increasing female/male gender ratio, which can give rise to some loss in total potential primary care capacity (2007; O'Dowd T, O'Kelly M, and F. 2006; RCGP 2006).

While this aggregate SD model provides an understanding of the overall demand/capacity structure of the system, a disaggregate model across the main provider sub-sectors is required for detailed simulation and experimentation, as shown in Figure 3. These flows enable the simulation of policy options for addressing the structural and organisational foundations for sustainability.

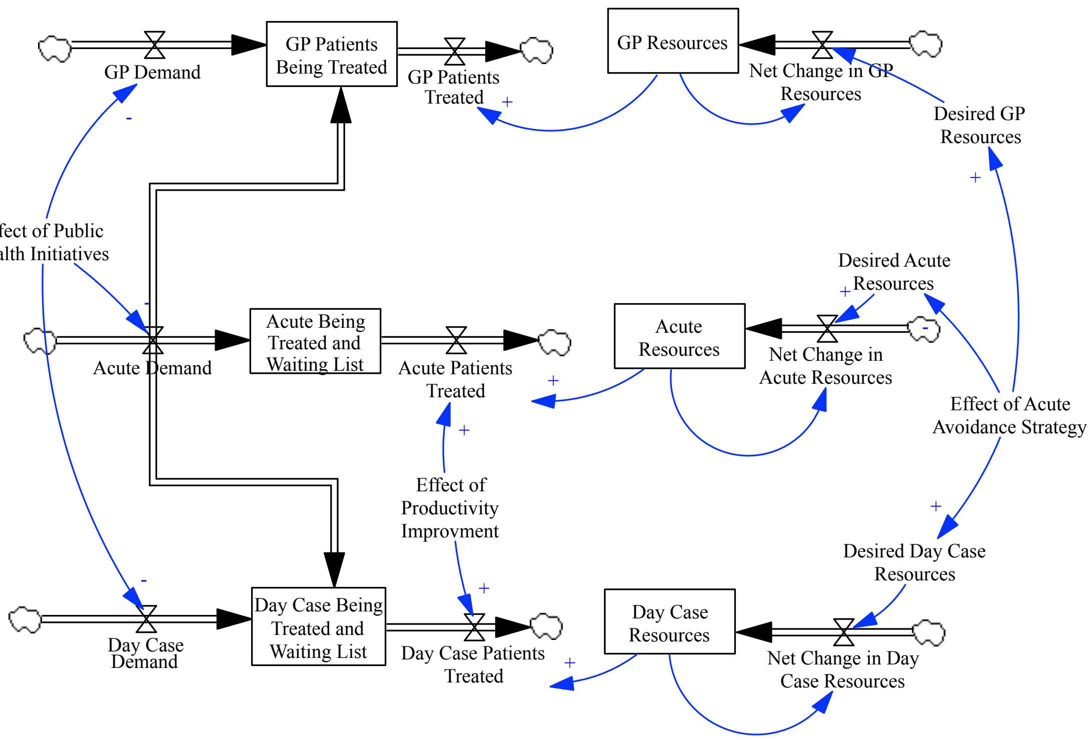

Figure 3: Disaggregated model by service type: GPs, Acute and Day Patients.

4. Empirical Study in Healthcare Sustainability

The SD sustainability modelling approach is validated through our direct engagement in the analysis and design of the Irish public health system over several years, and by specific reference to a number of detailed independent reports on healthcare demand and supply dynamics in this jurisdiction (2007; DoHC 2010; Layte *et al.* 2009). For the purposes of illustrating the application of our model in this paper, we have drawn on recent population projections from the Irish Central Statistics Office (CSO 2013), and detailed demand and capacity data from the Irish Department of Health & Children (DoHC 2012), Health

Service Executive (ESRI 2012) and the Competition Authority (CompAuthority 2010).

