Enabling Mobility for Persons with Major Lower-Limb Amputations:

A Model-based Study of the Impact of Digital Prosthetics Service Provision on Mobility Outcomes

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A Thesis Submitted in Partial Fulfilment of the Requirements
for the Degree Master of Philosophy in System Dynamics

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Abstract

The World Health Organization has predicted a doubling in the global population for persons with amputation by 2050 because of steady population growth, ageing populations, and climbing rates chronic conditions such as peripheral arterial disease and diabetes mellitus. Without proper and timely prosthetic interventions, amputees with major lower-limb loss experience adverse mobility outcomes, including the loss of independence, lowered quality of life, and decreased life expectancy. Yet, a vast majority of amputees still do not have access to prosthetic services given the present capacity constraints, lack of proximity to services, high costs and poor healthcare coverage. Today, the entry of digital technology to the prosthetics services industry (e.g., 3D-printed sockets) is touted to be a plausible solution to this problem.

This thesis aims to assess the impact of digital prosthetics on the amputee mobility outcomes – specifically, the proportion of amputees who successfully regain mobility from using a prosthesis and the health-economic consequences of such mobility. Using the system dynamics approach, this study presents a computational simulation model – representing the patient-care continuum and digital prosthetics system – that provides a feedback-rich causal theory of how digital prosthetics impacts amputee mobility outcomes over time. In general, this study has found that with sufficient resources for market formation and capacity expansion for digital prosthetics services, substantial improvements to mobility outcomes for amputees can be expected. In doing so, it serves as proof-of-concept for the viability of scaling digital prosthetics for enabling mobility and bolstering the social impact of providing a prosthesis. Based on the high-leverage policy levers found in the system, this study further discusses the model-based insights that could inform policy design for alleviating the barriers to access and enhancing the health-economic outcomes of prosthetics care.

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List of Abbreviations

BAU	Business as Usual
ECS	Expanded Capacity Scenario
HRS	Heightened Resources Scenario
PAD	Peripheral Arterial Disease
R&D	Research and Development
SD	System Dynamics
TIS	Technological Innovation Systems
UK	United Kingdom
WHO	World Health Organisation

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1. Introduction

Problem Orientation

Major Lower-Limb Amputations & Mobility

Although lacking definitive and reliable data, the World Health Organization (WHO) estimates that around 0.5% of any given population require prosthetics and orthotics services (World Health Organization, 2017). This figure is further expected to double by 2050 due an ageing population (exacerbated by the growing life expectancy) and rising rates of medical conditions. Diabetes mellitus, peripheral arterial disease (PAD), and sepsis are the most common culprits for disease-related lower limb amputations (Moxey et al., 2011). In most industrialised countries, traumatic injuries make up only a small percentage of major lower-limb amputations (i.e., above ankle), whereas over 90% is attributed to PAD (Ahmad et al., 2016; Geertzen et al., 2015; Kohler et al., 2009). PAD is a progressive vascular disease that causes obstruction in the peripheral arteries, most commonly in the lower extremities. PAD incidence is low for populations below the age 50, but sharply rises with age – particularly for populations in high-income countries (Criqui & Aboyans, 2015). Risk factors for PAD include cigarette smoking, diabetes mellitus, hypertension, and dyslipidaemia (Criqui & Aboyans, 2015; Meffen et al., 2020). Arterial obstruction, when symptomatic, leads to intermittent claudication (fatigue, cramping or pain) due to insufficient blood supply to the limbs (Criqui & Aboyans, 2015; Shu & Santulli, 2018). If not managed effectively at an earlier stage, PAD progresses to the more severe critical limb ischemia, which could eventually lead to amputation (Belch, 2003).

Major lower-limb amputation, without timely prosthetic intervention, leads to a loss of mobility, which has several ripple effects at both the individual and societal level. It worsens individual health and psychosocial outcomes, including the loss of independence, increased depression and self-esteem issues, lowered quality of life, and increased risk of comorbidities and mortality (Akarsu et al., 2013; Horgan & MacLachlan, 2004; Roberts et al., 2006). There is also high economic burden on patients, families (increased caregiving), health and welfare systems, as well as the workforce (lower rates of return to work) (Darter et al., 2018; Stewart et al., 2022; World Health Organization, 2017). Importantly, such negative externalities can be alleviated with the use of prostheses to regain mobility.

> *Increased prosthetic usage is associated with higher levels of employment, increased quality of life, decreased phantom limb pain, and lower levels of general psychiatric symptoms. Additionally, prosthetic use has been shown to facilitate a reduction in secondary health issues and therefore a larger degree of mobility and functional independence for those with amputation (Pasquina et al., 2015, p. 536).*

Hence, efficacious prosthetics service provision is a necessary component of amputee health care and their right to a dignified life (cf. Sustainable Development Goal 3, Convention for the Rights of Persons with Disabilities).

Prosthetics Service Provision

Yet, presently, prosthetics services are not accessible for a vast majority of amputees. WHO (2017) speculates that only 5 to 15% of the amputee population has access to them. Barriers to access include high financial costs for treatment, poor healthcare coverage, prosthetics service capacity constraints, lack of proximity to services, and inadequate continuity of care (Pasquina et al., 2015; ProsFit Technologies, 2022; Wyss et al., 2015).

Digital Solutions in Prosthetics

To alleviate this problem, Silva et al. (2015, p. 1312) raise awareness for "the potential application of 3-dimensional (3-D) printing as a method of improving access to care while reducing cost." Indeed, by then, ProsFit Technologies, an early entrant to digital prosthetics, had developed end-to-end digital solutions to the socket fitting process. The traditional fitting process has considerable delays in the Definitive Device stage (see Figure 1.1 below for a general timeline). Moreover, approximately 50% of amputees in this stage abandon the device due to improper fit, discomfort and pain (ProsFit Technologies, 2022; Raichle et al., 2008). Using traditional methods, the prosthetists must handcraft the sockets in clinics using plaster casts and test the fittings several times before a definitive socket is manufactured and assembled with the mechanical part (Kozbunarova, 2019). Manufacturing delays have adverse consequences for fitting success as the patient's limb and/or weight may have changed before receiving the prosthesis, resulting in an improper fit that causes discomfort and pain (ProsFit Technologies, 2022). Digital-solutions-based prosthesis (digital prosthesis henceforth), on the other hand, could be delivered within 5 to 10 days with a more streamlined manufacturing process; “the limb gets scanned, the prosthetist uses PandoFit software to create a model of the socket and sends the file for 3D printing” (Kozbunarova, 2019 para 5; ProsFit Technologies, 2022). According to ProsFit (correspondence), this has a much higher success rate as the digital design is more accurate and independent of variability in prosthetist’s skill-level, has a much shorter timeframe such that there is little time for limb changes, and results in a more comfortable fit for patients.

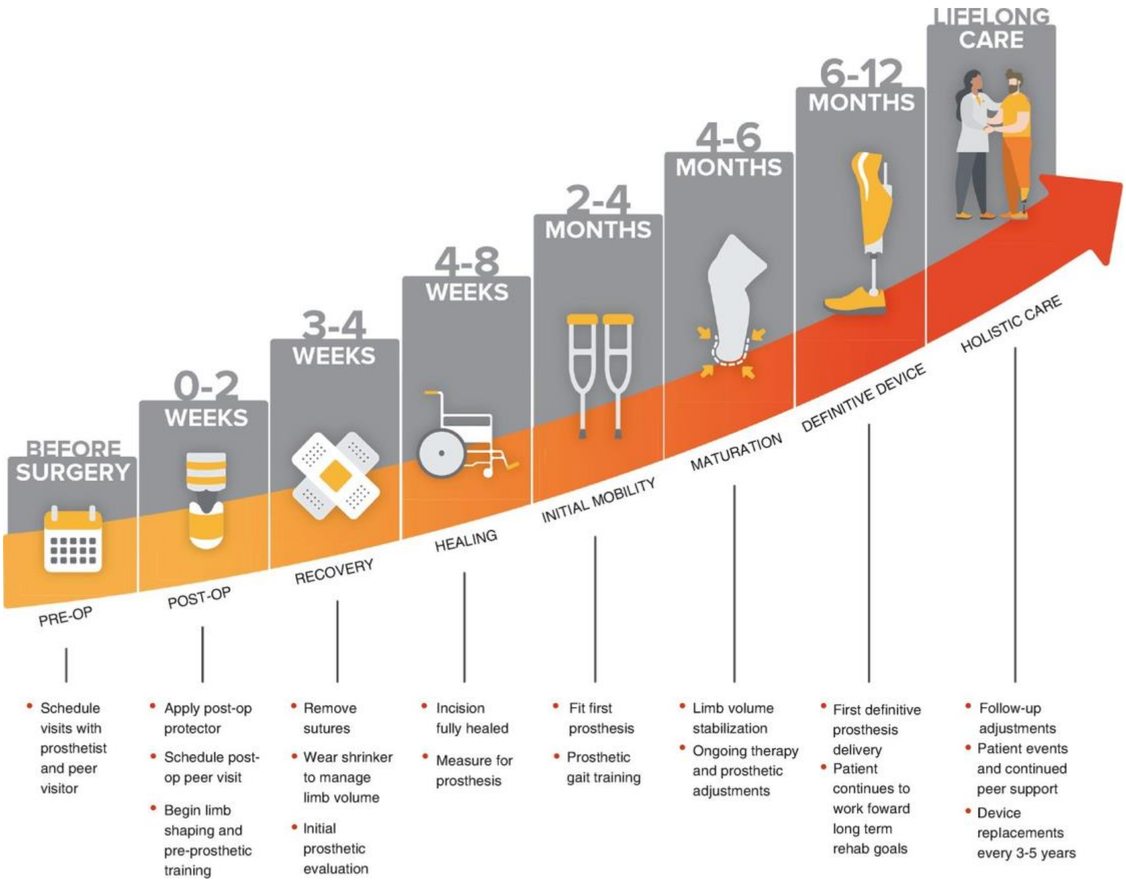


Figure 1.1 General Timeline for Prosthesis Fitting (Rheinstein et al., 2021)

With a more streamlined and effective fitting process, ProsFit believes that digital prosthetics is the solution to the accessibility problem – especially with the enhanced fitting capacity per prosthetist and the flexibility to bring the service to patients through distributed care networks (A. Hutchison, 2020). Consequently, ProsFit anticipates that there will be several positive externalities for amputees, their families, and the economy more broadly. They have attempted to demonstrate this social impact by developing a Health Economics Model, which calculates the returns on investment for providing prosthetics in 10 country cases (net benefit from calculated economic costs and benefits). The model is based on a comparison for scaling up traditional and digital approaches to fit 50% of the estimated amputee population (C.

Hutchison, 2021). In its current iteration, however, it remains as a static model that is unable to capture the dynamics in the amputee population over time. In other words, it holds the estimated amputee population constant, and estimates the economic costs and benefits of providing prosthetics services with no feedback on the decision choices for existing amputees. For a more nuanced understanding of the impact of digital prosthetics, then, a dynamic model should be considered.

Research Purpose

This study aims to assess the impact of digital prosthetics service provision on country-level mobility outcomes. Mobility outcomes, in this study, refer to the proportion of amputees who are able to successfully regain mobility from using a prosthesis as well as the health-economic consequences of such mobility, namely the economic contribution from returning to work and the economic costs incurred or avoided (healthcare, family opportunity cost, welfare payments, and prosthesis reimbursement). Moreover, this study aims to provide additional insight to the health economics model by capturing the feedback dynamics in the prosthetic care system in a system dynamics model. In doing so, it further aims to identify high-leverage policy levers for enhancing the mobility outcomes.

The purpose of this study is, thus, to conduct a model-based hypothesis testing of the anticipated impact of ProsFit's digital prosthesis fitting process and distributed healthcare delivery (i.e., digital prosthetics) as described in the preceding section – namely, that *scaling up digital prosthetics positively impacts mobility outcomes*.

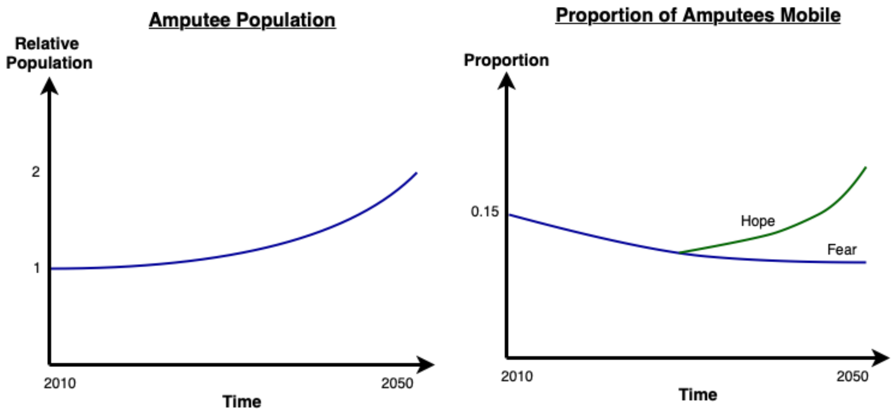


Figure 1.2 Qualitative Reference Modes for Hypothesis Testing

In Figure 1.2, I present the reference mode of behaviour for the prosthetic care system and the hypothesised development. Reference modes are graphical representations of the system's problem behaviour to be investigated; these are "stylized problem patterns" that can be constructed quantitatively from historical time-series data or qualitatively from estimates or speculations (Saeed, 2017, p. 13). A major challenge in prosthetics is the dearth of reliable data on the amputee population and their service needs (World Health Organization, 2017). As a result, the reference modes were constructed qualitatively based on guesstimates from WHO and expert opinion. Here, we observe a doubling of the amputee population across the time horizon (2010 to 2050). If the approach to prosthetics fundamentally remains unchanged (dominated by traditional approaches), then we can expect a decrease in the mobility proportion from the current estimate of 15% – fearing a decrease in prosthetics accessibility as the demand for prosthesis grows from a rising amputee population. Based on the research hypothesis, we hope for the proportion of mobile amputees to increase over time with the scaling up of digital prosthetics.

Research Questions

To guide our hypothesis testing effort, we consider the following research questions:

1) How does digital prosthetics service provision affect amputee mobility outcomes over time?
    a) What are the dynamic structures found in the patient-care continuum and the prosthetic service provision systems responsible for changes in amputee mobility outcomes over time?
    b) What are the key causal mechanisms that drive these changes and explain the impact of digital prosthetics on mobility outcomes?
2) What are the model-based insights for bolstering the social impact of digital prosthetics?
    a) What are the leverage points in the system that can enhance the effects of digital prosthetics service provision on mobility outcomes?
    b) What are the plausible implications for policy design?

Research Methods

Methodological Approach

To examine the research questions and test the overall hypothesis posited above, this study employs the system dynamics (SD) method, using compartment models, for conducting a model-based hypothesis testing. The SD approach seeks to simulate and explain problematic system developments by modelling the underlying structural interdependencies within the system (Sterman, 2000). Importantly, SD models offer an "endogenous or feedback perspective" to structural problems (Hovmand, 2014, p. 1) that can aid "theory building, policy analysis, and strategic decision support" (Richardson, 2019, p. 11). This endogenous perspective refers to two fundamental tenets: (1) problem behaviours arise from the complex interaction of interrelated components *within* a closed boundary of a system, and (2) the system components are connected in *feedback loops* (circular chains of causal relationships), which endogenously generate the observed system behaviour (Forrester, 1968; Richardson, 2011). In this sense, the SD approach "helps construct a causal-loop theory of system behavior in terms of feedback linkages" (Sohn & Surkis, 1985, p. 400).

SD is well-suited to and has a history of being applied to a wide array of domains in public health (for a review, see Darabi & Hosseinichimeh, 2020; Davahli et al., 2020). The "dynamic complexity in public health" (particularly due to nonlinear effects of multiple interacting variables within the system that affect health outcomes) makes it "difficult to know how, where, and when to intervene" (Homer & Hirsch, 2006, p. 452). SD simulation modelling can effectively address this challenge and "elucidate the counterintuitive behavior of complex healthcare problems" (Davahli et al., 2020, p. 1). While there has been over 300 applications of SD to health and medicine (Darabi & Hosseinichimeh, 2020), to our knowledge there is no application of SD to prosthetic service provision or major lower limb amputations in the academic literature. Hence, this research further contributes to the SD literature in the domain of public health.

Importantly, SD simulation modelling is a powerful tool for testing alternative policy options and scenarios "in a systematic way that answers both 'what if' and 'why'" (Homer & Hirsch, 2006, p. 452). Through experimentation under different assumed conditions, we can anticipate plausible future system behaviours and pinpoint the structural reasons for such observed developments. In turn, this exercise could identify leverage points – "places in the system where a small change could lead to a large shift in behavior" (Meadows, 2009, p. 145)

– that are capable of mitigating problematic behaviours, and thus generate useful policy insights. Particularly for prosthetics, SD modelling can aid decision-making under uncertainty. As mentioned, the domain of prosthetics services is mired by the lack of robust data collection, contributing to a high level of uncertainty surrounding policy planning (ProsFit Technologies, 2022; World Health Organization, 2017). SD models, however, can "admit more variables on the basis of logic or expert opinion and for which solid statistical estimates may not be available" (Homer & Hirsch, 2006, p. 453) and still generate useful insights under such uncertainty. For these reasons, the SD approach is an excellent fit for our research purpose.

Data Collection

Primary Sources

The iterative model building process, from conceptualisation, quantification, to validation, was conducted in collaboration with two partners: (1) ProsFit Technologies – digital prosthetics service provider, and (2) Toyota Mobility Foundation – expert in system dynamics and human centred design for promoting mobility. Including problem owners in the model building process has been a longstanding tradition in SD since they possess important domain expertise, experiential knowledge, and mental models of the system under study (Forrester, 1961; Király & Miskolczi, 2019; McCardle-Keurentjes et al., 2018). Over the course of this research project, several iterations of the model were presented to the collaborators for validation. In terms of model parameterisation, ProsFit provided numerical estimates for some parameter values where existing data was not available. In such instances, ProsFit relied on its network of prosthetists in the field to corroborate their assumptions and understanding. Estimates and comments from these domain experts were anonymised and shared via email correspondence. Such estimates represent the best available data at the time of the model development.

Secondary Sources

Apart from expert opinion, existing peer-reviewed literature was utilised extensively for model conceptualisation – especially so for the conceptual market formation subsystem in the model. As for quantification, parameter values were obtained either from epidemiological data reported in the literature or from secondary datasets. The various datasets are described in Table 1.1 below.

Table 1.1 Description of Secondary Datasets

Source	**Type**	**Description**	**Use**
Office for National Statistics, UK (2015, 2020, 2021, 2022a, 2022b, 2022c)	UK Population Statistics	Datasets on population estimates and projections, fertility rates, mortality rates as well and international migration rates	Parameterisation; Validation
Healthcare Quality Improvement Partnership (2015, 2016, 2018a, 2018b, 2019, 2020) on behalf of the National Vascular Registry	UK PAD-related Amputation Statistics	A composite dataset was constructed from annual reporting on clinical outcomes from major lower-limb amputation in the UK from 2015 to 2020 – data points were averaged to generate parameter estimates mainly for the Primary Care Sector in the model	Conceptualisation; Parameterisation
Global Burden of Disease Collaborative Network (2020)	UK PAD & Traumatic Amputation Statistics	Datasets on yearly prevalence and incidence estimates on PAD as well as lower limb amputations from injuries as a cause between 2010 and 2019	Parameterisation
Christopher Hutchison (2021) on behalf of ProsFit Technologies	UK Health Economics Data	Dataset from ProsFit's Health Economic Model estimating the economic costs and net benefits of prosthetic service provision	Conceptualisation; Parameterisation;
ProsFit Technologies (2022)	Digital Prosthetics Care	Internal document reporting data on the problem context, prosthetics service provision, patient journey mapping, and ProsFit's digital-based solutions	Conceptualisation; Parameterisation

Ethical Considerations

Research Standards

This research adheres to the guidelines set by The Norwegian National Research Ethics Committees (2022) in its entirety. As a researcher, I am obligated to observe the professional standards and best practices set in both research praxis, in general, and the more specific SD sub-field. To that end, this research conforms to the guidelines on model development, validation, and documentation as described in seminal SD literature (Barlas, 1996; Rahmandad

& Sterman, 2012; Sterman, 2000). Briefly, Chapters 2 and 3 provide detailed descriptions of the model structure and hypothesised structural relationships, while making transparent the main assumptions built into the model. Model validation results are also reported in Chapter 3. Appendix C contains the full model documentation, where each variable in the model is described and validated.