Model Data

The Population data is based on a mid-range CSO forecast (M2F2) that takes account of net migration and fertility levels over a planning horizon up to 2046 (CSO 2013). This forecast highlights the pressures of an ageing demographic, as the only cohorts to grow significantly in this period are ages 65+. It also confirms a near trebling of the elderly dependency ratio (DR) over the planning period, while the young DR is cyclical around a flat profile. However, Ireland retains a relatively high fertility rate of 1.8-2.1, which should help to support a sustainable healthcare sector. The low and falling fertility rates in other parts of the developed world will present a greater sustainability challenge.

The impact of ageing on the demand-side of healthcare is highlighted in (Table 1) an age- cohort analysis of admissions to the acute sector for 2011 (both Acute In-Patient and Acute Day-Case settings). This is based upon detailed discharge data from the Irish health service (ESRI 2012). Coupled with the Population forecasts this provides a detailed disaggregated picture of demand and capacity utilisation patterns (with respect to ALOS). Ageing of the population is thus an important contributory factor to an analysis of healthcare sustainability.

	Acute Visit Rate		Day Visit Rate		Acute ALOS
Cohort	***Male***	***Female***	***Male***	***Female***	***ALL***
Age 0-1	0.43	0.35	0.08	0.07	5.8
Age 1-14	0.07	0.06	0.06	0.04	2.4
Age 15-24	0.05	0.05	0.05	0.06	3.2
Age 25-34	0.05	0.05	0.08	0.10	3.9
Age 35-44	0.06	0.06	0.12	0.16	4.5
Age 45-54	0.09	0.08	0.20	0.25	5.6
Age 55-64	0.14	0.12	0.39	0.36	6.9
Age 65-74	0.25	0.20	0.66	0.50	8.7
Age 75-84	0.44	0.35	0.87	0.55	11.2
Age 85+	0.62	0.46	0.73	0.30	13.3

Table 1: Visit Rates (2011) for Acute and Day, along with ALOS Data (by cohort)

Earlier studies of Irish public healthcare have also examined the influence of changes in disease prevalence for individual disease types (Diagnosis Related Groups – DRGs), chronic disease incidence and healthcare expectation levels. For the purposes of model validation in this paper, we have applied a net aggregate additional year-on-year exogenous demand increment of 2%, driven by these factors. This average level of incremental impact has been previously adopted in earlier independent studies (PA 2007; Layte *et al.* 2009). However, our model allows the analyst to test a range of assumptions using a set of *demand modifiers* (Figure 2) for such influencing variables, where definitive relationships or parameters are not readily supported by strong empirical evidence.

Our SD model evaluates the sustainability impact of the forecast population on component primary and acute care settings, and in particular underlines the effect of population ageing. It also allows us to examine the ability of available system capacity to cope with increased demand, and highlights the changes in "backlog" for each care setting. Growing capacity deficits over time reflect an economically unsustainable healthcare system, and this allows us to identify the incremental capacities needed at each stage to maintain demand-capacity equilibrium in the system. System backlog indicators with values greater than 1 represent un-met needs or delayed access to healthcare resources, and thus provide a useful proxy measure for social sustainability. That is, an increasing backlog indicator represents a net deterioration in healthcare access and thus reduced overall social sustainability of the healthcare system.

Sustainability Impacts and Policy Scenarios

Based upon these detailed demographic forecasts and demand drivers, we illustrate the application of the model using 3 sustainability scenarios: a baseline model to evaluate the raw impact of changing demand on sustainability, and 2 models to evaluate various policy options to improve sustainability.

Scenario 1: Baseline resource levels held constant. This maintains healthcare resources at existing levels, with no improvement in provision. For instance, the ratio of GPs to population is maintained at current levels (0.61 per 1,000). While this ratio is low relative to European averages, the current demographic profile means that wait times for primary care in Ireland are extremely low. Similarly, acute bed capacity *per capita* is high relative to the baseline demographic.

Scenario 2: Productivity and public health policy improvements. As a policy response to sustainability, investment in productivity measures is focused on individual care settings, particularly the acute in-patient sector. Public health policy intervention is also implemented to reduce source demand for services, for instance in the early prevention of chronic disease.