Research Participants

As this study did not involve systematic primary data collection, considerations for informed consent and protected groups are not applicable. Nevertheless, it is prudent to make transparent the nature of the relationship between the modeller (myself) and the collaborators, ProsFit Technologies and Toyota Mobility Foundation, who have been involved in the research project. From the outset, this collaboration did not involve any monetary compensation and did not entail any known conflict of interests between parties. This project commenced with the signing of a Partnership Agreement between all parties involved. Obligations covered issues of intellectual property, prior inventions, confidentiality, and storage of sensitive data. Of particular note, is the clause in the Agreement that specifies, "the Student should not be constrained to reach any particular conclusion or to make any particular recommendation in the exercise of their functions." Here, we have codified my independence as a researcher against pressure and control (The Norwegian National Research Ethics Committees, 2022).

Reflections on Subjective Values

Diekmann & Peterson (2013, p. 207) contend that "non-epistemic values, including moral ones, play an important role in the construction and choice of models." Such subjective values influence the modelling process, including problem selection, boundary demarcation, and representational choices and are as such subject to ethical considerations (Diekmann & Peterson, 2013; Pruyt & Kwakkel, 2007). Here, the problem selection was intrinsically tied to the collaborators' interests, who are stakeholders in prosthetics service provision (ProsFit) and improving mobility, especially for underserved communities (Toyota Mobility Foundation). Their worldview and perspectives are tied into the model, and thus cannot fully represent the interests of other key stakeholders. This should be kept in mind when interpreting the findings of the research. Choices related to model boundary and structural representations are not only influenced by the collaborators, but also the time-bound nature of this thesis research project. Hence, certain exclusions were necessary to keep the scope of the research relatively small. While ProsFit's experiential knowledge is relied upon for representational activities such as parameterisation, there have been attempts to corroborate it with existing literature and third parties.

Moreover, Walker (2009, p. 1054) reminds us that modellers occupy both the analyst and the advocate positions, and thus must "make clear which of these role he/she is playing at any given time." This study is meant to evaluate the impact of digital prosthetics on the mobility outcomes of amputees. By design, it is meant to elucidate model-based insights that could potentially influence policy making. To that end, I do occupy the advocate position. However, Palmer (2017) emphasises the need for transparency about model uncertainty not just for the sake of model validation, but also for policy decisions that may follow from the modelling pursuit. SD models are "a set of aggregated causal assumption ("observed operation relationships") – and regardless of validation – are by definition uncertain, because causality is assumed" (Palmer, 2017, p. 92). This fundamental uncertainty is then spilled over to any policy insights generated by the model. Hence, decision-makers should be cognisant of this limitation prior to carrying out any form of policy implementation.

2. Dynamic Hypothesis

In system dynamics, a dynamic hypothesis refers to “an abstract and aggregate mental model” of the hypothesised system structure that can explain the reference mode of behaviour (Saeed, 2017, p. 11). It serves as an explanation of how various system components interact to endogenously cause the observed behaviour (Forrester, 1968; Oliva, 1996; Richardson, 2011). Endogeneity, as mentioned in the previous chapter, is reflected in the main feedback loops driving the behaviour. Here, I present my dynamic hypothesis in the form of a hybrid stock-and-flow model that clearly demarcates the main interacting feedback loops. Given the size of the model, the simplified structure is split into the main top-level Prosthetic Care System and the Market Formation Subsystem. For each feedback loop, I describe the hypothesised causal relationships, supported by the relevant literature and assumptions that underpin the hypothesis.

The Prosthetic Care System

‘Aging chains’ that capture the flow of populations across different stages or compartments are commonly used to represent health care systems. This structure has become the “main backbone” of SD health models for its simplicity and effectiveness, especially in identifying accumulations and key bottle-necks to patient flows (Darabi & Hosseinichimeh, 2020, p. 50). Similarly, the prosthetic care system is represented as an aging chain in the model presented here. With reference to Figure 2.1 below, we represent the flow of people to acute or primary care for amputation, before they journey on to the prosthetic care stage. To best estimate the accumulation level in each of these stages, patients are drawn from the general population stock and the peripheral arterial disease (PAD) population stock. From the Prosthetic Care stage, amputees either become successfully fitted with a prosthesis and achieve Full Mobility or they abandon the prosthesis fitting process and maintain Limited Mobility.

Beyond the aging chains, the hypothesised model structure includes several feedback mechanisms that influence the flows. It was conceptualised with input from ProsFit to better reflect the reality of the prosthetic care system. To test the main working hypothesis of this project, most of the feedback mechanisms, presented below, strive to explain how the emergence of digital prosthetic market could impact population flows, patient or healthcare provider decisions at each aging chain step, and yield better mobility outcomes for persons with major lower-limb loss.

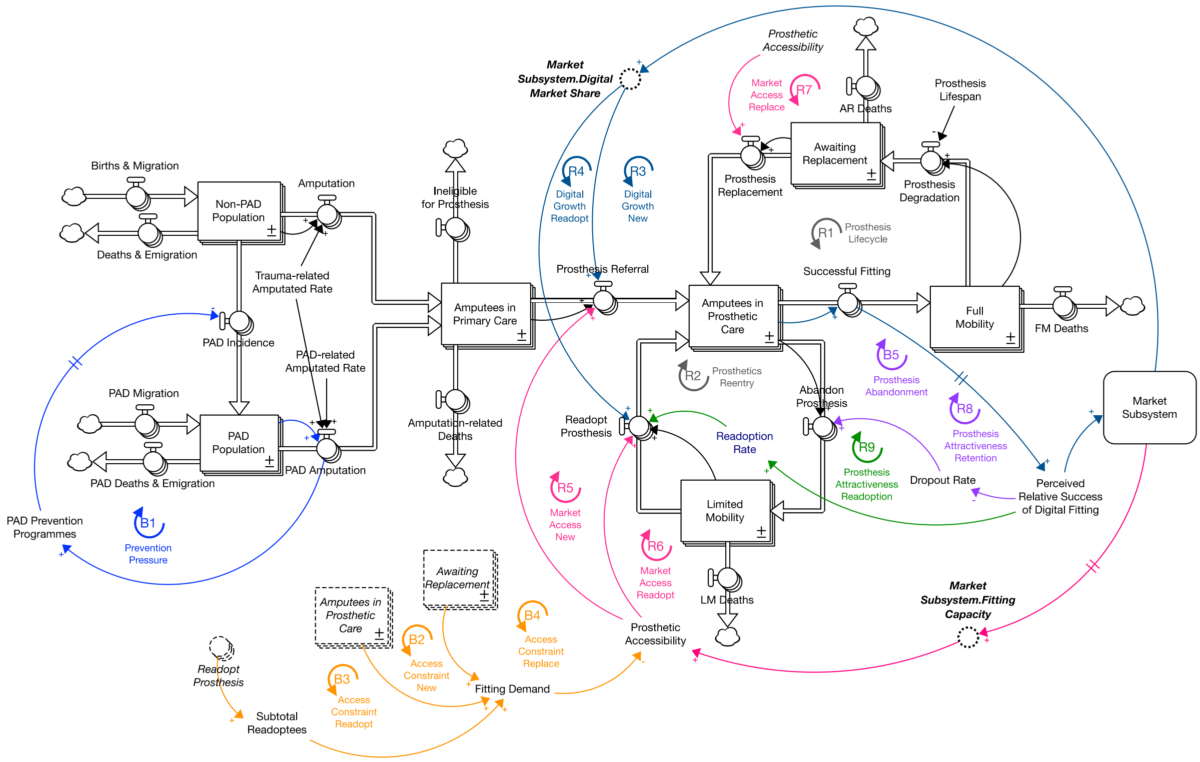


Figure 2.1 Simplified Model Structure of Prosthetic Care System

Feedback Loop Description

For ease of interpreting the causal loops, each description includes the causal pathway shown in Figure 2.1. The arrow symbol (→) represents a causal link between two variables. The corresponding polarity is provided: (+) indicates a positive polarity and (–) indicates a negative polarity. Polarities simply indicate the directionality of the correlation. For instance, “A →(–) B →(+) C” should be interpreted as such: when A increases, B decreases, and in turn C decreases. Here, the positive polarity between B and C indicates that both vary in the same direction.

Prevention Pressure – B1 Loop

B1 Pathway: PAD Amputation →(+) PAD Prevention Programmes →(–) PAD Incidence →(+) PAD Population →(+) PAD Amputation

This balancing feedback loop represents the prevention pressure faced by public health agencies to address the prevalence of PAD. As PAD-related amputation rates increases over time, we expect reporting from medical professionals to raise the alarms for stepping up efforts towards primary prevention. This is observed, for instance, in trend studies of PAD incidence and risk factors, calling for better detection and prevention interventions (Cea-Soriano et al., 2018; Farndon et al., 2018; Stansby et al., 2011). With increased reporting, we can expect more resources directed towards prevention interventions such as screening, smoking cessation, nutritional and activity programmes (Farndon et al., 2018). In the long run, such interventions could lead to a decrease in PAD incidence rate. Indeed, there is evidence that PAD incidence have declined in the UK, which have been attributed to the uptake of prevention strategies (Cea-Soriano et al., 2018). A declining PAD incidence would lead to a reduction of the PAD Population over time, which would eventually decrease the PAD Amputation Rate. Since an initial increase in amputation rate ends up with an eventual decrease in amputation rate, this feedback loop has a negative polarity overall and is thus described as a balancing loop.

Prosthesis Lifecycle – R1 Loop

R1 Pathway: Amputees in Prosthetic Care →(+) Successful Fitting →(+) Full Mobility →(+) Prosthesis Degradation →(+) Awaiting Replacement →(+) Prosthesis Replacement →(+) Amputees in Prosthetic Care

This reinforcing loop describes the lifecycle that is part of the lifelong holistic care for amputees successfully fitted with a prosthesis (Rheinstein et al., 2021). As more amputees enter the prosthetic care continuum, there will be more people who are successfully fitted with a prosthesis thus increasing the number of amputees with full mobility. However, the prosthesis device has an average lifespan of three years (ProsFit Technologies, 2022; Rheinstein et al., 2021). Hence, over time, prosthesis degradation increases the number of amputees awaiting replacement of their devices before re-entering the prosthetic care continuum to be fitted for a new device again. In this regard, this loop represents a growing pressure emanating from our best efforts to successfully fit individuals with a prosthesis.

Prosthetics Re-entry– R2 Loop

R2 Pathway: Amputees in Prosthetic Care →(+) Abandon Prosthesis →(+) Limited Mobility →(+) Readopt Prosthesis →(+) Amputees in Prosthetic Care

R2 represents the Prosthetic Care Re-entry process for amputees. Not all amputees who enter the care continuum end up with a prosthesis; some individuals dropout from the fitting process or some abandon the device due to an unsuccessful fit (Davie-Smith et al., 2018; ProsFit Technologies, 2022). Hence, with more people in the continuum abandoning prosthesis, there will be more people who are left with limited mobility due to the lack of a prosthesis device. However, more amputees might later decide to readopt a prosthesis, thus re-entering the prosthesis fitting process.

Digital Growth – R3 & R4 Loops

R3 Pathway: Amputees in Digital Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(+) Digital Market Size →(+) Digital Market Share →(+) Digital Prosthesis Referral →(+) Amputees in Digital Prosthetic Care

R3 is a reinforcing loop that represents the hypothesis for the market growth of digital prosthesis solutions – namely, the use of digital technology for prosthesis measurements and 3D-printed sockets. As more amputees get referred to a digital prosthetic clinic and more people become successfully fitted with a prosthesis with better outcomes, we expect favourable word-of-mouth diffusion about the success of digital prosthesis (Chernicoff et al., 2014). This is captured with the Perceived Relative Success of Digital Fitting, which represents the mental perceptions of people's comparison of success between the digitally fitted prosthesis and traditional plaster-casted device. Over time, we expect the attractiveness of digital fitting to grow the digital market size and thus the market share of the digital prosthetics relative to traditional. With a higher market share, more amputees are probabilistically to be referred to a digital prosthetist and thus driving up the number of amputees in the digital prosthetic care continuum as opposed to the traditional one.

R4 Pathway: Amputees in Digital Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(+) Digital Market Size →(+) Digital Market Share →(+) Digital Prosthesis Readoption →(+) Amputees in Digital Prosthetic Care

Similarly, R4 loops drives up the number of amputees in Digital Prosthetic Care by way of readoption. As the digital market share increases, potential re-adoptees looking to restart their prosthetic fitting journey are more likely to seek out a digital prosthetist. The assumption here is that as digital fittings experience more success, people are more likely to be motivated to try the digital process and experience a similar success as others (Chernicoff et al., 2014;

Nieuwenhuijsen et al., 2018). Thus, more re-adoptees enter the digital prosthetic care continuum as opposed to the traditional one.

Access Constraint – B2, B3 & B4 Loops

B2 Pathway: Amputees in Prosthetic Care →(+) Fitting Demand →(-) Prosthetic Accessibility →(+) Prosthesis Referral →(+) Amputees in Prosthetic Care

The balancing feedback loop B2 counteracts the reinforcing Digital Growth loops. As more Amputees in Prosthetic Care are attracted to the digital prosthesis fitting process, the Fitting Demand for digital prosthesis increases. In turn, this drives down Prosthetic Accessibility if demand outweighs the fitting capacity, which then reduces the amount of people who can enter the prosthesis fitting process. Hence, the Amputees in Prosthetic Care declines to a level lower than it otherwise would have been. Through this balancing feedback, B2 dampens the strength of the R3 and R4 loops.

B3 Pathway: Prosthesis Readoption →(+) Subtotal Re-adoptees →(+) Fitting Demand →(-) Prosthetic Accessibility →(+) Prosthesis Readoption

B4 Pathway: Amputees Awaiting Replacement →(+) Fitting Demand →(-) Prosthetic Accessibility →(+) Prosthesis Replacement →(+) Amputees Awaiting Replacement

Fitting Demand is not solely determined by the number of Amputees in Prosthetic Care. Amputees who have previously abandoned the fitting process and those seeking to replace their degraded prosthesis device also make up the demand. Hence, B3 captures a similar mechanism whereby more Prosthesis Readoption brings up the demand and consequently reduces the Prosthetic Accessibility. B4, on the other hand, reduces the Accessibility through the Prosthesis Replacement process. All three balancing loops work in concert to counteract the reinforcing loops seeking to increase the demand for digital prosthesis fitting.

Market Access – R5, R6 & R7 Loops

R5 Pathway: Amputees in Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(+) Digital Market Size →(+) Fitting Capacity →(+) Prosthetic Accessibility →(+) Prosthesis Referral →(+) Amputees in Prosthetic Care

The Market Access loops, however, interplay with the balancing Access Constraint loops described above. In the longer term, these loops work to increase the Fitting Capacity so as to improve the Prosthetic Accessibility that was driven down by increased demand. With reference to R5 loop, when more Amputees in Prosthetic Care get successfully fitted with the prosthesis and the perceived success of digital prosthesis relative to traditional increases, the digital market share grows. The growth in market share is likely to lead to the expansion of digital prosthetic clinics, which in turn drives up the Fitting Capacity. Hence, with more capacity, more people have access to prosthetic services, and thus the care continuum can accommodate a larger number of new amputees seeking a prosthesis.

R6 Pathway: Amputees in Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(+) Digital Market Size →(+) Fitting Capacity →(+) Prosthetic Accessibility →(+) Readopt Prosthesis →(+) Amputees in Prosthetic Care

R7 Pathway: Amputees in Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(+) Digital Market Size →(+) Fitting Capacity →(+) Prosthetic Accessibility →(+) Prosthesis Replacement →(+) Amputees in Prosthetic Care

Likewise, R6 enables a larger number of people seeking to readopt the prosthesis fitting process to enter the Prosthetic Care, whereas R7 enables more people waiting to replace their old prosthesis to re-enter the care continuum at any one point in time. However, it must be noted that increasing capacity involves a delay as it takes time to assess the market and set up new clinics. Hence, the effects of Market Access loops are delayed.

Prosthesis Attractiveness – R8 & R9 Loops

R8 Pathway: Amputees in Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(–) Dropout Rate →(+) Abandon Prosthesis →(–) Amputees in Prosthetic Care

R9 Pathway: Amputees in Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(+) Re-adoption Rate →(+) Readopt Prosthesis →(+) Amputees in Prosthetic Care

As previously described, when people perceive digital prosthesis to be more successful than traditional ones, the attractiveness of digital prosthesis is expected to increase through word-of-mouth diffusion (Chernicoff et al., 2014). Hence, R8 captures the process by which a higher attractiveness translates to a lower dropout rate as individuals might be more motivated to see through the process and experience a similar success as others. This could lead to fewer people abandoning the prosthesis fitting process and therefore increasing the number of Amputees in Prosthetic Care to a level higher than it otherwise would have been. R9, on the hand, works to increase the re-adoption rate amongst those who have previously abandoned the process. The higher attractiveness of digital fitting would then increase the number of people readopting a prosthesis and thus re-entering the prosthetic care continuum.

Prosthesis Abandonment – B5 Loop

B5 Pathway: Amputees in Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(–) Dropout Rate →(+) Abandon Prosthesis →(+) Limited Mobility →(+) Readopt Prosthesis →(+) Amputees in Prosthetic Care

This balancing feedback loop counteracts the effects of R2 and R9, by draining the number of people available for entering readoption process. When more Amputees in Prosthetic Care results in more successful fitting and thus more attractiveness of digital fitting, less people abandon the prosthesis fitting process. As a result, the number of people with Limited Mobility is at a lower level than it otherwise would have been. Hence, the readoption rate would consequently be lower, resulting in a lower number of Amputees in Prosthetic Care than it otherwise would have been. However, this is a positive effect that prevents prosthesis abandonment altogether and thus yielding better mobility outcomes in the grand scheme of things.

The Market Formation Subsystem

In the top-level Prosthetic Care System, we made the leap of faith that the relative success of digital prosthetics would increase the share of the digital market. Inherently, we understand that market growth for new technologies is a complex process that necessarily requires market formation. Lee et al. (2018) and Struben et al. (2020) emphasise the collective action problem in early market formation. It requires market-oriented action from diverse actors to collectively develop “shared market infrastructure” for “supporting the functioning of a stable market” (Lee et al., 2018, p. 244). Indeed, “technological change is a complex non-linear interactive process” concerning several actors and institutions (Uriona & Grobbelaar, 2019, p. 28). It is, thus, better served to explicitly represent this complexity than the alternative: a simplistic table function.

To elucidate the feedback story, I rely on the work of Walrave & Raven (2016a, 2016b), who have translated the literature on Technological Innovation Systems (TIS) framework (Bergek et al., 2008; Hekkert et al., 2007; Markard & Truffer, 2008) into a system dynamics model. TIS theory posits that seven key functions undergird the formation and growth of innovation systems, namely, “(1) entrepreneurial activities, (2) knowledge development, (3) knowledge diffusion, (4) guidance of search, (5) market formation, (6) mobilization of resources, and (7) creation of legitimacy” (Hekkert et al., 2007; Walrave & Raven, 2016b, p. 1834; Wicki & Hansen, 2017). These functions power the ‘motors of innovation’ through complex interactions and have been described through informal causal loop diagrams (see Suurs, 2009; Suurs et al., 2009, 2010; Suurs & Hekkert, 2012). These loops were, in turn, formalised and operationalised into a SD simulation model (Walrave & Raven, 2016b). This TIS modelling approach was selected over the more common Bass Diffusion Model as it captures more feedback mechanisms beyond the simple “innovator and imitator adoption mechanisms” (Uriona & Grobbelaar, 2019, p. 34).

In the section, I (re-)present the main feedback loops that could endogenously explain the market formation and thus growth of digital prosthetic market share over time. This is meant to be a conceptual model that was after all built from theory (Walrave & Raven, 2016b). As a result, it is bound to introduce more uncertainty to the relatively empirical top-level model. Nevertheless, as George E.P. Box famously stated, “all models are wrong, but some are useful.” Here, understanding how digital prosthetic market formation may plausibly occur from a feedback perspective could prove to be a useful exercise for ProsFit, who is an early market actor in the emerging digital prosthetic technology, as well as health policy leaders seeking to improve mobility outcomes and maximise the impact of limited resources.

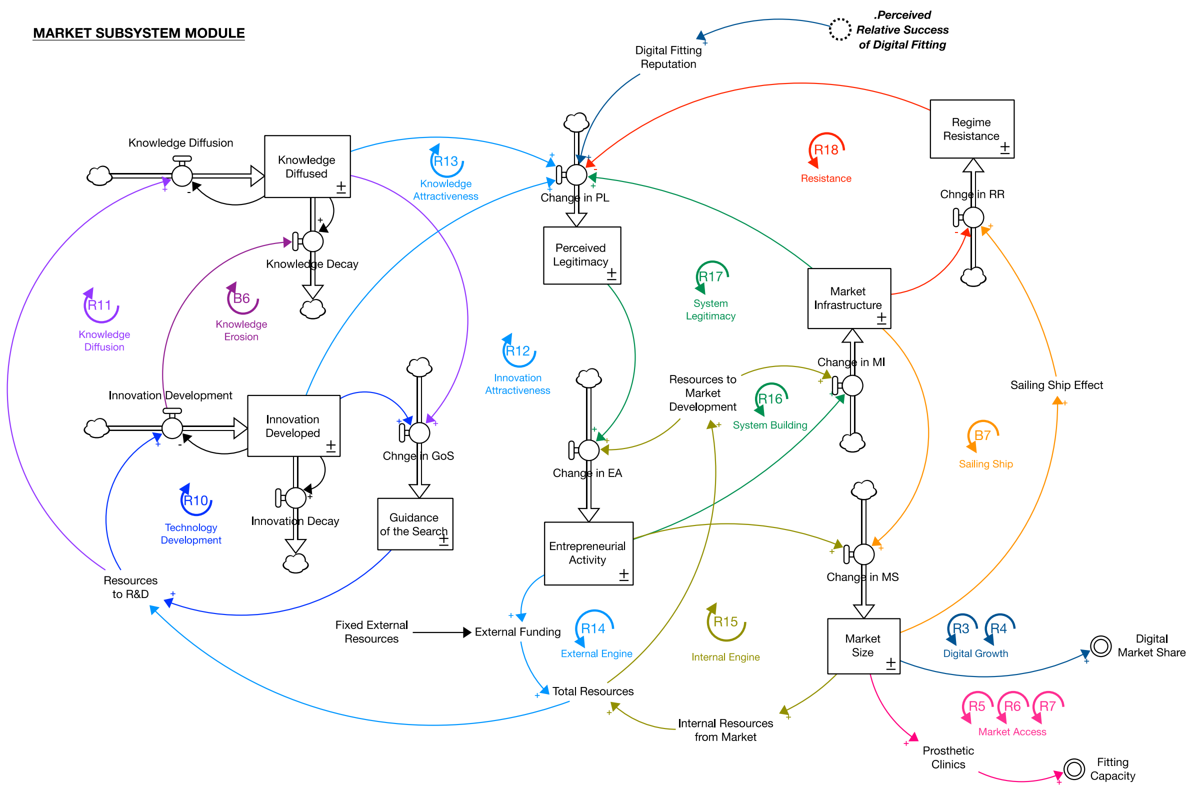


Figure 2.2 Simplified Model Structure of Market Subsystem

Feedback Loop Description

Technology Development – R10 Loop

R10 Pathway: Innovation Developed →(+) Guidance of Search →(+) Resources to R&D →(+) Innovation Development →(+) Innovation Developed

This feedback loop represents the process of technological knowledge development, typical of research and development (R&D), required for any TIS to grow (Hekkert et al., 2007; Suurs, 2009). As more innovation is developed, the Guidance of Search for the technology increases. Guidance of search refers to the "visibility and clarity" of the state of the art (Hekkert et al., 2007, p. 423) that reflects the "promises and expectations of the emerging technology" (Suurs, 2009, p. 56). It helps in the priority-setting process for R&D resource allocation and "thus the direction of technological change" (Hekkert et al., 2007, p. 423). Hence, in this context, increased Guidance of Search for the digital solutions in prosthetic fittings, would help increase the Resources to R&D, which would enable further Innovation Development that increases the Innovation Developed even more (Nieuwenhuijsen et al., 2018).

Knowledge Diffusion – R11 Loop

R11 Pathway: Knowledge Diffused →(+) Guidance of Search →(+) Resources to R&D →(+) Knowledge Diffusion →(+) Knowledge Diffused

Knowledge Diffusion, R11 loop, refers to process by which various actors in the TIS interact and exchange knowledge and thus establish "a mutual understanding" that enables institutions to gradually adjust to new technologies (Suurs, 2009, p. 55). Since Guidance of Search is also "an interactive and cumulative process of exchanging ideas" (Hekkert et al., 2007, p. 423), it increases with more Knowledge Diffused (Walrave & Raven, 2016b). In turn, this works to increase the Resources to R&D, which further enables more Knowledge Diffusion.

Knowledge Erosion – B6 Loop

B6 Pathway: Knowledge Diffused →(+) Guidance of Search →(+) Resources to R&D →(+) Innovation Development →(+) Knowledge Decay →(–) Knowledge Diffused

B6 loop represents the process of Knowledge Erosion, which counteracts R11. Knowledge Diffused can become "obsolete over time (due to new technological developments, etc.)" (Walrave & Raven, 2016a, p. 4). When knowledge diffusion increases guidance of search, and thus secures more resources for R&D to further develop innovation, previously diffused knowledge become outdated, and thus increases the Knowledge Decay. In turn, this drains the body of Knowledge Diffused.

Innovation Attractiveness – R12 Loop

R12 Pathway: Innovation Developed →(+) Perceived Legitimacy →(+) Entrepreneurial Activity →(+) External Funding →(+) Total Resources →(+) Resources to R&D →(+) Innovation Development →(+) Innovation Developed

According to Hekkert et al. (2007) and Surrs (2009), entrepreneurs are central to any TIS. Entrepreneurs refer to actors within the system whose "actions are directed at conducting market-oriented experiments with an emerging technology" (Suurs, 2009, p. 54). The Innovation Attractiveness loop represents the process of attracting new entrepreneurs to the system through innovation. When the Innovation Developed increases, "technological legitimacy" of the innovation system increases (Walrave & Raven, 2016b, p. 1837). As potential entrants perceive the legitimacy of the emerging technology positively, they are more willing to enter the market, thus increasing the Entrepreneurial Activity. Entrepreneurial activities indicate the health and sustainability of an innovation system (Hekkert et al., 2007). Higher levels of Entrepreneurial Activity thus increase the Total Resources in the system by way of attracting more External Funding or resources from private or public actors (Suurs, 2009; Walrave & Raven, 2016b). In turn, more resources become available for R&D, which spurs further development of innovation that increases the attractiveness to entrepreneurs even more.

Knowledge Attractiveness – R13 Loop

R13 Pathway: Knowledge Diffused →(+) Perceived Legitimacy →(+) Entrepreneurial Activity →(+) External Funding →(+) Total Resources →(+) Resources to R&D →(+) Knowledge Diffusion →(+) Knowledge Diffused

R13 loop works in a similar mechanism in attracting entrepreneurs. Technological legitimacy is a function of both Innovation Developed and Knowledge Diffused. The more knowledge about the technological innovation diffused in various networks, the higher the perceived legitimacy of the technology. Loops R12 and R13, thus, work concurrently and in concert to shore up the attractiveness of the emerging technology to potential market actors.

External Engine – R14 Loop

R14 Pathway: Entrepreneurial Activity →(+) External Funding →(+) Total Resources →(+) Resources to Market Development →(+) Entrepreneurial Activity

The External Engine loop represents the effect of external funding in reinforcing the growth of entrepreneurial activity within the emerging market. As explained previously, Entrepreneurial Activity can build confidence in the prospect of investment, thus increasing funding and resources from external actors, either private funders or governmental bodies. This increases the Total Resources available for market development. External backing reduces the perceived entrepreneurial risks involved, and consequently is better able to attract further entry into the market to spur even more Entrepreneurial Activity (Suurs, 2009; Walrave & Raven, 2016b).

Internal Engine – R15 Loop

R15 Pathway: Entrepreneurial Activity →(+) Market Infrastructure →(+) Market Size →(+) Internal Resources from Market →(+) Total Resources →(+) Resources to Market Development →(+) Entrepreneurial Activity

While the external engine stimulates entrepreneurial activity temporarily, the Internal Engine endogenously generates internal ("financial, material, human capital") resources over the longer term through market formation to become self-sufficient (Suurs, 2009, p. 57). With reference to R15, increased Entrepreneurial Activity leads to the development of Market Infrastructure (Lee et al., 2018). Entrepreneurs contribute to the "development of formal market rules, establishment of intermediary networks, the building of infrastructure, or the development of formal regulations" (Walrave & Raven, 2016a, p. 1837). Through establishing the Market Infrastructure for market formation, entrepreneurial activity "contribute to the creation of a demand for the emerging technology" (Suurs, 2009, p. 56). This increases the Market Size for the technology that generates Internal Resources from the Market. In turn, with more Total Resources in the innovation system, Entrepreneurial Activity can further flourish by attracting more entrants to the system.

System Building – R16 Loop

R16 Pathway: Perceived Legitimacy →(+) Entrepreneurial Activity →(+) Market Infrastructure →(+) Perceived Legitimacy

Previously, we discussed how innovation diffusion increases the technological legitimacy of the emerging technology. Here, we consider market legitimacy, which stems from established market structures (Walrave & Raven, 2016b). When market infrastructure is developed, it reduces market formation uncertainty and the perceived cost to participation (Lee et al., 2018). With reference to R16, as the Perceived Legitimacy of the emerging technology increases, more entrepreneurs are willing to overcome perceived risks and enter the market. Consequently, the development of Market Infrastructure increases with the growth of Entrepreneurial Activity. This feeds back into increasing the market legitimacy of the emerging technology.

System Legitimacy – R17 Loop

R17 Pathway: Entrepreneurial Activity →(+) Market Size →(+) Internal Resources from Market →(+) Total Resources →(+) Resources to Market Development →(+) Market Infrastructure →(+) Perceived Legitimacy →(+) Entrepreneurial Activity

The System Legitimacy loop, R17, encompasses the aforementioned smaller loops R15 and R16, and "constitutes the most powerful self-reinforcing loop, potentially able to drive the whole system" (Walrave & Raven, 2016b, p. 1838). Following the previous explanations provided for the individual links between variables, we observe that when Entrepreneurial Activity increases Market Size through market formation, Internal Resources from the Market burgeon and increase the Total Resources. This translates to more Resources for Market Development, which enables further development of Market Infrastructure. Consequently, the market legitimacy of the technological innovation flourishes, and thus begets even more Entrepreneurial Activity.

Resistance – R18 Loop

R18 Pathway: Regime Resistance →(–) Perceived Legitimacy →(+) Entrepreneurial Activity →(+) Market Infrastructure →(–) Regime Resistance

Market formation of a new technology is bound to precipitate "resistance from actors with interests in the incumbent" regime (Suurs, 2009, p. 57). This Resistance is captured in R18. Regime Resistance decreases the market legitimacy of the emerging technology, for instance "when regime actors try to influence public discourses, or lobby against favourable support" (Walrave & Raven, 2016b, p. 1837). In turn, entrepreneurs might be less willing to enter the market due to higher perceived risks, thus reducing the Entrepreneurial Activity to a lower level than it otherwise would have been. In turn, there will be less Market Infrastructure development to counter Regime Resistance, which further emboldens resistance given the inverse relationship. The underlying mechanism for the negative link is supported by the fact that market infrastructure enables the system "to become less dependent on external dynamics and counter-balance regime-resistance" (Walrave & Raven, 2016b, p. 1838). Importantly, R18 could work in a virtuous or vicious manner, depending on whosever perspective, either working to reinforce more resistance or reduce it.

Sailing Ship – B7 Loop

B7 Pathway: Perceived Legitimacy →(+) Entrepreneurial Activity →(+) Market Infrastructure →(+) Market Size →(+) Sailing Ship Effect →(+) Regime Resistance →(–) Perceived Legitimacy

As the emerging market grows and competes with the incumbent regime, resistance could also come in the form of innovation. Given the new threat, regime actors would "increase their efforts to improve the performance of the existing regime through innovation" (Walrave & Raven, 2016b, p. 1838). This "response aimed at improving the incumbent technology" is referred to as the sailing-ship effect (De Liso et al., 2022; De Liso & Filatrella, 2008, p. 593). The Sailing Ship effect is thus represented in the balancing loop, B7. When the Perceived

Legitimacy of the emerging technology increases, which attracts more entrepreneurial activity and thus market formation, the Sailing Ship Effect increases. This contributes to a stronger Regime Resistance, which consequently reduces the Perceived Legitimacy of the emerging technology. This loop thus seeks to counteract the effect of the System Legitimacy loop, R17.

Digital Growth – R3 & R4 Loops

In the top-level Prosthetic Care System, we made the assumption that the Perceived Relative Success of Digital Fitting will lead to an increase in Digital Market Size, thus masking the underlying structure between that link. Here, we consider the conceptual model in the Market Formation subsystem that could possibly explain how exactly the two variables are linked. Since R3 & R4 share a similar pathway in the subsystem, I will only comment on R3.

R3 Pathway: Amputees in Digital Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(+) Digital Fitting Reputation →(+) Perceived Legitimacy →(+) Entrepreneurial Activity →(+) Market Infrastructure →(+) Digital Market Size →(+) Digital Market Share →(+) Digital Prosthesis Referral →(+) Amputees in Digital Prosthetic Care

When the perceived relative success of digital fittings increases, we expect the emerging digital technology for prosthesis fitting to start amassing a reputation. This formed reputation improves the technological legitimacy, which would attract more Entrepreneurial Activity to the emerging technological innovation system. Hence, the System Legitimacy loop works to increase the Market Infrastructure as well as Market Size for digital prosthetics. Consequently, the Digital Market Share rises to compete with the traditional prosthetics industry. The Digital Growth loops and the System Legitimacy loop thus work in tandem to increase the number of Amputees in Digital Prosthetic Care.

Market Access – R5, R6 & R7 Loops

R5 Pathway: Amputees in Prosthetic Care →(+) Successful Fitting →(+) Perceived Relative Success of Digital Fitting →(+) Digital Fitting Reputation →(+) Perceived Legitimacy →(+) Entrepreneurial Activity →(+) Market Infrastructure →(+) Digital Market Size →(+) Prosthetic Clinics →(+) Fitting Capacity →(+) Prosthetic Accessibility →(+) Prosthesis Referral →(+) Amputees in Prosthetic Care

Similarly, we expect the interaction of the Market Access loops and the System Legitimacy loop. As Digital Fitting Reputation forms over time and builds the Digital Market Size, through the same pathway described above, we expect the expansion of digital prosthetic clinics that increases the Fitting Capacity. This improves the Market Access in the digital prosthetic continuum, which enables more people to be fitted with a prosthesis and improves the overall mobility outcomes.

3. Model Structure & Validation

The dynamic hypothesis, described in the preceding chapter, was operationalised into a SD simulation model for hypothesis testing. Simulation modelling not only helps us visualise the impact of digital prosthetics on mobility outcomes, but also conduct experimentations to better understand the dynamic complexity of the prosthetic care system (Homer & Hirsch, 2006; Sterman, 2000). Here, I report the results of the model validation procedure, as proposed by Forrester & Senge (1980) and Barlas (1996), including direct structure tests, structure-oriented behaviour tests, and behaviour pattern test. Validation tests help us build confidence in the outputs of the simulation model by ensuring that "the structure and behavior of the model correspond to existing knowledge about the system" (Homer, 2012, p. 282) and that "the right outputs are being generated for the right reasons" (Barlas, 1996, p. 189).

Direct Structure Tests

Structure Verification

The structure verification test ensures that the model does not "contradict the knowledge about the structure of the real system" (Senge & Forrester, 1980, p. 212). This can be done *empirically*, by comparing the model's structural relationships to the real system (Senge & Forrester, 1980), *theoretically*, by comparing it to generalised knowledge as reported in literature (Barlas, 1996), or *qualitatively* by consulting problem owners (D. L. Andersen et al., 2012). Here, I report the main basis on which each sector was constructed and further discuss the main assumptions in the structure that could have introduced uncertainty into the model.

Population Sector

Though meant to be a model generalisable to other contexts, in this iteration, the model is calibrated to the United Kingdom (UK); this context was selected as ProsFit had knowledge of the system structures (as well as access to more of the data) pertaining to the country. The population is disaggregated into the PAD Population and Non-PAD Population (see Figure 3.1 below). In most industrialised countries, including the UK, more than 90 percent of major lower-limb amputations are attributed to PAD alone, whether primary or secondary to the onset of diabetes (Ahmad et al., 2014; Kohler et al., 2009). Hence, we simplify the model to only account for PAD-related and traumatic-injury-related amputation, which in turn could lead to small underestimation in the amputee population. Since PAD incidence is dependent on age with different rates for each age group, the model is arrayed by age cohorts: Under 15, 15 to 44, 45 to 59, 60 to 79, and 80+. In doing so, we can better estimate the amputation rates and changes in the amputee population.

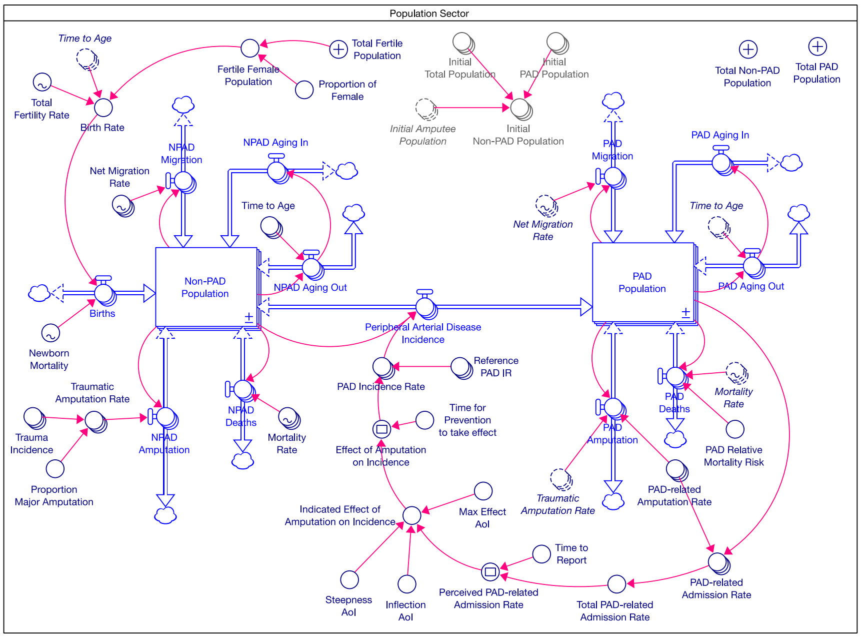


Figure 3.1 Model Structure: Population Sector

As mentioned previously, public health agencies respond with interventions when the prevention pressure amasses. Since it takes time for prevention programmes to influence behaviour, we know that this has a delayed effect on the incidence rate. Hence, the effect was smoothed with a 10-year delay. Moreover, this effect was formulated as an inverse Sigmoid function (z-shaped), where a lower prevention pressure increases the incidence rate and higher pressure decreases the incidence rate. To reduce the uncertainty introduced, a conservative effect was used that at most doubles the fractional rate.

Primary Care Sector

The primary care sector (Figure 3.2) mainly represents the hospital setting where amputation is performed. The model structure was elicited from UK's National Vascular Registry (Healthcare Quality Improvement Partnership, 2015, 2016, 2018a, 2018b, 2019, 2020), which also provided the data points for parameter estimation in this sector. The structure was corroborated by reported Patient Journey Mapping (ProsFit Technologies, 2022).