Scenario 3: Chronic disease management structures. In this case the policy response takes a whole-systems perspective to chronic disease management, with a rebalancing of resources across the care sectors, requiring investment in the primary and day-case sectors. This is additional to the productivity and public health measures implemented in Scenario 2.

The raw demographic impact on future sustainability is illustrated in Figure 4 for the Scenario 1 assumptions. This forecasts an emerging demand-capacity shortfall, illustrated here for both the Primary (GP) and the Acute In-patient sectors, caused by population growth and ageing, as well as an increasing underlying disease prevalence and health technology advances. The early oscillation in GP capacity is due to the working-out of an impending deficit caused by near-term retirements, with a lag in additional supply from training schemes. In order to maintain a level of equilibrium in the system, significant additional investment in capacity would be needed, driving-up the overall and *per capita* system costs. This amounts to a net incremental requirement to create 26,000 acute in-patient beds by 2046, and an expansion (over current numbers) of 1,200 general practitioners in the primary care sector. Should the current ratio of GPs per 1,000 population be retained at current levels, this would result in a 2046 planning deficit of 520 primary care doctors.

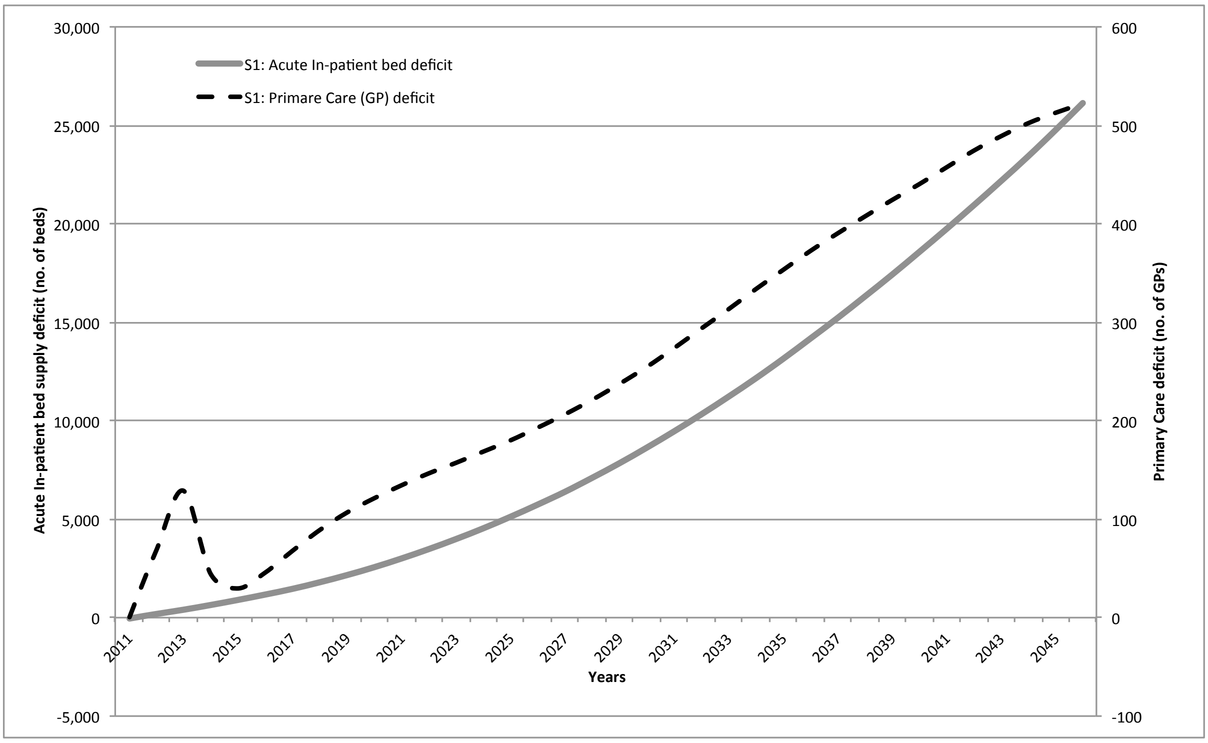

Figure 4: Scenario 1 – Capacity sustainability indicator in primary and acute care