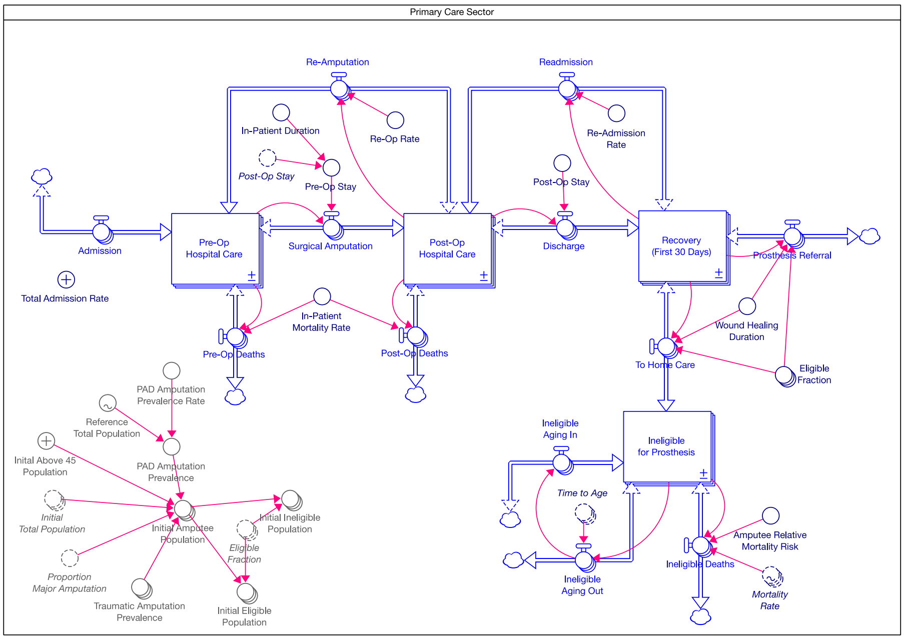


Figure 3.2 Model Structure: Primary Care Sector

Prosthetic Care Sector

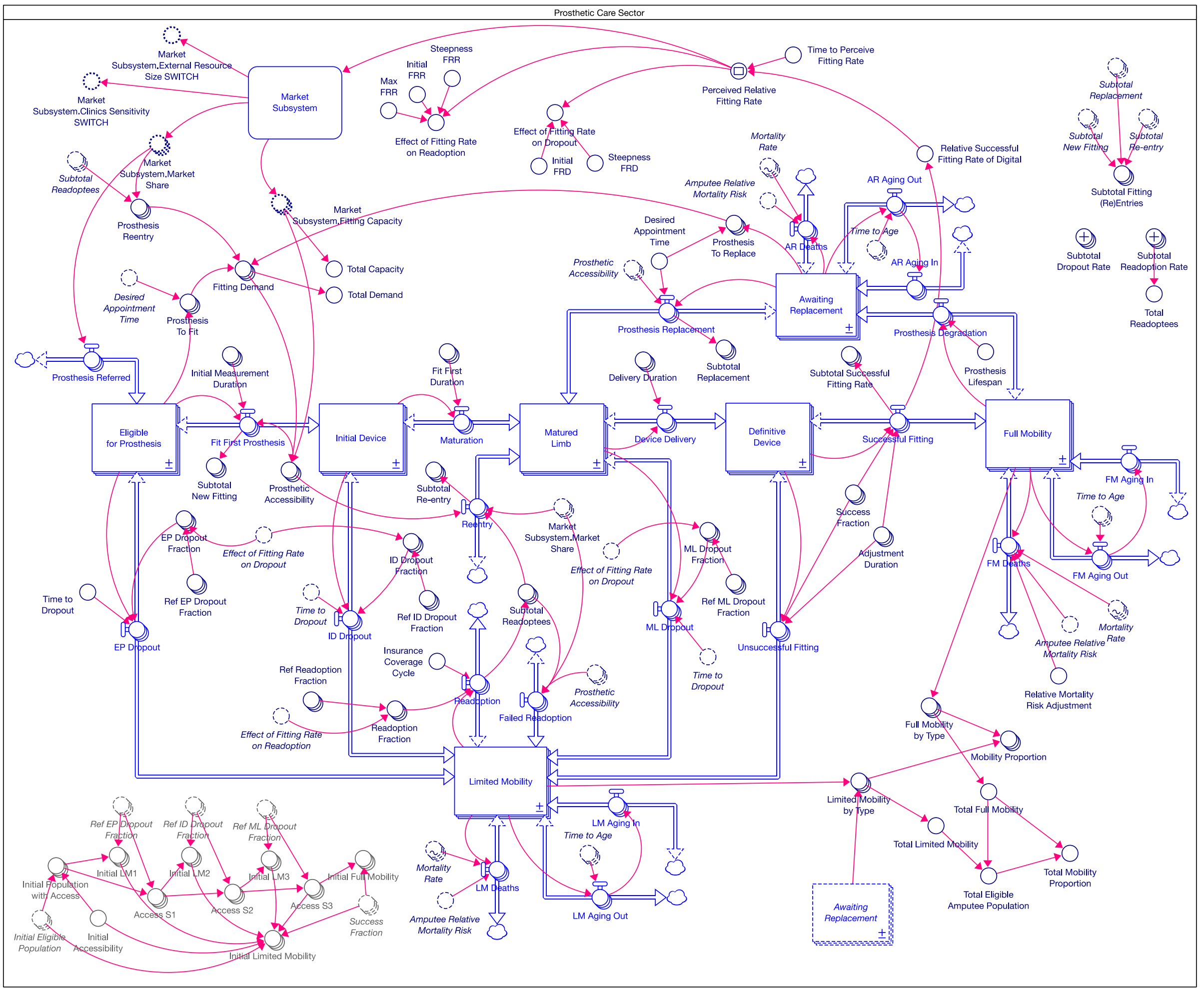


Figure 3.3 Model Structure: Prosthetic Care Sector

The prosthetic care sector (Figure 3.3) captures the prosthesis fitting process and lifecycle for amputees. Here, the prosthesis fitting process has been disaggregated into the various stages according to the general timeline for major lower-limb amputee rehabilitation (Rheinstein et al., 2021) and corroborated by ProsFit, a digital prosthetics service provider. The choice in disaggregation is motivated by the utility in capturing the endogenous disposition of amputees in relation to dropout and readoption of the fitting process at various stages (Paine, 2022). This disposition to dropout or readopt is simplified with a fractional rate that responds to changes in the perceived relative success of digital prosthetics.

As mentioned in Chapter 2, we expect such dispositional changes due to word-of-mouth diffusion processes that affects consumer preferences in technology adoption and abandonment (Chernicoff et al., 2014). This is simplified and captured with effect variables that increases adoption and decreases dropout as the perceived relative success increases (see Figure 3.4). As digital prosthetics' success grows, we expect the fractional dropout rate to exponentially decay towards 0 from its normal or reference value. On the other hand, we expect readoption to grow exponentially as perceived success and word-of-mouth diffusion picks up steam. Since the effect is assumed, we remain conservative by at most doubling the fractional rate.

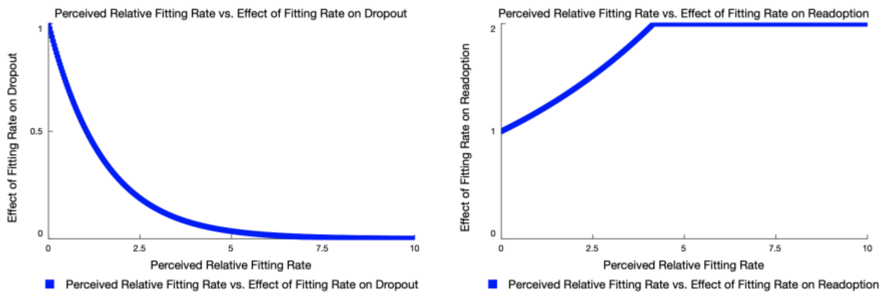


Figure 3.4 Effects of Perceived Relative Fitting Success on Dispositions

The prosthetic care sector is further arrayed by an additional dimension: prosthesis type (digital or traditional). According to ProsFit (2022), although the digital and traditional fitting process is essentially identical, they have different input parameter values; the digital process has a much shorter manufacturing (and thus delivery) duration and a higher success fraction in the final prosthesis fitting.

Lastly, the prosthetics in-progress stocks were initialised with 0 amputees, assuming that at the start of the simulation the initial amputees have already been (un)successfully fitted. This had to be done as there are no data available on the amputee population in relation to the prosthetic fitting process. This simplification, thus, produces estimation errors in the initial part of the results – instances where the results show a step up from 0.

Health Economics Sector

This sector exogenously calculates to the Total Economic Cost and Contributions associated with the amputee population, which is meant to assess the net benefit of prosthetics service provision (see Figure 3.5). The conceptualisation of this sector was heavily drawn from the variables and data points used in ProsFit's Health Economics Model (C. Hutchison, 2021). The boundary of this sector was defined as such since one of our research objectives is to provide dynamic inputs from the SD model into an otherwise static model. Given the exogenous nature of the calculations, this sector can be easily expanded in the future to account for other indicators of interest to relevant stakeholders.

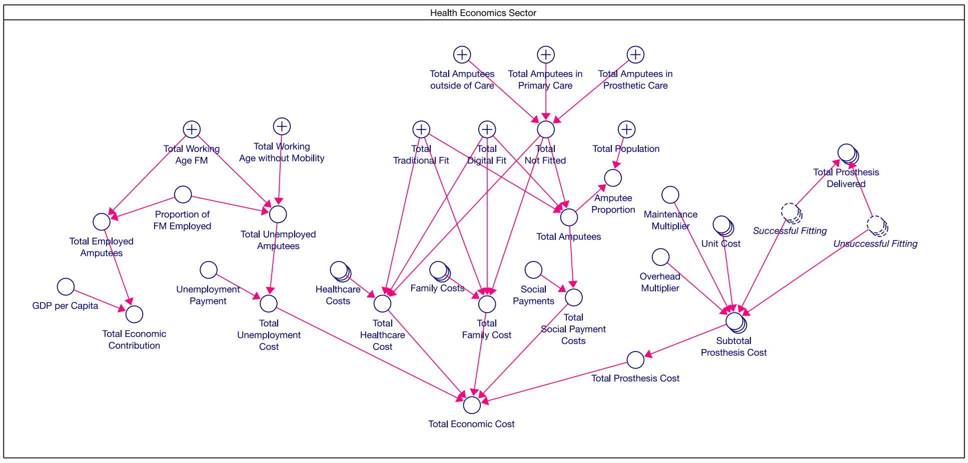


Figure 3.5 Model Structure: Health Economics Sector

Market Subsystem

As discussed previously, this subsystem (Figure 3.6) was adapted from a published SD model by Walrave & Raven (2016a, 2016b), which adequately represents the complexity of market formation in technological innovation systems – and thus appropriate for the nascent digital prosthetics market. Here, I discuss the main differences in modelling choices.

In this model, we replace absolute values for resources (as in the original model) with relative values – where a relative value of 1 indicates the typical value, which is then adjusted above and below the normal level. This simplification was necessary as there is no knowledge on the absolute level of resources in the digital prosthetics market system. Moreover, the absolute values used in the original model seem suspect as there was no documentation provided for those parameters related to resources and the resources to stock changes ratio (e.g., resources to knowledge ratio, resources to infrastructure ratio, resources to entrepreneurial activity ratio). To avoid unsubstantiated inputs, I opted to introduce relative resources and their corresponding effects on market development. With reference to Figure 3.7, when total relative resources increase beyond 0, we expect an increase in entrepreneurial activities and market infrastructure that exponentially decays towards their maximum levels – the assumption here is based on the economic principle of diminishing return of investment.

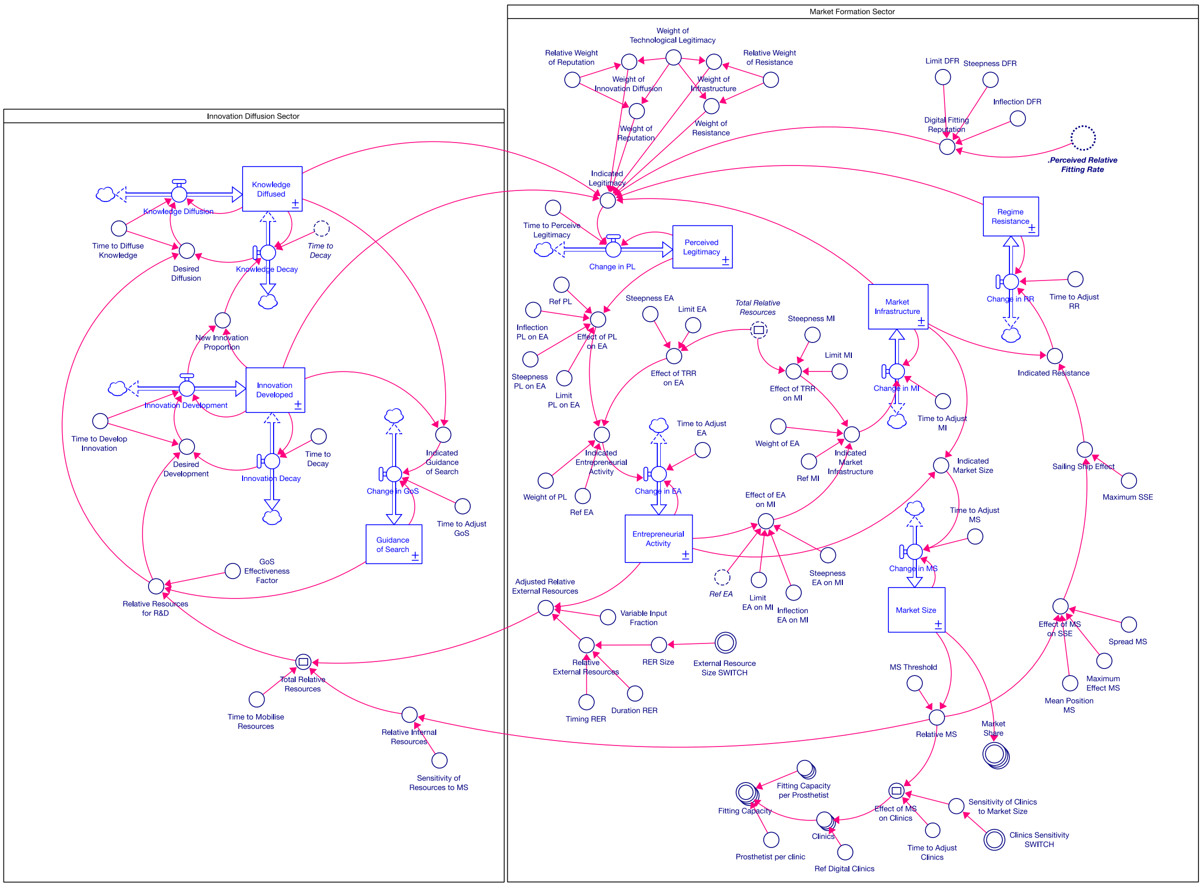


Figure 3.6 Model Structure: Market Subsystem Module

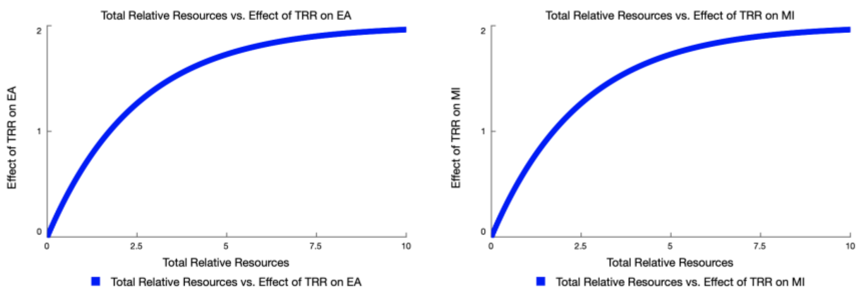


Figure 3.7 Effects of Resources on Entrepreneurial Activity and Market Infrastructure

Moreover, the subsystem is connected to the top-level system through Digital Fitting Reputation, which was introduced as part of technological legitimacy. Here, weights for different types of legitimacy were added as part of an additive relationship. This is different from the original model that opted for a multiplicative relationship. Multiplicative relationship did not hold up to direct extreme condition test, where a full technological legitimacy and 0 market legitimacy results in an indicated legitimacy of 0. People's perception of legitimacy adds up over time by taking in various input sources and need not be completely negated when it falls short in one aspect. However, the relative weights for the input sources are assumed in this model based on reason given the lack of data.

Parameter Verification

The parameter verification test ensures that the exogenous parameters conceptually correspond to elements of the real system, and numerically lies within a range of plausible values (Barlas, 1996; Senge & Forrester, 1980). For the top-level Prosthetics Care System, most parameter values were obtained from empirical data reported in the literature. In instances where data was not available, the values were estimated from expert opinion. This mainly pertains to the reference fractional dropout and readoption rates, which are estimates from ProsFit and their network of prosthetists. More details can be found in the Model Documentation (Appendix C).

Importantly, numerical verification is challenging for the conceptual Market Subsystem. The values for the parameters correspond to the values set in the original model that was adapted here (Walrave & Raven, 2016b). While this introduces uncertainty to the model, it is arguably less uncertain than the alternative, which is simplifying the entire subsystem into a single table function. At the very least, this conceptual model that is based on literature, provides more confidence that the market subsystem matches elements of the real system (conceptual correspondence). Moreover, the uncertain parameters are subject to further tests (sensitivity analysis), which could reduce the level of uncertainty if they are found to be insignificant to the model's sensitivity.

Direct-Extreme Conditions

Through partial model testing, each equation in the model was subjected to direct-extreme conditions tests to ensure that they are robust and perform expectedly under extreme conditions. To prevent computational errors, MIN or MAX functions were used, where necessary, to prevent variables from taking on unreasonable values. Where relevant, a maximum effect was set for nonlinear effect variables to ensure a reasonable output under extreme conditions. With these preventative measures, there were no computational errors detected in the model and results conform to values that are within bounds.

Dimensional Consistency

All variables and constants in the model were found to be dimensionally consistent, meaning that their units of measurement are both mathematically consistent and conceptually consistent – they have 'real world' meaning and were not arbitrarily included (Barlas, 1996; Sterman, 2000). Mathematical consistency is further validated by the modelling software (Stella Architect 3.0) that has found no unit errors. In the Model Documentation, each variable's real-world equivalency is described.

Boundary Adequacy

To evaluate the model's level of aggregation and inclusion of all relevant structure in the model boundary (Senge & Forrester, 1980), we need to consider its purpose. As mentioned, the main purpose of this model is to provide proof-of-concept for the causal theory on digital prosthetics' impact on amputee mobility outcomes. For this purpose, numerical accuracy is not sought as there are uncertainties surrounding digital prosthetics market that is in its infancy – there is no historical data nor systematic data collection presently available. Hence, simplification in the market subsystem structures is justifiable as it is meant to simply show us plausible endogenous market growth scenarios. As for the main prosthetics care system, the level of aggregation has been fully justified in the structure verification section. The boundary of the model has also been validated by the collaborators and secondary literature to adequately capture the patient journey from pre-amputation, acute care, and prosthesis fitting.

Structure-Oriented Behaviour Tests

Integration Error

The integration error test ensures that the model results are not "sensitive to changes in either the applied integration method or the chosen integration interval" (Schwaninger & Groesser, 2011, p. 773). The Euler integration method is applied to the model settings with an interval (time-step) of 1/64 months. This interval was chosen since it is smaller than the minimum plausible adjustment time (1/30) for parameters that take on values corresponding to days, and it is set to a power of 2 (i.e., 2^6) to prevent round-off errors in numerical calculations (Sterman, 2000). The model outputs were not sensitive to changes in the time-step, which was halved and doubled, producing the same results. Using an alternative integration method, RK4, also yielded no difference.

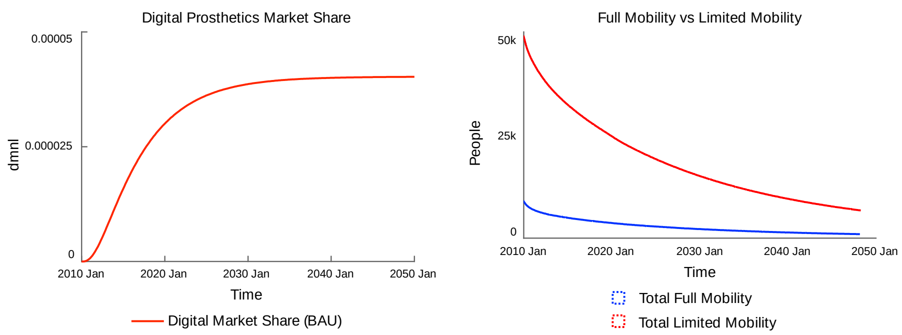
Indirect Extreme Conditions

While the direct test ensures that each variable is robust under extreme conditions, the indirect test involves the entire model's response. Extreme values are assigned to selected parameters and the generated system behaviour is compared to "expected behavior of the real system under the same extreme conditions" (Schwaninger & Groesser, 2011, p. 773). Here, we simulate the unlikely extreme conditions where amputation incidence is completely eradicated, and the market subsystem has no external resources flowing into it. Table 3.1, below, show the relevant parameter values assigned.

Table 3.1 Parameter Values under Extreme Conditions

Parameter	Sector	Extreme Condition
RER Size	Market Formation	0
Trauma Incidence	Population	0
PAD-related Amputation Rate	Population	0

The system's response conforms to behavioural expectations. First, we expect that the digital Market Share will not increase. In Figure 3.8, we observe that the Market Share is effectively 0 (though exponentially decaying from 0 to 0.0000402). The slight increase is due to the initial values of the innovation diffusion stocks that are set slightly above zero to push the stocks out of an unstable equilibrium for exponential growth, which in turn results in other stocks accumulating to a value that is slightly above 0. Second, we expect that the amputee stocks would exponentially decay towards zero since the inflows are cut off and the death outflows would continue to drain the stocks. This is evident in the remaining graphs in Figure 3.8, where the Full Mobility and Limited Mobility stocks are exponentially decaying towards 0, and consequently the Total Economic Cost and Contribution is falling towards 0. Hence, we can conclude that the model structure is robust under extreme conditions.



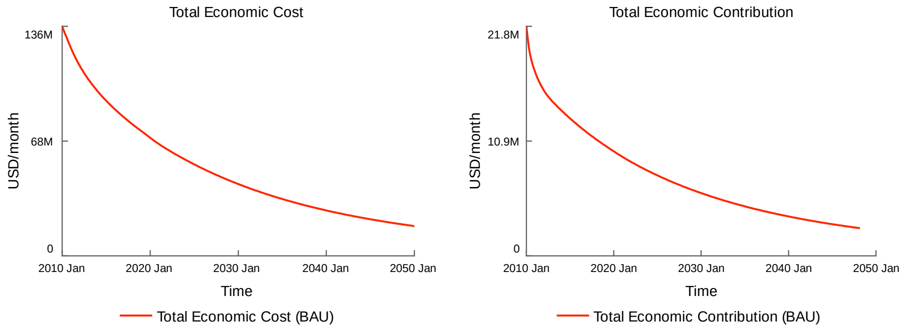


Figure 3.8 System Behaviour under Extreme Conditions

Behaviour Sensitivity

Sensitivity analysis reveals the model's behavioural sensitivity to systematic variations in the parameter values (Schwaninger & Groesser, 2011, p. 773). If the model's sensitivity does not correspond to a similar expected sensitivity in the real world system, then the confidence of the structure is put to question (Barlas, 1996). Where sensitivity is expected, those points in the system could be plausible policy levers for intervention. There are three types of sensitivity: (1) numerical sensitivity – significant changes in numerical value but behavioural pattern is retained; (2) behavioural sensitivity – significant changes in behavioural modes; and (3) policy sensitivity – reversals in "the impacts or desirability of a proposed policy" (Schwaninger & Groesser, 2011; Sterman, 2000, p. 883). Since we are less concerned with the numerical accuracy of results, given the conceptual nature of the market subsystem, we define significant sensitivity in the model to constitute behavioural sensitivity or policy sensitivity. Here, I summarise the results of the sensitivity analysis (available in Appendix B) and discuss the more salient findings.

Top-level Prosthetic Care System

The main top-level structure was largely insensitive to variations in its input parameters, suggesting robustness in the model structure. Of the 34 parameters, the model exhibited moderate numerical sensitivity to only 2 (summarised in Table 3.2 below).

Table 3.2 Top-Level Parameters resulting in Model Sensitivity

Parameter	Variation	Sensitivity Type	Uncertainty
PAD-related Amputation Rate	Uniform (Halved to Doubled)	Moderate (numerical)	Low; values were estimated from data
Reference PAD Incidence Rate	Uniform (Halved to Doubled)	Moderate (numerical)	Low; values were estimated from data

Both parameters produced similar moderate numerical sensitivity in the model's output for the mobility outcomes. This is expected as lower incidence rates would lead to lower amputee population in the first place. Since we are quite confident in the parameterisation, these results suggest that lowering these rates are high-leverage policies for consideration. Though we will keep this in mind for the discussion on policy insights, policy experimentation on this parameter will not be conducted in the following chapter for two reasons: (1) this is a common insight for public health interventions, and (2) this relates to the effect of the balancing B1 Prevention Pressure loop, which has little interplay with the other feedback loops.

Market Subsystem Module

Given the conceptual nature of the market subsystem, the model is unsurprisingly more sensitive to the parameters in this module. Of the 32 parameters, the model was moderately sensitive to 9 and significantly sensitive to 3 (see Table 3.3).

Table 3.3 Market Subsystem Parameters resulting in Model Sensitivity

Parameter	**Variation**	**Sensitivity**	**Uncertainty**
Relative External Resources Size	Uniform (0 to 9)	Significant (behavioural)	Leverage Point discussed in Chapter 4
Weight of Entrepreneurial Activity	Uniform (0.3 to 0.7)	Significant (behavioural)	High; assumption in the model
Market Size Threshold	Uniform (0.025 to 0.075)	Significant (behavioural)	Moderate; logical assumption and expected output
Steepness EA	Uniform (1 to 5)	Moderate (numerical)	Moderate; assumption in the model
Steepness EA on MI	Uniform (0.2 to 0.8)	Moderate (numerical)	Moderate; table function in original model
Steepness MI	Uniform (1 to 5)	Moderate (numerical)	Moderate; assumption in the model
Time to Adjust MI	Uniform (30 to 120)	Moderate (numerical)	Moderate; value obtained from original model and expected output
Time to Adjust MS	Uniform (12 to 48)	Moderate (numerical)	Moderate; value obtained from original model and expected output

Weight of PL	Uniform (0.3 to 0.7)	Moderate (numerical)	Moderate; assumption in model
Steepness PL on EA	Uniform (0.2 to 0.8)	Moderate (numerical)	Moderate; table function in original model
Ref Digital Clinics	Uniform (1 to 6)	Moderate (numerical)	Low; calibrated value to projected clinics
Sensitivity of Clinics to Market Size	Uniform (0.5 to 1.5)	Moderate (numerical)	Leverage Point discussed in Chapter 4

Based on the results, it is evident that the model results exhibit sensitivity, particularly around the effect variables affecting the Entrepreneurial Activity and Market Infrastructure stocks. The accumulation level of these stocks is dependent on four effect variables whose structural relationships have been assumed. For a more accurate estimation in digital market growth, we need more data collection to better quantify the extent to which (1) total resources will affect the entry of new entrepreneurs and the development of market infrastructure; (2) perceived legitimacy affects entrepreneurial activity; and (3) entrepreneurial activity affects market infrastructure growth. Despite the numerical uncertainty observed in the analysis of the effect variables, the overall behaviour mode is retained and thus gives us confidence in the directionality of the change in the model results.

However, in the development of market infrastructure, we observe that when more weight is allocated to entrepreneurial activity, the behaviour mode of market share changes (see Figure 3.9 and Table 3.4). When infrastructure development is disproportionately dependent on entrepreneurial activities (>0.5 weight) as opposed to available resources for market development, then market infrastructure growth is stunted. Through the feedback processes in the system, market growth stagnates over time and even declines slowly. While this constitutes a high level of uncertainty, we can reason that a higher weight is an unlikely condition as infrastructure development typically is strongly influenced by resources. Consequently, the conservative parameter value for Weight of EA set at 0.4 need not betray the confidence of the simulation results.

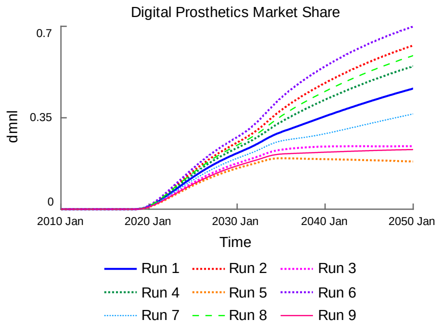


Figure 3.9 Sensitivity Runs of Market Share for variation in Weight of EA

Table 3.4 Parameter Values for Sensitivity Runs for variation in Weight of EA

Parameter	**Run 1**	**Run 2**	**Run 3**	**Run 4**	**Run 5**	**Run 6**	**Run 7**	**Run 8**	**Run 9**
Weight of EA (Input)	0.5	0.4	0.6	0.45	0.65	0.35	0.55	0.425	0.625
Market Share (Output)	0.46	0.63	0.24	0.55	0.18	0.70	0.36	0.59	0.23

Behaviour Reproduction Tests

This set of tests aims to evaluate "how well model-generated behavior matches the observed historical behavior of the real system" (Schwaninger & Groesser, 2011, p. 774). In other words, we compare the system performance against the reference mode of behaviour. This, however, proves to be particularly difficult for the prosthetic care system given the dearth of data available as mentioned in Chapter 1. Instead, here, we compare the simulated system behaviour to the qualitative reference modes presented previously and other sources of estimations.

Firstly, the only available historical and projected dataset pertains to UK's population size. In Figure 3.10, we observe that the model produces a relatively good fit of the Reference Total Population, largely because population is exogenous. Nevertheless, since the population includes the various amputee stocks that are subject to the system feedback, it is important to ensure that the total population does not radically differ from known data.

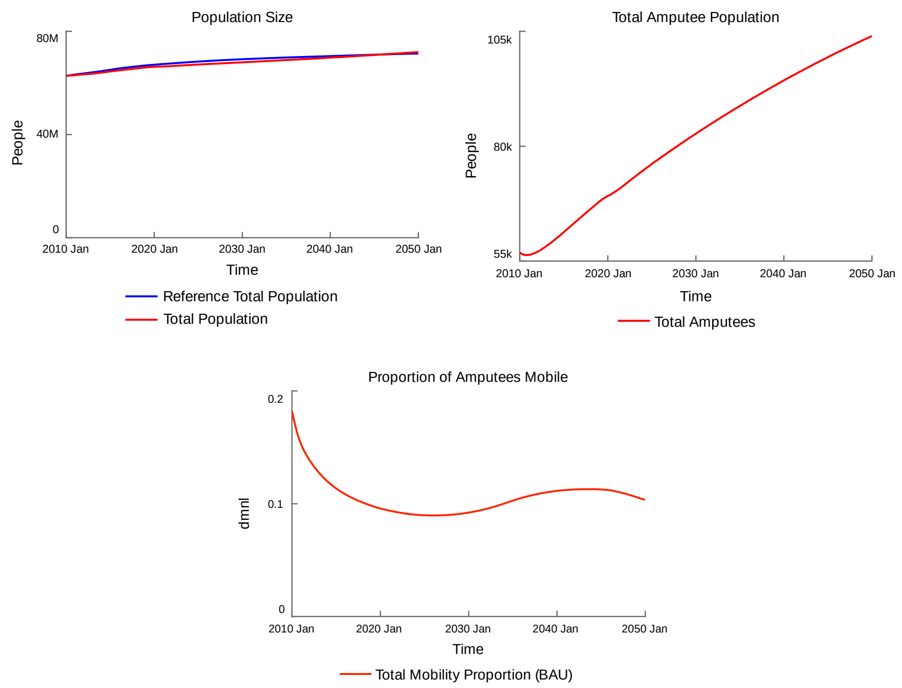


Figure 3.10 System Performance for Behaviour Reproduction Test

Second, the WHO (2017) estimates that the amputee population will double in size by 2050. The model estimates 1.83 times increase in amputee population, from 56.9K people to 104K people in 2050. In Figure 3.10 we observe a slight initial decrease in this population before steady growth; this is due the amputation rates for those aged 80 and above. Given that fractional mortality rate is much higher for this population (but decreases over time to simulate an ageing population) and further amplified with the relative mortality risk from PAD, there are more PAD deaths (outflow) for this age group than incidence of PAD (inflow). Hence, there is a transient stock adjustment. While the fractional mortality rate and initial stock value were obtained from known estimates in the literature, this could perhaps suggest an error in those estimates.

Third, the WHO (2017) also reckons that only 5 to 15% of amputees have access to prostheses. The model's baseline results show a 18% mobility proportion that eventually declines to about 10% by 2050 – an anticipated result due to the increase in amputee population over time. A slightly higher proportion is also not surprising as the range provided by WHO is a global estimate, whereas this is more specific to a high-income country expected to have an above-average healthcare system.

Given that the system's performance is close to available estimates, we can qualitatively conclude that the model is adequately able to reproduce the behaviour of the real system – thus building confidence in the simulation results generated by the model.

4. Analysis of Simulation Results

In this chapter, I present the simulation results generated by the SD model for the business-as-usual scenario (BAU) that provides the baseline performance for our key indicators: digital market share, mobility proportion, economic cost, and economic contribution. I, then, provide an endogenous explanation for the observed behaviour in terms of the feedback loops identified in Chapter 2. Thereafter, I experiment with leverage points in the system in two other scenarios – heightened resources (HRS) and expanded capacity (ECS)– and further provide explanations for the observed differences in behaviour.

Business As Usual Scenario

Experimental Setup

The BAU is set up such that the Relative External Resources is 1 (External Resource Size SWITCH = 0 & Clinic Sensitivity SWITCH = 0). Although set to 1, the actual amount is dependent on the level of Entrepreneurial Activity, where the variable portion of the external resources increases with more activity. So long as Entrepreneurial Activity is low, the amount of external stream of resources will be lower than normal. This represents the scenario wherein the exogenous funding (e.g., investment backing for early entrepreneurial entrants from private or public actors) is relatively low. In the model, the external resource stream kicks in at 96 months (year 2018) for a duration of 180 months, as shown in Figure 4.1.

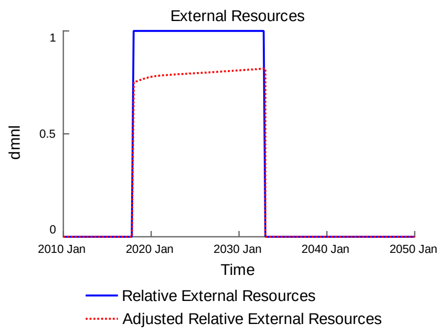


Figure 4.1 Set up of Relative External Resources variable in BAU

Results Overview

The graphs in Figure 4.2, below, present the simulation results for the key indicators in the BAU scenario. We observe that the digital prosthetics market share increases increasingly to about 6.4% before falling back down to about 3% by 2050. This suggests that with business as usual, we can expect a temporary market growth that does not successfully take off. The impact of this short-lived growth is seen in the total proportion of amputees who have achieved full mobility. The proportion declines from about 18% to 9% before rising to a maximum of about 11% some time in 2038 (after the time when the digital market share has reached its peak growth), and eventually declining back down to 10% as digital market share dwindles. As a result, the Total Economic Contribution from amputee participation in the workforce follows a similar development – since it is dependent on the total number of mobile amputees who have been reintegrated into the workforce. The Total Economic Cost for supporting the amputee population, however, steadily increases throughout the simulation duration. These results, thus, indicate that digital prosthetics do in fact impact the mobility outcomes for the UK. An increased digital market growth improves the mobility proportion and leads to increased economic contribution, vice versa.

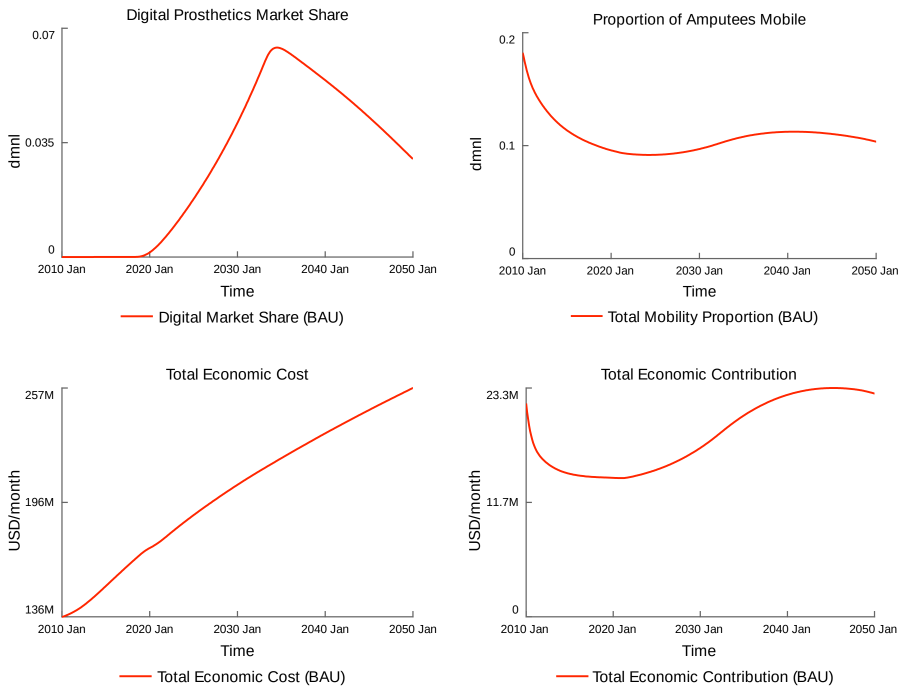


Figure 4.2 Results of Key Indicators with Business as Usual

Behavioural Explanation

Digital Prosthetics Market Share

We begin with a structural explanation for the development observed in the market share. The External Engine loop (R14) kick-starts the dynamics in the market subsystem when external resources first pour in. As mentioned previously, external backing reduces entrepreneurial risks, which enables the self-reinforcing growth in Entrepreneurial Activity – as observed in Figure 4.3, where it increases sharply from 2018.[1] External resources and entrepreneurial activities, in turn, foster the development of Market Infrastructure, which does not increase as quickly due to the longer delay time. This lends strength to the System Building loop (R16), which works to endogenously increase the market legitimacy of digital prosthetics. Hence, we observe the level of Perceived Legitimacy rising, albeit to a slower and lower extent. This dampened development is due to a low level of technological legitimacy, which is dependent on digital prosthetics reputation and innovation diffusion.

For one, the small digital market share means a smaller number of people being fitted with a digital prosthesis. In Figure 4.3, we see the Rate of Successful Fitting for both the traditional and digital prosthetics. There is an abrupt increase in the traditional rate due to the estimation error introduced from initialising all the "in-progress" stocks at 0, as explained in the preceding chapter. Importantly, we observe that the performance of digital prosthetics is much lower than the incumbent for the entire simulation duration. In turn, the Digital Growth loops (R3 & 4), meant to reinforce market growth and digital fitting rate, remains too weak to effectively increase the reputation of digital prosthetics over time.

Moreover, the relatively small External Resources Size and the low guidance of search result in a lower-than-normal resources available for R&D (<1) up until 2027. In turn, the innovation development rate and knowledge diffusion rate (inflows) are lowered below the respective decay rates (outflows). Hence, the Innovation Developed and Knowledge Diffused stocks decline for the first part of the simulation and contribute to a low level of technological legitimacy of digital prosthetics. A low level of Perceived Legitimacy consequently holds back the strength of the System Legitimacy loop (R17), which powers the smaller market loops that

[1] Note that the Entrepreneurial Activity, Market Infrastructure, and Perceived Legitimacy stocks are at a level slightly above 0 prior to the exogenous increase in external resources. As explained in Chapter 3, this is due to the initial value of the Innovation Developed and Knowledge Diffused stocks at 0.001 (meant to kick it out of an unstable equilibrium). This is a product of mathematical computation, and for all intents and purposes the respective levels should be interpreted as 0.

seek to reinforce the growth in Entrepreneurial Activity, Market Infrastructure and Market Size. Importantly, it holds back the strength of the Internal Engine loop (R15) – when market size increases, internal (financial, material and human) resources increase, which then enables the growth of further entrepreneurial activities and market infrastructure development that consequently reinforce the growth in market size. By holding back this loop, R17 essentially dampens the market's ability to grow and endogenously generate its own internal resources.