Social sustainability is more clearly illustrated in Table 2, which shows the deterioration in healthcare access caused by increasing backlogs at each of the main care settings throughout the planning period. A backlog indicator of 1.0 indicates that the system is in demand-supply equilibrium. Values greater than 1.0 suggest increasing patient access difficulties as the demand/capacity mismatch grows, leading to a deterioration in social acceptability of the service.

Scenario 1: Planning Year:	2011	2016	2021	2026	2031	2036	2041	2046
Primary (GP) care backlog:								
Backlog Indicator	1.02	1.03	1.06	1.08	1.10	1.13	1.15	1.17
% Annual Change on 2011 Baseline		2%	5%	6%	9%	11%	14%	15%
Acute In-patient backlog:								
Backlog Indicator	1.00	1.11	1.28	1.54	1.90	2.36	2.91	3.54
% Annual Change on 2011 Baseline		11%	29%	55%	91%	137%	192%	255%
Day-case backlog:								
Backlog Indicator	1.00	1.10	1.20	1.31	1.42	1.51	1.60	1.66
% Annual Change on 2011 Baseline		10%	21%	32%	42%	52%	60%	67%

Table 2: Scenario 1 -- Service backlog ratio and change over 2011 baseline

In summary, the effect of demographic change over the planning horizon, coupled with the additional influence of increased prevalence and health technology advances, creates a clearly unsustainable level of demand relative to the economically available baseline capacity throughout the healthcare system. The social sustainability impact is even more pronounced, with significant reductions in access to all health provider care settings.

In response to these sustainability challenges, healthcare managers could focus policy on improved productivity and ALOS in acute care. Investment in public health measures, to reduce disease prevalence, could also be considered. These are explored in Scenario 2 (see Figure 5). Finally in Scenario 3, we examine the policy impacts of addressing sustainability with a more comprehensive whole-system approach to chronic disease management in the health system, in addition to the Scenario 2 productivity measures. This policy would see: (1) a rebalancing of the acute sector in favour of a greater mix of day-case patients; and (2) avoidance of the acute sector for chronic disease management (CDM), by improving the capacity and service range of primary care.

Figure 5 summarises the results for both Scenarios 2 and 3. While acute sector productivity measures (Scenario 2) result in a substantial improvement in both demand-capacity balance and patient access over the near term, these are not sustained as demand continues to escalate over time. However taking a whole-system approach towards chronic disease management (Scenario 3) results in a balanced healthcare system over the planning horizon, with sustainable demand-capacity and patient access performances (Figure 5 and Table 3).

However, in order to achieve sustainability objectives, investment in primary care and day-bed capacities is essential, albeit at significantly lower costs to developing a corresponding capacity in acute in-patient care. The net addition in GPs required over the planning horizon is of the order of 1,300, which would take the GP/population ratio in Ireland to 0.74/1000, still well below the European average. The incremental capacity in day-beds is equivalent to an 85% increase in the baseline capacity. Such measures are being attempted throughout Europe, and early efforts to move in this direction are being explored in Ireland.