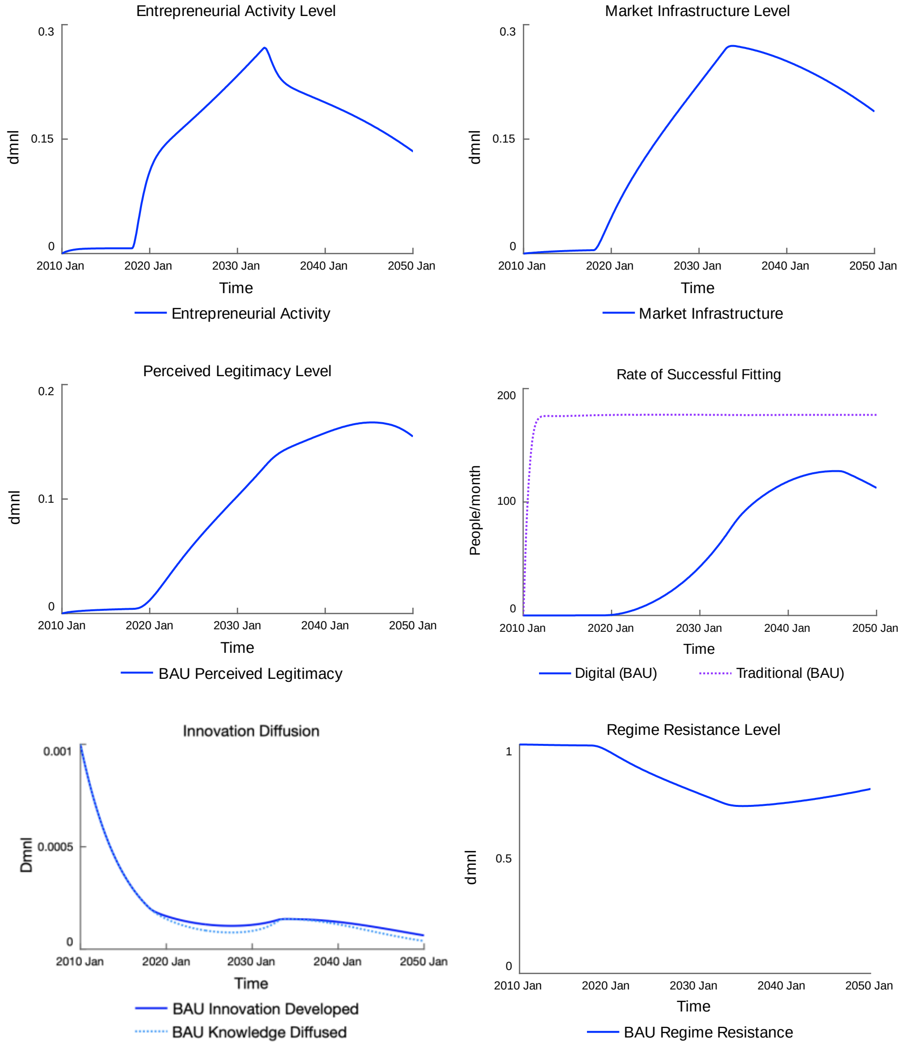


Figure 4.3 Key Explanatory Variables for Market Share (BAU)

By 2033, when the External Engine is cut off, we observe a sharp decline in the level of Entrepreneurial Activity and Market Infrastructure. The weakened Internal Engine (R15) fails to generate sufficient internal resources for the market system to be self-sufficient, instead contributing to its decline. Hence, we observe the market share decrease increasingly. The most powerful driver of the system, R17, is reinforcing negative growth, which is boosted by the smaller reinforcing loops in the system. We further observe this in the exponentially increasing

Regime Resistance (due to R18), and rapidly declining Innovation Developed and Knowledge Diffused (due to R10 and R11). This feedback story explains the rise and fall in market share as observed in Figure 4.2.

Mobility Outcomes

Prior to the growth in digital market share, we observed a declining mobility proportion for the amputee population. There are two reasons: (1) the total UK population is increasing and as a result the Total Amputees is increasing proportionally and (2) the Total Capacity for prosthetic fitting is held constant. Hence, we observe in Figure 4.4 that the gap between the Total Limited Mobility and Total Full Mobility is increasing over time, thus leading to a declining mobility proportion up until the market share of digital prosthetics grows.

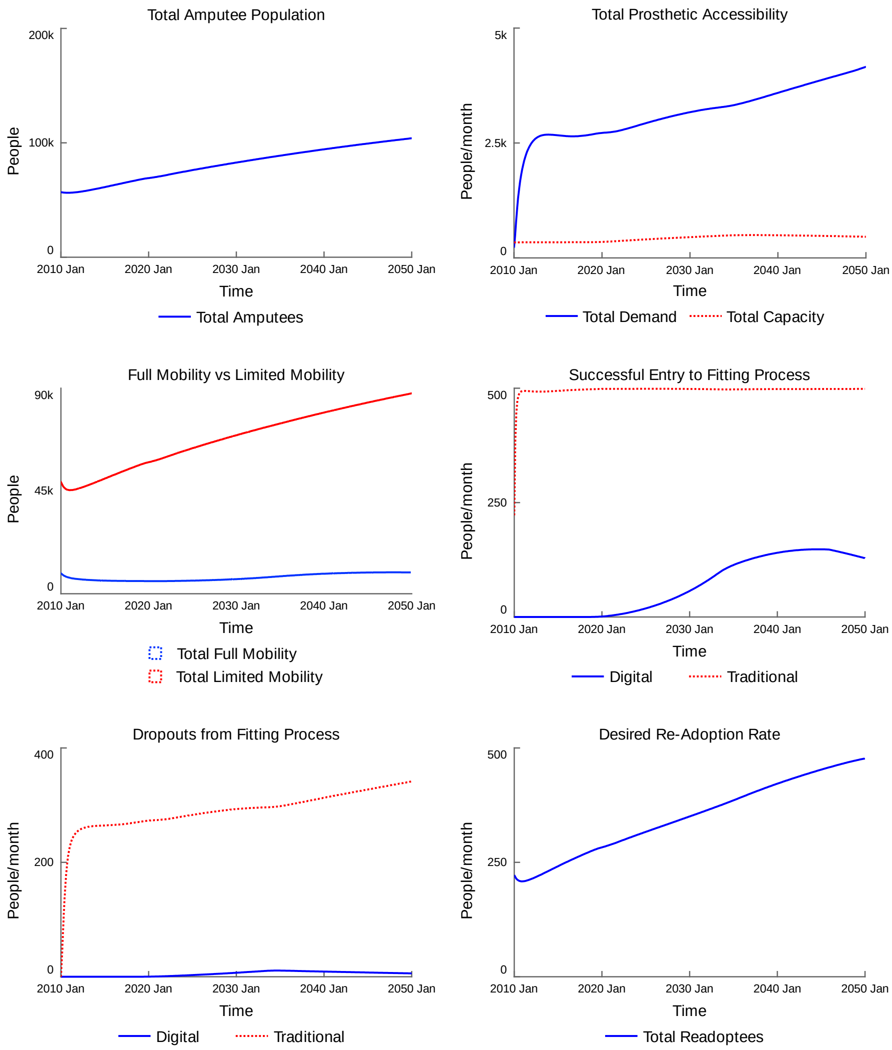


Figure 4.4 Key Explanatory Variables for Mobility Outcomes (BAU)

Once the market share of digital prosthetics grows, the mobility proportion increases slightly before coming back down again, albeit with a delay, as more people are successfully fitted with a prosthesis. The delay is explained by the fitting process that involves multiple aging chains with delays and, more importantly, by the fact that Limited Mobility is increasing at a faster rate given low prosthetic accessibility. Nevertheless, the Total Full Mobility increases as a result of the Digital Growth Loops (R3 & 4) and Prosthetic Attractiveness loops (R8 & 9). R3 enables additional eligible new entrants to the digital prosthesis fitting process while R4 enables more of the Limited Mobility population to successfully take-up the process once again. Again, the limited market growth translates to a relatively weak reinforcing effect, as evidence by the lower Rate of Successful Fitting for digital prosthetics (Figure 4.3).

As for R8, it reduces the digital prosthesis dropout rates as its relative success encourages retention in the process. In Figure 4.4, we observe the Digital Dropout first increases as more people enter digital prosthetics, but starts decreasing some time in 2034, when Digital Successful Fitting Rate is increasing at its fastest. R9, on the other hand, makes prosthesis readoption more attractive to those in the Limited Mobility stock, hence partially contributing to the increasing number of people desiring to re-adopt a prosthesis. Note that the development of Desired Re-Adoption Rate is proportional to the Limited Mobility; and as such it increases so long as the Limited Mobility stock grows. Similarly, the Digital Dropout is also decreasing partially due to the declining number of Successful Entries to the prosthesis fitting process at the tail end of the simulation as the market share drops.

As alluded to, the strength of the reinforcing loops is also being dampened by the Access Constraint loops (B2 to 4). As more people attempt to enter the prosthetics care system, the Total Demand for a prosthesis increases (see Figure 4.4), and consequently these loops prevent entry by reducing the Prosthetic Accessibility so long as demand outpaces capacity. In this case, the Market Access loops (R5 to 7) barely make a dent as they involve a long delay in expanding capacity, coupled with a minimal digital market expansion.

Lastly, the economic indicators are exogenous parameters which are dependent on the dynamics of the feedback loops in the model. As mentioned, the Total Economic Contribution calculate the contribution of amputees in the workforce. Since only a portion of the fully mobile populations participate in the workforce, the development follows the mobility proportion. As for the Total Economic Cost, it increases as the Total Amputee Population is increasing, thus incurring more unemployment and social payments, healthcare and family costs, and a higher prosthesis cost, which is covered by the National Health Service in the UK.

Heightened Resources Scenario

Experimental Setup

The Heightened Resources scenario (HRS) represents the situation where the Relative External Resources is amplified from 1 to 5 (External Resource Size SWITCH = 1 & Clinic Sensitivity SWITCH = 0). In setting up the external resources to a much higher than normal level, we heighten the reinforcing feedback of the External Engine (R14) that initially powers the market subsystem.

Results Overview

With reference to the comparative results presented in Figure 4.5 and Table 4.1, it is evident that a well-resourced digital prosthetics market results in much improved mobility outcomes. The digital market subsystem is self-sufficient, increasing steadily to capture 63% of the market share by 2050. The mobility proportion increases at a much faster rate and to a higher level, more than doubling by the end of the simulation. Consequently, the total economic contribution more than doubles as well. While the monthly cost rises steadily, given the increasing amputee population, it does so at a slower rate. Based on the simulation results, we can calculate the Net Economic Benefit of the successful re-integration of amputees in society, which is represented by the area between the lines in the Total Economic Contribution (additional contributions) and Total Economic Cost (cost saving). This is calculated to be about US$7.73 billion.

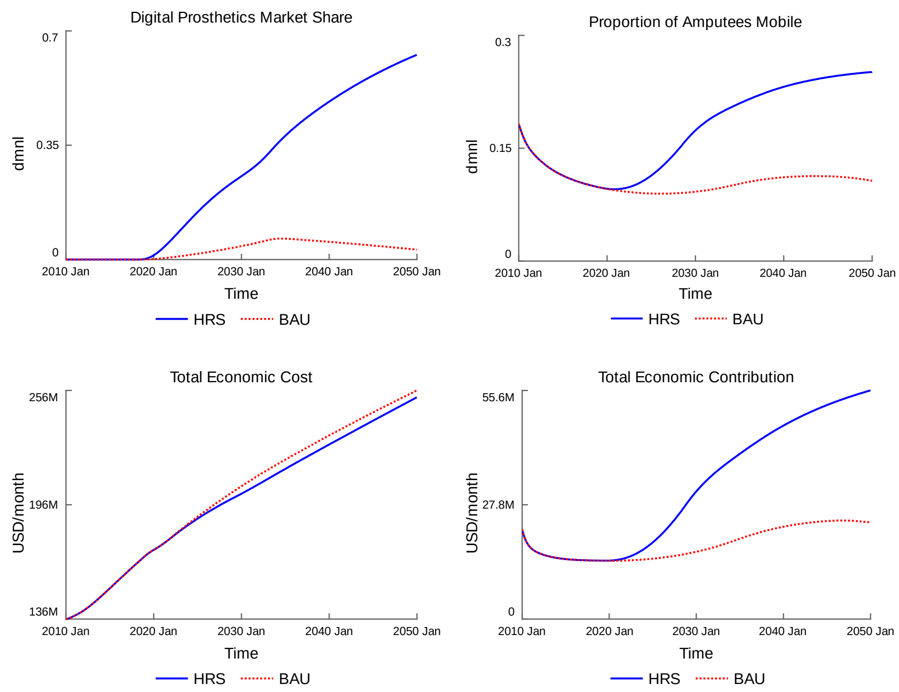


Figure 4.5 Results of Key Indicators for Heightened Resources Scenario (HRS)

Table 4.1 Numerical Simulation Results in 2050 Jan for BAU, HRS

Indicator	**BAU**	**HRS**
Digital Market Share	0.03	0.63
Mobility Proportion	0.1	0.25
Total Economic Cost	$256.5M/month	$252.9M/month
Total Economic Contribution	$23.5M/month	$55.6M/month
Cumulative Net Benefit		$7.73B

Behavioural Explanation

Digital Prosthetics Market Share

With a heightened effect of the External Engine (R14), we observe a much steeper increase in Entrepreneurial Activity and Market Infrastructure from the get-go (see Figure 4.6). This, then, bolsters the strength of the System Building loop (R16) that increases the market legitimacy of digital prosthetics. However, we observe that Perceived Legitimacy increases at a slower rate initially, as there are delays involved in increasing the technological legitimacy. It takes time for the Technology Development loop to kick-off, hence initially holding back the strength of the Innovation Attractiveness loop (R12) that seeks to increase legitimacy for attracting new entrants to the system. Moreover, the Digital Growth loops (R3 & 4) requires time to increase the Rate of Successful Fitting for digital prosthetics and hence its reputation. Once the digital successful fitting rate increases beyond the traditional successful fitting rate, and innovation development is increasing at its fastest, we observe a steep increase in Perceived Legitimacy some time in 2028. Consequently, the System Legitimacy loop (R17) is at its full strength to power the rest of the reinforcing loops in the system, enabling the build-up of the digital market and thus the internal resources. This strength is further evidenced by the weak Sailing Ship loop (B7), which is unable dampen R17 despite experiencing a spike in Regime Resistance due to the sailing ship effect, and, more importantly, the continued growth in digital market despite cutting off the External Engine loop. In essence, there has been sufficient internal build-up for self-sufficiency.

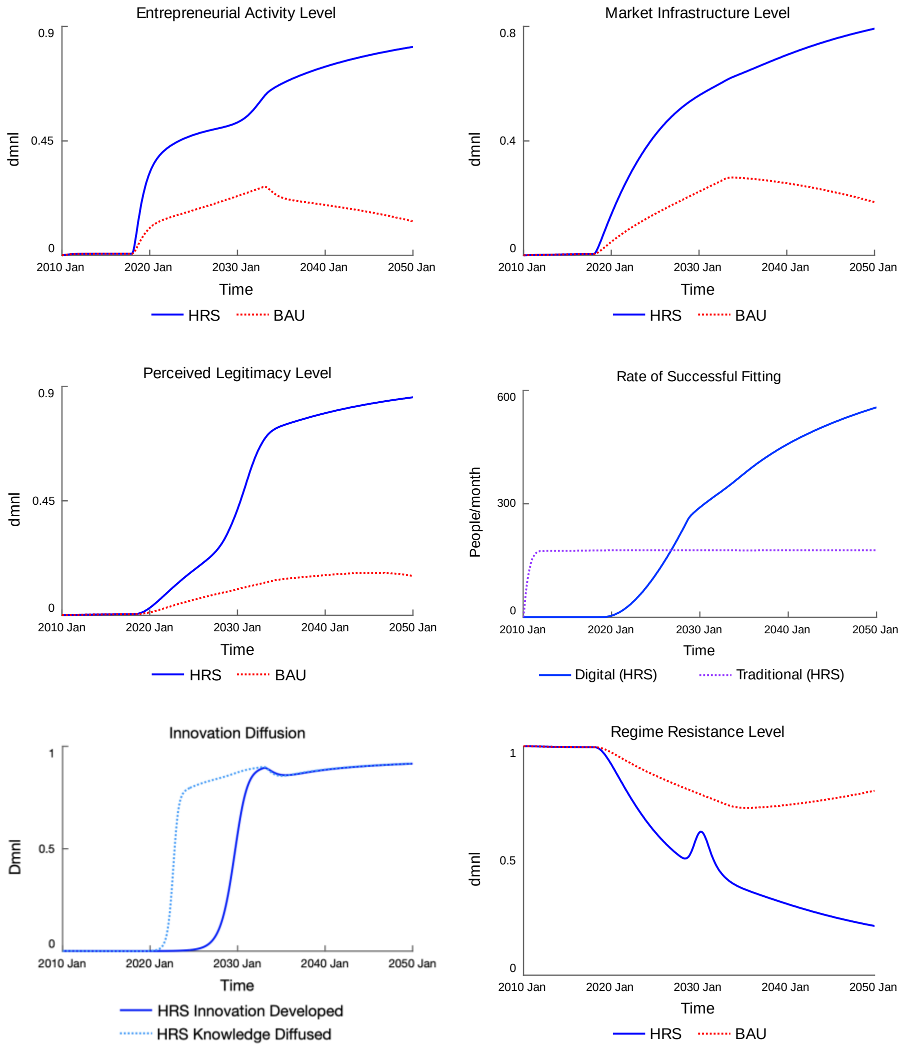


Figure 4.6 Explanatory Variables for Market Share (HRS)

Mobility Outcomes

As for the mobility proportion, it increases to a higher level since the Full Mobility stock grows to a significantly higher level as compared to the BAU (see Figure 4.7 below). As the digital prosthetics market share increases, the Digital Growth loops (R3 & 4) and the Prosthesis Attractiveness loops (R8 & 9) work in tandem to exponentially increase the number of successful entries to the digital prosthetic fitting process. However, the strength of these loops is counteracted over time as the Access Constraint loops gains dominance. We observe this in the digital Prosthetic Accessibility, which dramatically falls as demand outpaces capacity after 2030. Consequently, we observe that the growth in Full Mobility and Mobility Proportion tapers off towards the end of the simulation duration.

As explained, the Total Contribution increases pro rata. However, the Total Economic Cost is dependent not only on the mobility proportion but also the Total Amputee Population.

As the mobility proportion increases, lower costs are incurred. An overall increase in Total Amputee Population, as observed in Figure 4.7, incurs higher costs. If the amputee population had not risen, then the total economic costs would have been at a lower level. This is due to deaths. Fully Mobile amputees have improved health outcomes, including a lower mortality risk. Hence, as we fit more people successfully, we are preventing more deaths. And to sustain this otherwise dead population, we incur higher costs. This is a counterintuitive insight that is not readily made apparent due to open loop thinking, which we can overcome with modelling.

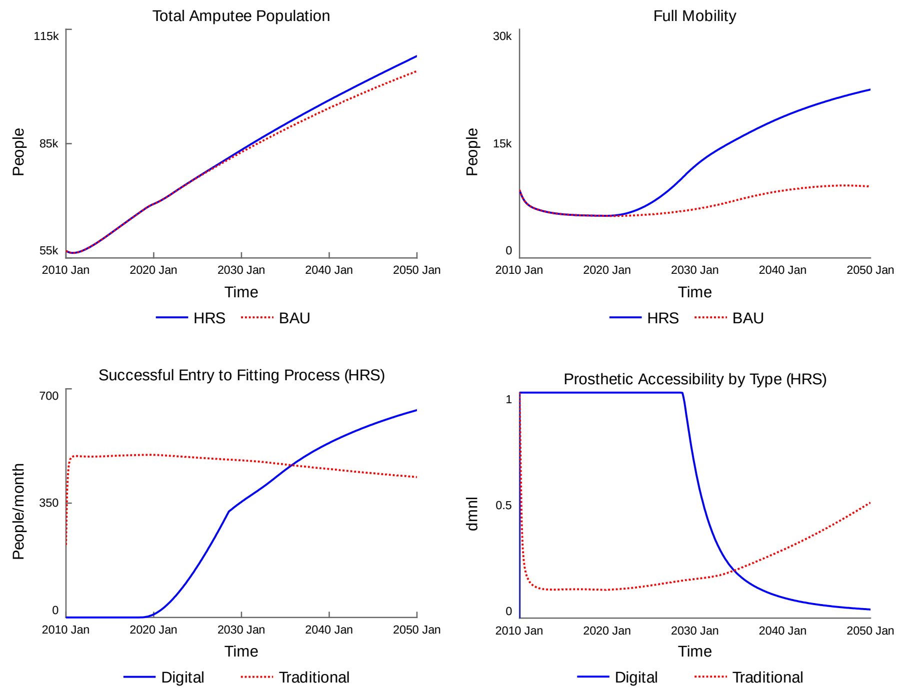


Figure 4.7 Explanatory Variables for Mobility Outcomes (HRS)

Expanded Capacity Scenario

Experimental Setup

To alleviate the bottleneck in the prosthetics fitting entry, we experiment by strengthening the Market Access loops in the Expanded Capacity scenario (ECS) on top of the previous scenario. Here, the Sensitivity of Clinics to Market Size is doubled from 0.5 to 1 (External Resource Size SWITCH = 1 & Clinic Sensitivity SWITCH = 1). In the model, digital prosthetics capacity adjustment was simplified with a nonlinear function that adjusts the number of digital clinics according to changes in the Market Size. We modelled a conservative adjustment with a sensitivity of 0.5; so, a change in Market Size leads to a less than proportional change in digital Clinics. With a sensitivity of 1, this relative change is perfectly proportional. In doing so, we can increase the number of Digital Prosthetics Clinics to a much higher level as the digital market grows, as shown in Figure 4.8.

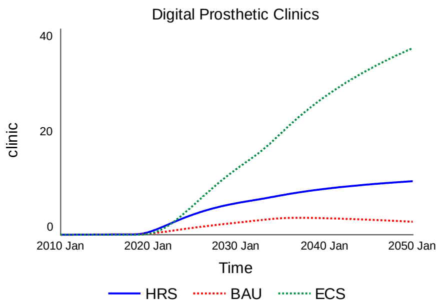


Figure 4.8 Results for Digital Prosthetics Clinics in ECS

Results Overview

The expanded capacity leads to substantial differences in the mobility proportion and economic indicators as seen in Figure 4.9 and Table 4.2, which suggest a significant improvement in the mobility outcomes. The mobility proportion exponentially increases to a much higher level (5 times more than the BAU). Given the amplified Total Economic Contribution and reduced Total Economic Cost, the Net Economic Benefit swells to $19.4 billion, about 2.5 times more than the previous scenario.

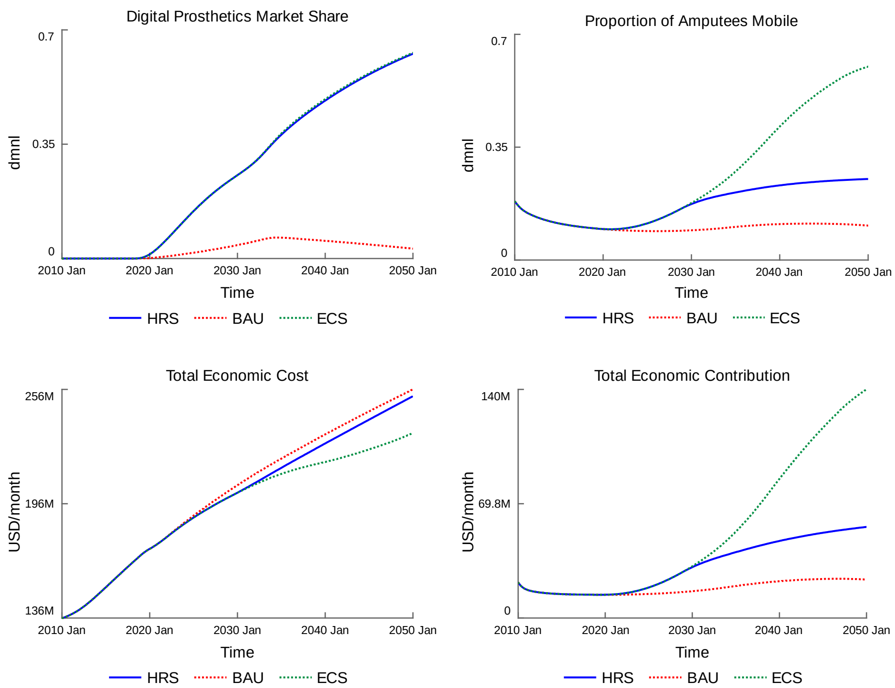


Figure 4.9 Results of Key Indicators for Expanded Capacity Scenario (ECS)

Table 4.2 Numerical Simulation Results in 2050 Jan for BAU, HRS, ECS

Indicator	**BAU**	**HRS**	**ECS**
Digital Market Share	0.03	0.63	0.63
Mobility Proportion	0.11	0.25	0.60
Total Economic Cost	$256.5M/month	$252.9M/month	$233.5M/month
Total Economic Contribution	$23.5M/month	$55.6M/month	$139.6M/month
Cumulative Net Benefit	–	$7.73B	$19.4B

Behavioural Explanation

Mobility Outcomes

There is not much change in the Market Share since the Digital Fitting Reputation contribution to Technological Legitimacy is already at its maximum in the previous scenario. Hence, we go right into explaining the observed developments in the mobility outcomes. Very simply put, the enhanced Market Access loops (R5 to 7) have weakened the Access Constraint loops (B2 to 4), which were previously dampening the effects of the Digital Growth loops (R3 &4) and the Prosthesis Attractiveness loops (R8 & 9).

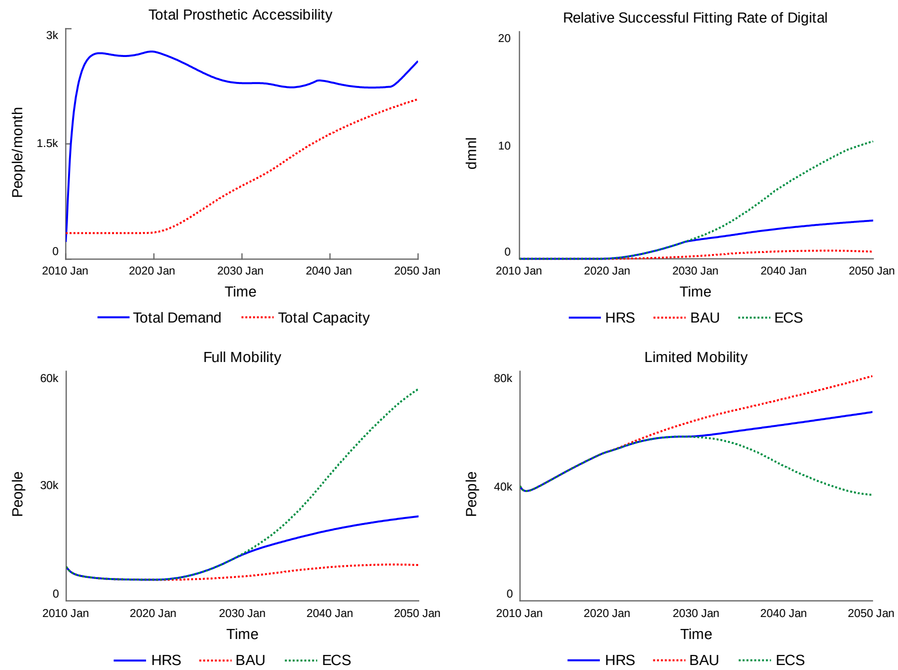


Figure 4.10 Explanatory Variables for Mobility Outcomes (ECS)

With reference to Figure 4.10, we observe that the gap between Total Demand and Total Capacity is generally closing; this shows that the strength of Access Constraint is becoming weaker as Market Access grows stronger. With much better Prosthetic Accessibility, more amputees can successfully enter the fitting process than previous scenarios. Moreover, the R8 & 9 are working to increase the desired re-adoption rate while driving down the dropout rate from the digital prosthetic care system. Hence, in Figure 4.10 we see that the Limited Mobility stock is draining quickly and to a larger extent. Furthermore, as more people move on down the digital fitting process to be successfully fitted with a prosthesis, we observe that the Relative Successful Fitting Rate increases by more than 10 times. As a result, substantially more people are achieving Full Mobility who would otherwise have entered the Limited Mobility stock. These developments thus enable the mobility proportion to rise significantly and result in a much-improved Net Economic Benefit (for the same reasons explained before).

5. Discussion

Hitherto, we have only addressed the first research question: *how does digital prosthetics service provision affect amputee mobility over time?* In this chapter, I begin with a summary of the impact of digital prosthetics revealed from our dynamic hypothesis testing exercise. Thereafter, I transition from the analyst position to that of an advocate (Walker, 2009) in order to answer the second research question: *what are the model-based policy insights for bolstering the social impact of digital prosthetics?* Lastly, we consider the limitations of this study and opportunities for further research.

Impact of Digital Prosthetics

We began this study with the intent to test the hypothesis that scaling up digital prosthetics positively impacts the mobility outcomes for the amputee population, which is thought to be a viable solution for alleviating the prosthetics accessibility problem as described in Chapter 1. To that end, we opted for the system dynamics method to construct a dynamic simulation model that could provide a feedback-rich explanation for the dynamics found in the prosthetic care system and the digital prosthetics market subsystem in relation to amputee mobility outcomes.

> *RQ1(a): What are the dynamic structures found in the patient-care continuum and the prosthetic service provision systems responsible for changes in amputee mobility outcomes over time?*

To represent the dynamic structures found in the respective systems, I conceptualised the model and the constituent feedback mechanisms from secondary literature and experiential knowledge from stakeholder involvement in the model building process (Chapter 2). We then reviewed the computational model structure in Chapter 3 and evaluated its validity in representing the system for the purpose of our investigation. While we are confident in the dynamic structures of the patient-care continuum (from PAD incidence to amputation and to the prosthesis fitting process), the digital prosthetics market subsystem engenders uncertainty given its conceptual nature. Nevertheless, this conceptual model was able to generate plausible market growth conditions, which was then used to evaluate the impact on the main system. We were also able to reproduce the behaviour patterns anticipated in the reference modes presented in Chapter 1. This means that the model was not only able to capture the dynamics of the system, but it has done so with some level of confidence. In this respect, it allows us to adequately test the hypothesis without offering numerical accuracy for simulation results. Moreover, this research has contributed to the health-related SD literature as the first application of SD modelling to prosthetic care.

> *RQ1(b): What are the main causal mechanisms that drive these changes and explain the impact of digital prosthetics on mobility outcomes?*

Based on the structural explanations discussed in Chapter 4, I now summarise the key feedback loop mechanisms responsible for explaining the impact of digital prosthetics on mobility outcomes. The Digital Growth Loops and Prosthesis Attractive Loops were the key drivers for increasing prosthetic accessibility and successful prosthesis fitting, which in turn improved the mobility outcomes. The Market Access loops are particularly important for determining the extent of accessibility by increasing capacity over time and counteracting the Access Constraint loops. As for the market subsystem, the External Engine loop is key for fuelling the various endogenous market formation loops. Particularly, the System Legitimacy loop, the most powerful driver of market growth, requires sufficient resources and momentum to increase and sustain entrepreneurial activities, market infrastructure development, perceived legitimacy of digital prosthetics, and its market size.

In summary, the findings of the simulation results (Chapter 4) lend support to the research hypothesis, namely that the scaling up of digital prosthetics positively impacts the mobility outcomes for the amputee population. We observed in all experimental scenarios that an increase in digital prosthetics market share was associated with an increase in the mobility proportion, a decrease in total economic costs and an increase in total economic contributions. However, the scenarios also revealed that the level of improvement in mobility outcomes is dependent on the extent of digital prosthetics market growth, which in turn requires sufficient resources and capacity expansion. To better reflect these caveats, we modify the hypothesis: *with sufficient resources for market formation and capacity expansion for digital prosthetics services, we can expect substantial improvements to the mobility outcomes for the amputee population*. Regardless, this model-based study of the prosthetics system serves as proof-of-concept for the expansion of digital prosthetics, which bears with it positive social impact for amputees and the country alike.

Model-Based Policy Insights

Likewise, we consider the sub-questions to fully address the second research question on the policy insights gleaned from the modelling exercise.

> *RQ2(a): What are the leverage points in the system that can enhance the effects of digital prosthetics service provision on mobility outcomes?*

Based on the scenario analyses in Chapter 4, we found that the size of external resources used to kickstart the dynamics in the market subsystem was a leverage point in the system as it involved significant behavioural changes. For low levels of external resources, we observe a rise and decline in market share over time, but high levels resulted in sustained growth; consequently, the mobility outcomes followed similar behaviour patterns. We also found that the effect of market size on changes in prosthetic clinics was a high-leverage point in the system. If the clinics increased to a higher level for every increase in market size, then we had a much expanded prosthetics fitting capacity. In turn, the mobility outcomes improved to a much larger extent.

> *RQ2(b) What are the plausible implications for policy design?*

Based on the identified leverage points, here, we discuss their implications for policy design. Specifically, I offer the model-based insights regarding resources and capacity for digital prosthetics service provision, as well as upstream prevention. We first consider the need for sufficient resources to power the System Legitimacy loop, and thus enable digital prosthetics to experience sustained growth in the future. We then consider the need for intervention in prosthetics capacity expansion, especially since demand far outpaces capacity even in highly resourced digital prosthetics conditions. Afterall, improving prosthetic accessibility is key for significant improvements in the mobility outcomes. Lastly, we consider upstream prevention that is not directly related to prosthetics service provision. Bringing down the PAD incidence rate as well as amputation rates would not only address the root cause of the problem, but also ameliorate the prosthetics capacity constraint and reduce the economic costs associated with caring for the amputee population.

Resources for Market Formation

Based on the simulation results from the business-as-usual and heightened resources scenarios, it is evident that a key factor in determining the extent of digital prosthetics market growth is the total amount of resources flowing in the market subsystem. Here, we observed radically different behaviour modes, where insufficient external resources to kickstart the dynamics resulted in a small increase in market share before its eventual decline. This suggest that there is a tipping point in the model parameter for resources. Let us further consider the effect of increasing the Relative External Resource Size incrementally from 1 to 9; in Figure 5.1 each run number corresponds to the relative size. So long as the relative resource size is above 1, we shift the dynamics in BAU and expect sustained growth in the digital market share, albeit with varying speed and extent. For the HRS, a relative value of 5 was chosen since beyond that the sensitivity considerably reduces – perhaps indicative of diminishing returns of investment. Nevertheless, given the conceptual nature of the model and the use of relative values, we cannot identify the exact tipping point in terms of the absolute number of external resources required for sustained market growth. An understanding of the feedback loop interplay in the market subsystem, however, can help us postulate on the key areas for intervention.

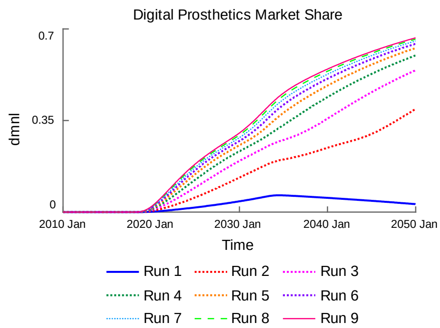


Figure 5.1 Results of variation in RER Size (range: 1 to 9)

We know that external resources are key for fuelling the External Engine loop responsible for accumulating Entrepreneurial Activity, a key stock that is intertwined with several other feedback mechanisms. Resources refer to “financial, material and human capital” allocated to both innovation and market development (Suurs, 2009, p. 57). External resources brought into digital prosthetics through investments or subsidies, could not only reinforce the growth of entrepreneurial activities, but also contribute to market infrastructure and market legitimacy building through the System Building loop. In turn, this powers the Internal Engine loop through the creation of a niche market that endogenously generates further resources for the system.

In the real system, we are already starting to observe this with ProsFit (start-up) that is supported by angel investors, Toyota Mobility Foundation, and other industry partners like HP. As an early entrant, ProsFit has been increasing the level of entrepreneurial activities; for instance, through setting up contracts with rehabilitation centres in countries like Singapore, France, and the Middle East (Kozbunarova, 2019). They have also experimented with a niche market that led to innovations in their 3D-printed socket design (HP Development Company, 2022). Further, they have spurred knowledge development through partnerships with Toyota Mobility Foundation, University of New South Wales, and University of Bergen (this project). While such entrepreneurial activities are promising, the model insight gleaned from the simulation result questions if this is sufficient to create enough momentum for sustainable market growth. Hence, for ProsFit, their efforts to build technological and market legitimacy of digital prosthetics should be strengthened.

However, market formation is a collective action problem “beyond the ability and resources of any one actor” (Lee et al., 2018, p. 245), and thus ProsFit should not aim to trudge it out alone. Efforts to build market legitimacy should go beyond building one’s own internal capabilities, and oriented towards developing market infrastructure even if those benefits could spill over to potential competitors (Lee et al., 2018). Regardless, the resources required for infrastructure building, where it is lacking, is considerably high and thus could be subsidised by public actors (Lee et al., 2018; Struben et al., 2020; Suurs, 2009). Public health agencies, for instance, could provide resources (financial, regulatory, supportive policies etc.) for infrastructure development. The amount of support provided could be crucial for determining the extent to which digital prosthetics market share grows and distributed delivery of prosthetic care expands, which consequently determines the extent to which the mobility outcomes may be improved. Regardless, the results of this simulation model suggests that so long as the market grows, there will be a net economic benefit accrued – this could potentially justify the need for public investment.

Fitting Capacity Expansion

The simulation results also revealed that there is a bottleneck in prosthetic service provision – the demand for fittings outpaces fitting capacity. This validates WHO’s concern that a large majority of people who require prosthetic services do not have access – partially due to the “limited availability of products” and “lack of qualified personnel” – which could worsen as the population is expected to grow (World Health Organization, 2017, p. xxviii). By expanding capacity, with the increased through put of digital and distributed service provision, we not only mitigate the bottleneck but also improve the mobility outcomes. In the expanded capacity scenario, we saw that an improved accessibility led to a significant increase in the mobility proportion and net economic benefit from re-integrating amputees in society. To that end, training existing and new prosthetists for implementing digital solutions in the fitting process could prove to be fruitful – particularly since digital prosthetics allow for expanding fitting capacity per prosthetist. Moreover, emboldening ProsFit’s foray into Distributed Care Networks for providing mobile digital prosthetic services (see A. Hutchison, 2020) could be a productive business model for stepping up digital fitting capacity and improving prosthetic accessibility more generally. Regardless of the medium, the simulation results highlight a need for policy intervention in the supply of prosthetic service provision for better mobility outcomes.

Upstream Prevention

Thus far, we have only considered plausible downstream intervention at the prosthetics service provision level. However, as the field of public health has moved towards upstream root-cause prevention for chronic conditions (Kansagra & Isac, 2021), we also ought to consider the model insights for upstream intervention. The behaviour sensitivity test revealed that the model was numerically sensitive to the parameters PAD incidence rate and PAD-related amputation rates. Naturally, this points to the importance of primary prevention that could bring down these rates. Given the gravity of PAD as a chronic condition, there have been calls to action for scaling up public health interventions for raising awareness, screening for early detection, and treatment for deterring progression (Belch, 2003; Farndon et al., 2018). Hence, public health agencies should not lose sight of prevention efforts – be it to prevent PAD incidence altogether, or to prevent progression to critical limb ischemia for those diagnosed. Effective intervention in this area would not only improve populational health in general, but also dampen the growth in the amputee population over time. Consequently, we can expect more prosthetic accessibility from a reduced demand for prosthesis fitting, improved mobility proportion, and a lowered total economic cost associated with major lower limb amputations and the loss of mobility.

Limitations & Further Work

Policy Implementation and Costs

While I have advocated for policy interventions in the prosthetics care system, based on the identified policy levers, it bears repeating that there are uncertainties involved for policy implementation. For one, all models inherently involve some level of uncertainty since they constitute a set of causal assumptions that may not represent "reality accurately enough to build policy" (Palmer, 2017, p. 90). Importantly, the SD model presented in this study is an explanatory model, and does not concern itself with robust policy implementation modelling (Palmer, 2017; Wheat, 2010). Consequently, it cannot comment on the effectiveness of policy implementation that follow from the discussed policy implications, nor anticipate plausible policy resistance. Hence, the discussion here can only partially inform policy design – by stimulating further research on policy implementation either through further modelling of explicit policy structures or other forms of policy research.

Moreover, there are costs involved in policy implementation – be it public health intervention campaigns, governmental investments or funding in digital prosthetics, or costs of expanding capacity. These costs are not captured in the model, given that those structures are not explicitly represented. In turn, the Total Economic Cost for persons with major lower limb loss (as conceptualised in this study) does not involve these additional costs borne by the health care system. The Net Economic Benefit of providing prosthetic services, as described in Chapter 4, could be much lower if we were to account for these additional costs. Instead, here, it should be interpreted as the net benefit of re-integrating amputees in society as opposed to return of investment in prosthetics.

Market Subsystem Operationalisation

In terms of the model structure, its main limitation is in its partially conceptual nature – specifically, the market subsystem, which has been extensively discussed. There is uncertainty in the parameter values and non-linear functions formulated in this module, which in turn translates to a low level of numerical accuracy for the simulation results. Though numerical estimation was never part of this research scope, further modelling work could be carried out to increase the model's ability to do so. Further, the boundary of the subsystem could be expanded for the inclusion of fitting capacity adjustment structures that are more responsive to market dynamics (demand, supply, profits etc.). Here, a much larger research scope is required to empirically study the digital prosthetic market and should involve robust data collection for operationalising the various identified relationships. Regardless, for the purpose of our research, the market subsystem in its current iteration suffices in providing a structural explanation for digital prosthetics market growth and reasonable projections for its anticipated development under different conditions.

Individual Factors

On the other hand, the main limitation in the top-level prosthetic care sector pertains to the uncertainties involved in modelling individual predispositions or decisions – the propensity to dropout from the fitting process or readopt a prosthesis. For a more accurate numerical estimation, vigorous data collection is required to ascertain the fractional dropout and readoption rates. Moreover, they remain as simplifications that could benefit from further work. Such predispositions are not simply functions of attractiveness, but also dependent on a broad array of individual factors, including mental health state, level of social support, and occurrence of limb pain (Webster et al., 2012). In addition, we have excluded individual factors related to quality of life for amputees (Pell et al., 1993) – which is particularly difficult to operationalise without the involvement of amputees in the model building process. In this research, we have mainly represented the interest of the prosthetic service provider at the expense of amputees themselves. Including amputees, through Group Model Building (D. F. Andersen et al., 1997), could be a potent avenue for further research in this field. This could lead to a more robust model boundary that includes individual predispositions as well as quality of life measures.