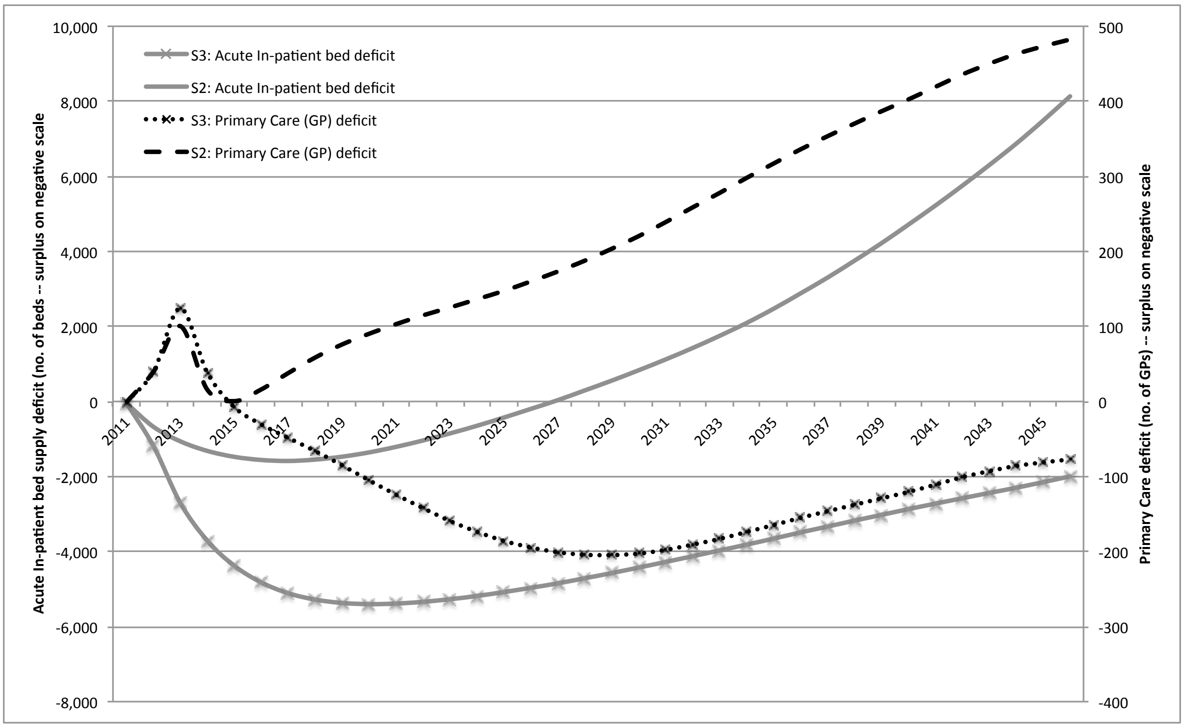

Figure 5: Scenarios 2 & 3 – Capacity sustainability indicator: primary and acute

Scenario 3: Planning Year:	2011	2016	2021	2026	2031	2036	2041	2046
Primary (GP) care backlog:								
Backlog Indicator	1.02	1.01	0.98	0.96	0.96	0.98	0.99	1.00
% Annual Change on 2011 Baseline		-1%	-4%	-5%	-5%	-4%	-3%	-2%
Acute In-patient backlog:								
Backlog Indicator	1.00	0.56	0.50	0.54	0.61	0.68	0.75	0.82
% Annual Change on 2011 Baseline		-44%	-49%	-45%	-39%	-32%	-25%	-18%
Day-case backlog:								
Backlog Indicator	1.00	0.93	0.89	0.91	0.94	0.99	1.04	1.08
% Annual Change on 2011 Baseline		-7%	-11%	-9%	-5%	-1%	4%	8%

Table 3: Scenario 3 -- Service backlog ratio and change over 2011 baseline.

5. Healthcare systems dynamics whole-system conceptual model

Building upon our initial evidence-based simulation, we now explore a broader conceptual model to further understand key macro-level feedbacks in health care sustainability analysis. System dynamics provides an excellent methodology for this broader task, as its overarching goal is to expand the boundary of our mental models to observe patterns of behavior created by the underlying feedback structure (Sterman 2000). This closed-boundary perspective also allows modellers to confirm that there are no significant dynamic influences coming from outside the system boundary. The resulting models, crucially, are endogenous, where the dynamics of the system are generated within the system boundary (Richardson 2011).

Our macro-level conceptual model offers a whole-systems perspective of the public health system within a wider public policy context (Figure 6). This model retains the two initial stocks, that capture *supply* and *demand*, and their associated feedback loops. The main difference with this enlarged model is that previously exogenous variables (e.g. variables that are not part of a feedback structure) are now endogenous. The most prominent of these is *Population Wellbeing,* which – while challenging to measure – is an important community level metric for the social sustainability of healthcare systems. Targeted investments in policy areas such as health promotion should lead to an increase in wellbeing, and this, in turn, has a cascading effect in terms of reducing the overall pressure on the health system by reducing patient demand for services. The remaining exogenous variables (*Health Expectations, Disease Prevalence, Health Technology* and *Public Health Interventions*) that were treated as *demand modifiers* in the first model, also become part of new feedback loops. These new feedback structures can be used to inform policy debate, guide further model refinement and data validation, and support the decision making process.

From a policy perspective, the conceptual model provides a concise summary of public policy options, and emphasises their possible side-effects or unintended consequences. The model illustrates feedback loops for 5 specific policy areas (P1-P5), including: targeted funding of health system capacity; process improvement; chronic disease management; development of long-stay residential and home care initiatives; and health promotion activities. These policies have a balancing effect on overall patient demand, and can be seen as practical measures to support future sustainability.

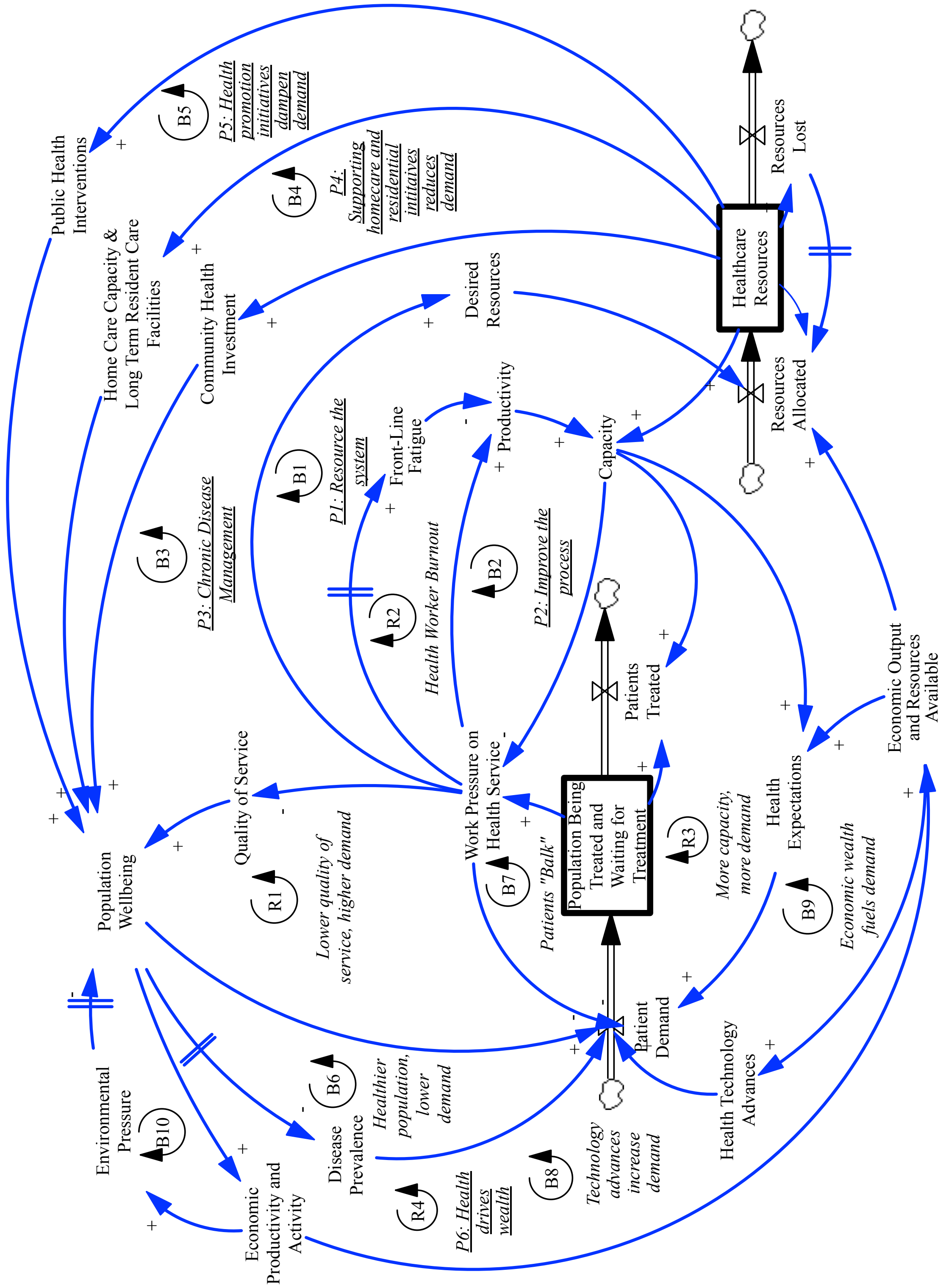

Figure 6: Conceptual high-level model of public health system

Apart from specific healthcare policies, the model also illustrates the interaction with wider public policy areas (including economic and social policy). For example, P6 reflects an overall political philosophy of better health contributing to greater public productivity and wealth creation. This virtuous cycle can be seen from the reinforcing loop R4, whereby a policy of investing in improvements to population wellbeing can lead to higher economic productivity, which in turn leads to more available resources, that can be invested to improve health and wellbeing.

Finally, our model illustrates the effect of policy time-lag, where the impact of policy actions may take significant time to manifest. For example, reinforcing behaviours such as R1 – a lower quality of service (QOS) – give rise to higher demand (vicious cycle effect), producing unchecked work pressure; here, a slow policy response to capacity resourcing leads to front-line fatigue (R2), ultimately reducing effective capacity. Other unexpected side effects are expressed through loops B8 and B9, where technological advances (e.g. improved diagnostics) can lead to increased demand for early intervention, or the increase in economic wealth may drive higher expectations of the health system.

In summary, this conceptual model expands our boundary of analysis by observing system feedbacks that may act on the exogenous variables from Figure 2, and so facilitates high-level policy exploration.

6. Conclusions and Future Work

Our whole-system SD approach provides quantitative simulation and qualitative conceptual models for long-term policy analysis, investment and development planning in sustainable healthcare. It is tested and calibrated based on currently available data and demographic projections. In summary, our model demonstrates the utility of the system dynamics method for addressing long-term sustainability problems of dynamic complexity. It facilitates whole-system impact analysis and allows the exploration of multiple individual and combined policy options, as well as an examination of their interdependency with other areas of public policy. The case study clearly demonstrates the value of simulation in healthcare sustainability planning and reinforces the need for a whole-system approach to such societal challenges.

There is much scope for future work using SD in healthcare sustainability. At a macro-level, the wider policy and feedback relationships in our conceptual model (Figure 6) need primary research to build reliable data sets for model validation and refinement. At a structural level, our models can be further developed across a number of dimensions. In line with similar studies such as (Hirsch *et al.* 2005; Jones *et al.* 2006), the models could be extended to include specific aggregations of disease prevalence in the population. This could be achieved through the addition of population stocks such as *Healthy, At Risk* and *Chronic and Afflicted.* Such a prevalence structure can then be used to drive an endogenous (Ghaffarzadegan *et al.* 2011) aging chain model for population prediction, so that health state also influences population change (thereby simulating loop B11 from our conceptual model). Furthermore, the model could be re-focused on a specific disease type, such as Type II diabetes or cancer prevalence. Finally, there is an opportunity to extend the model scope to include endogenous economic loops, such as funding and payment models, to explore the differential impact of economic incentives. This work, which would be extensive in terms of effort and data requirements, could further capture the interactions between public and private healthcare sectors (or funding models) in terms of the impact on available capacity, access and other measures of social equity, as well as the overall economic cost of the healthcare system.

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