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Appendices

A. Simulation Experiment Report

In this appendix, I provide the minimum simulation reporting guidelines recommended by Rahmandad & Sterman (2012).

Modelling Software: Stella Architect 3.0

Integration Method: Euler's Integration

DT = 1/64

Time Units: Months

Simulation Start Time: 0 (Jan 2010)

Simulation End Time: 480 (Jan 2050)

Business As Usual Scenario

Population Sector

Table A.0.1 Parameter Values and Units for Population Sector in BAU

Parameter Value	Units
Inflection_AoI = 1	dmnl
Initial_PAD_Population[Under_15] = 0	People
Initial_PAD_Population["15_to_44"] = 0	People
Initial_PAD_Population["45_to_59"] = 285116	People
Initial_PAD_Population["60_to_79"] = 974435	People
Initial_PAD_Population[Above_80] = 555477	People
Initial_Total_Population[Under_15] = 11053185	People
Initial_Total_Population["15_to_44"] = 25466363	People
Initial_Total_Population["45_to_59"] = 12197752	People
Initial_Total_Population["60_to_79"] = 11187462	People
Initial_Total_Population[Above_80] = 2854694	People
Max_Effect_AoI = 2	dmnl

Mortality_Rate[Under_15] = GRAPH(TIME)	dmnl/month
Mortality_Rate["15_to_44"] = GRAPH(TIME)	dmnl/month
Mortality_Rate["45_to_59"] = GRAPH(TIME)	dmnl/month
Mortality_Rate["60_to_79"] = GRAPH(TIME)	dmnl/month
Mortality_Rate[Above_80] = GRAPH(TIME)	dmnl/month
Net_Migration_Rate[Under_15] = GRAPH(TIME)	dmnl/month
Net_Migration_Rate["15_to_44"] = GRAPH(TIME)	dmnl/month
Net_Migration_Rate["45_to_59"] = GRAPH(TIME)	dmnl/month
Net_Migration_Rate["60_to_79"] = GRAPH(TIME)	dmnl/month
Net_Migration_Rate[Above_80] = GRAPH(TIME)	dmnl/month
Newborn_Mortality = GRAPH(TIME)	dmnl
PAD_Relative_Mortality_Risk = 1.86	dmnl
"PAD-related_Amputation_Rate"[Under_15] = 0	dmnl/month
"PAD-related_Amputation_Rate"["15_to_44"] = 0	dmnl/month
"PAD-related_Amputation_Rate"["45_to_59"] = 0.00414/12	dmnl/month
"PAD-related_Amputation_Rate"["60_to_79"] = 0.00278/12	dmnl/month
"PAD-related_Amputation_Rate"[Above_80] = 0.00181/12	dmnl/month
Proportion_Major_Amputation = 0.1	dmnl
Proportion_of_Female = 0.584	dmnl
Reference_PAD_IR[Under_15] = 0	dmnl/month
Reference_PAD_IR["15_to_44"] = 0	dmnl/month
Reference_PAD_IR["45_to_59"] = 28542/12197752/12	dmnl/month
Reference_PAD_IR["60_to_79"] = 95697/11187462/12	dmnl/month
Reference_PAD_IR[Above_80] = 27979/2854694/12	dmnl/month
Steepness_AoI = 2	dmnl
Time_for_Prevention_to_take_effect = 10*12	Months

Time_to_Age[Under_15] = 15*12	Months
Time_to_Age["15_to_44"] = 29*12	Months
Time_to_Age["45_to_59"] = 14*12	Months
Time_to_Age["60_to_79"] = 19*12	Months
Time_to_Age[Above_80] = 0	Months
Time_to_Report = 36	Months
Total_Fertility_Rate = GRAPH(TIME)	dmnl
Trauma_Incidence[Under_15] = 0.0000566/12	dmnl/month
Trauma_Incidence["15_to_44"] = 0.000105/12	dmnl/month
Trauma_Incidence["45_to_59"] = 0.000197/12	dmnl/month
Trauma_Incidence["60_to_79"] = 0.000453/12	dmnl/month
Trauma_Incidence[Above_80] = 0.00241/12	dmnl/month

Primary Care Sector

Table A.0.2 Parameter Values and Units for Primary Care Sector in BAU

Parameter Value	**Units**
Amputee_Relative_Mortality_Risk = 3.1	dmnl
Eligible_Fraction[Under_15] = 0.9	dmnl
Eligible_Fraction["15_to_44"] = 0.9	dmnl
Eligible_Fraction["45_to_59"] = 0.9	dmnl
Eligible_Fraction["60_to_79"] = 0.9	dmnl
Eligible_Fraction[Above_80] = 0.70	dmnl
"In-Patient_Duration" = 21.5/30	Months
"In-Patient_Mortality_Rate" = 0.08	dmnl/month
PAD_Amputation_Prevalence_Rate = 34/100000	dmnl
"Post-Op_Stay" = 14.5/30	Months

"Re-Admission_Rate" = 0.095	dmnl/month
"Re-Op_Rate" = 0.09	dmnl/month
Reference_Total_Population = GRAPH(TIME)	People
Traumatic_Amputation_Prevalence[Under_15] = 4716	People
Traumatic_Amputation_Prevalence["15_to_44"] = 68727	People
Traumatic_Amputation_Prevalence["45_to_59"] = 71724	People
Traumatic_Amputation_Prevalence["60_to_79"] = 120616	People
Traumatic_Amputation_Prevalence[Above_80] = 89340	People
Wound_Healing_Duration = 1	Months

Prosthetic Care Sector

Table A.0.3 Parameter Values and Units for Prosthetic Care Sector in BAU

Prosthetic Care Sector	**Units**
Adjustment_Duration[Prosthesis_Type] = 3	Months
Delivery_Duration[Digital] = 0.25	Months
Delivery_Duration[Traditional] = 1.5	Months
Desired_Appointment_Time = 1	Months
Fit_First_Duration[Prosthesis_Type] = 4	Months
Initial_Accessibility = 0.5	dmnl
Initial_FRD = 1	dmnl
Initial_FRR = 1	dmnl
Initial_Measurement_Duration[Prosthesis_Type] = 0.5	Months
Insurance_Coverage_Cycle = 36	Months
Max_FRR = 2	dmnl

Prosthesis_Lifespan = 36	Months
Ref_EP_Dropout_Fraction[Prosthesis_Type] = 0.1	dmnl
Ref_ID_Dropout_Fraction[Prosthesis_Type] = 0.1	dmnl
Ref_ML_Dropout_Fraction[Prosthesis_Type] = 0.1	dmnl
Ref_Readoption_Fraction[Prosthesis_Type] = 0.2	dmnl
Relative_Mortality_Risk_Adjustment = 0.5	dmnl
Steepness_FRD = 1.5	dmnl
Steepness_FRR = 6	dmnl
Success_Fraction[Digital] = 0.9 Success_Fraction[Traditional] = 0.5	dmnl dmnl
Time_to_Dropout = 1	Months
Time_to_Perceive_Fitting_Rate = 3*12	Months

Health Economics Sector

Table A.0.4 Parameter Values and Units for Health Economics Sector in BAU

Health Economics Sector	**Units**
Family_Costs[Not_Fitted] = 19845/12 Family_Costs[Traditional_Fit] = 13230/12 Family_Costs[Digital_Fit] = 8820/12	USD/person/month USD/person/month USD/person/month
GDP_per_Capita = 44100/12	USD/person/month
Healthcare_Costs[Not_Fitted] = 7277/12 Healthcare_Costs[Traditional_Fit] = 6064/12 Healthcare_Costs[Digital_Fit] = 5336/12	USD/person/month USD/person/month USD/person/month
Maintenance_Multiplier = 1.2	dmnl

Overhead_Multiplier = 1/0.75	dmnl
Proportion_of_FM_Employed = 0.8	dmnl
Social_Payments = 1191/12	USD/person/month
Unemployment_Payment = 2381/12	USD/person/month
Unit_Cost[Digital] = 1573	USD/person
Unit_Cost[Traditional] = 2186	USD/person

Innovation Diffusion Sector

Table A.0.5 Parameter Values and Units for Innovation Diffusion Sector in BAU

Innovation Diffusion Sector	**Units**
Market_Subsystem.GoS_Effectiveness_Factor = 0.25	dmnl
Market_Subsystem.Sensitivity_of_Resources_to_MS = 1	dmnl
Market_Subsystem.Time_to_Adjust_GoS = 3	Months
Market_Subsystem.Time_to_Decay = 60	Months
Market_Subsystem.Time_to_Develop_Innovation = 12	Months
Market_Subsystem.Time_to_Diffuse_Knowledge = 12	Months
Market_Subsystem.Time_to_Mobilise_Resources = 6	Months

Market Formation Sector

Table A.0.6 Parameter Values and Units for Market Formation Sector in BAU

Market Formation Sector	**Units**
Market_Subsystem.Clinics[Traditional] = 35	Clinics
Market_Subsystem.Clinics_Sensitivity_SWITCH = 0	dmnl

Market_Subsystem.Duration_RER = 180	Months
Market_Subsystem.External_Resource_Size_SWITCH = 0	dmnl
Market_Subsystem.Fitting_Capacity_per_Prosthetist[Digital] = 288/12	People/Prosthetist/Month
Market_Subsystem.Fitting_Capacity_per_Prosthetist[Traditional] = 58/12	People/Prosthetist/Month
Market_Subsystem.Inflection_DFR = 1	dmnl
Market_Subsystem.Inflection_EA_on_MI = 2	dmnl
Market_Subsystem.Inflection_PL_on_EA = 2	dmnl
Market_Subsystem.Limit_DFR = 1	dmnl
Market_Subsystem.Limit_EA = 2	dmnl
Market_Subsystem.Limit_EA_on_MI = 4	dmnl
Market_Subsystem.Limit_MI = 2	dmnl
Market_Subsystem.Limit_PL_on_EA = 4	dmnl
Market_Subsystem.Maximum_Effect_MS = 1	dmnl
Market_Subsystem.Maximum_SSE = 0.25	dmnl
Market_Subsystem.Mean_Position_MS = 5	dmnl
Market_Subsystem.MS_Threshold = 0.05	dmnl
Market_Subsystem.Prosthetist_per_clinic = 2	Prosthetist/Clinic
Market_Subsystem.Ref_Digital_Clinics = 3	Clinic
Market_Subsystem.Ref_EA = 0.5	dmnl
Market_Subsystem.Ref_MI = 0.5	dmnl
Market_Subsystem.Ref_PL = 0.5	dmnl

Market_Subsystem.Relative_Weight_of_Reputation = 0.6	dmnl
Market_Subsystem.Relative_Weight_of_Resistance = 0.6	dmnl
Market_Subsystem.RER_Size = 1	dmnl
Market_Subsystem.Sensitivity_of_Clinics_to_Market_Size = 0.5	dmnl
Market_Subsystem.Spread_MS = 0.25	dmnl
Market_Subsystem.Steepness_DFR = 0.2	dmnl
Market_Subsystem.Steepness_EA = 2.5	dmnl
Market_Subsystem.Steepness_EA_on_MI = 0.4	dmnl
Market_Subsystem.Steepness_MI = 2.5	dmnl
Market_Subsystem.Steepness_PL_on_EA = 0.4	dmnl
Market_Subsystem.Time_to_Adjust_Clinics = 24	Months
Market_Subsystem.Time_to_Adjust_EA = 12	Months
Market_Subsystem.Time_to_Adjust_MI = 60	Months
Market_Subsystem.Time_to_Adjust_MS = 24	Months
Market_Subsystem.Time_to_Adjust_RR = 12	Months
Market_Subsystem.Time_to_Perceive_Legitimacy = 12	Months
Market_Subsystem.Timing_RER = 96	Months
Market_Subsystem.Variable_Input_Fraction = 0.25	dmnl
Market_Subsystem.Weight_of_EA = 0.4	dmnl
Market_Subsystem.Weight_of_PL = 0.5	dmnl
Market_Subsystem.Weight_of_Technological_Legitimacy = 0.5	dmnl

Heightened Resources Scenario

In the heightened resources scenario, all parameter values from the BAU scenario are retained except for the following:

Market Formation Sector

Table A.0.7 Parameter Values and Units for Market Formation Sector in HRS

Market Formation Sector	**Units**
Market_Subsystem.External_Resource_Size_SWITCH = 1	dmnl
Market_Subsystem.RER_Size = 5	dmnl

Expanded Capacity Scenario

In the expanded capacity scenario, all parameter values from the HRS are retained except for the following:

Market Formation Sector

Table A.0.8 Parameter Values and Units for Market Formation Sector in ECS

Market Formation Sector	**Units**
Market_Subsystem.Clinics_Sensitivity_SWITCH = 0	dmnl
Market_Subsystem.Sensitivity_of_Clinics_to_Market_Size = 1	dmnl

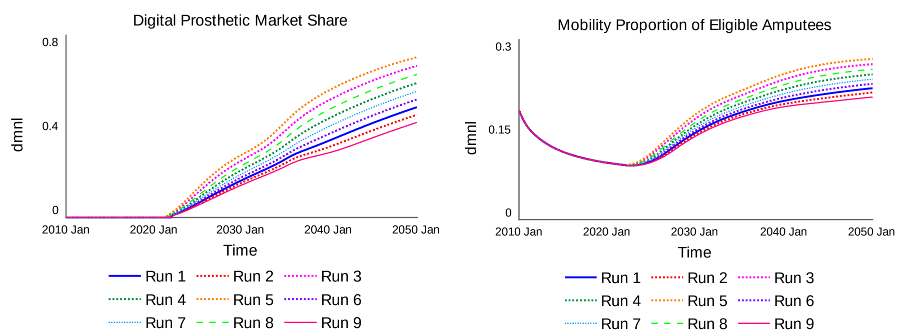
B. Sensitivity Analysis

Here, I present the results of the sensitivity analysis conducted as part of model testing and validation. The model's sensitivity was tested against the Heightened Resource scenario (External Resource Size SWITCH =1). A total of 66 constant parameters, excluding the arrayed dimensions, were tested using the Model Analysis Tools in Stella Architect 3.0. Sensitivity Analysis was configured for nine runs with Sobol Sequence sampling. The distribution type selected for each parameter and its range are specified in the individual results below. The results are grouped by parameter types: (1) *adjustment times*; (2) *nonlinear functions* – parameters affecting the shape; (3) *reference values* – known parameter values that have been validated; and (4) *assumed values* – uncertain parameter values that requires further validation. The output of the sensitivity runs is presented for the following indicators: Digital Prosthetic Market Share, Mobility Proportion of Eligible Amputees, Total Economic Cost, and Total Economic Contribution. For the sake of parsimony, only results with observed sensitivity are presented below.

Adjustment Times

In general, the model was not very sensitive to the adjustment times. Only one out of 25 parameters resulted in moderate numerical sensitivity. Seven parameters resulted in slight sensitivity, with slight changes to the outputs – the most sensitive of these will be shown below.

Time to Adjust Market Infrastructure (uniform distribution 30 to 120 months)



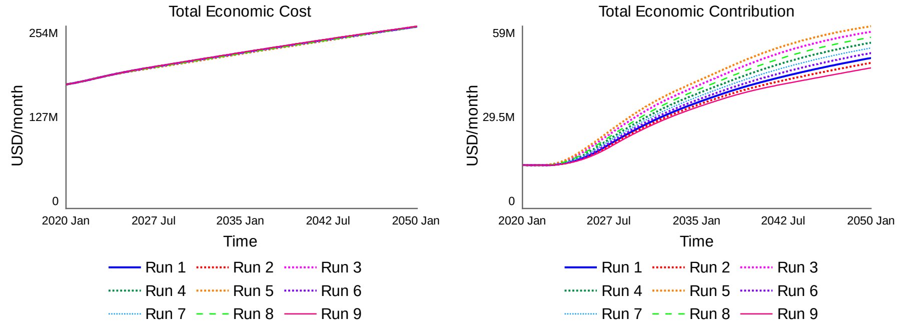


Figure B.0.1 Sensitivity Runs for Time to Adjust Infrastructure

The model is moderately sensitive to Market Infrastructure adjustment time, although this conforms to expectations. A shorter adjustment time leads to a faster adjustment of the Market Infrastructure stock, which in turn increases the Digital Prosthetic Market Share to a higher level than it otherwise would have been. A higher digital market share enables more eligible amputees to be fitted with a prosthesis, which expectedly increases both the mobility proportion and the total economic contribution as more people can work. The parameter value of 60 months was set by Walrave & Raven (2016a) in the original conceptual model. Regardless, more robust data collection can improve the certainty of the model results, particularly for the market share.

Desired Appointment Time (uniform distribution 0.5 to 2)

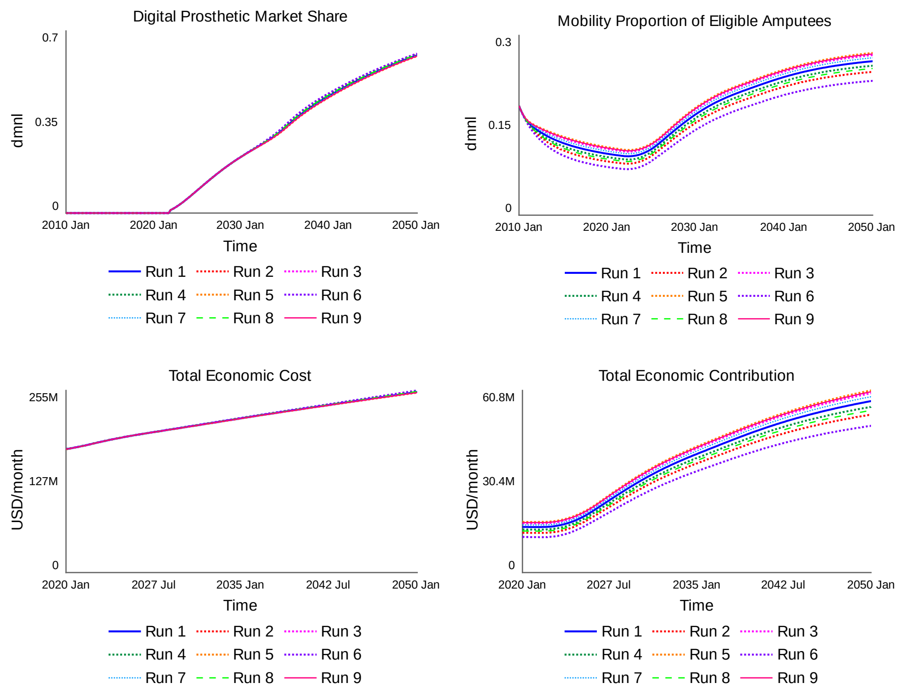


Figure B.0.2 Sensitivity Runs for Desired Appointment Time

Of the slightly sensitive parameters, Desired Appointment Time yielded the largest range of output in Mobility Proportion and Economic Contribution. The Desired Appointment Time controls the rate at which amputees are desiring to be fitted with a prosthesis (i.e., the fitting demand). This impacts the Prosthetic Accessibility, which in turn affects the flow of amputees through the prosthetic care sector. Hence, we observe slight variability in the proportion of amputees who become mobile and thus able to contribute to the economy. The parameter value of 1 month is a reasonable assumption, that nevertheless can be made more certain with data collection.

Nonlinear Functions

There were some measures of sensitivity in the model results to the nonlinear functions formulated as effect variables. The 11 parameters controlling the shape of these functions were tested, of which five resulted in moderate sensitivity.

Sensitivity of Clinics to Market Size (uniform distribution 0.5 to 1.5)

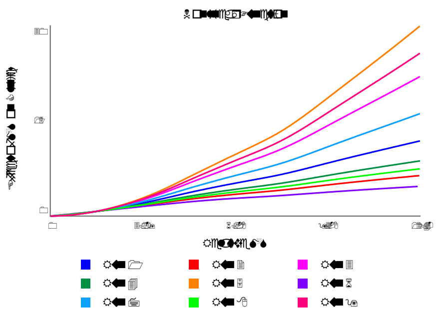


Figure B.0.3 Effect of Market Size on Clinics

The Sensitivity of Clinics to Market Size controls the steepness of the exponential growth curve that governs the relationship between the Relative Market Size and the Effect of Market Size on Clinics, as shown in the structure graph above. A higher sensitivity thus yields a steeper growth in digital clinics over time. With more clinics, the Prosthetic Accessibility increases for digital prosthesis, which enables more amputees to get fitted with a prosthesis. Hence, expectedly, we observe moderate sensitivity in the mobility proportion and economic contribution (see Figure B.0.4 below).

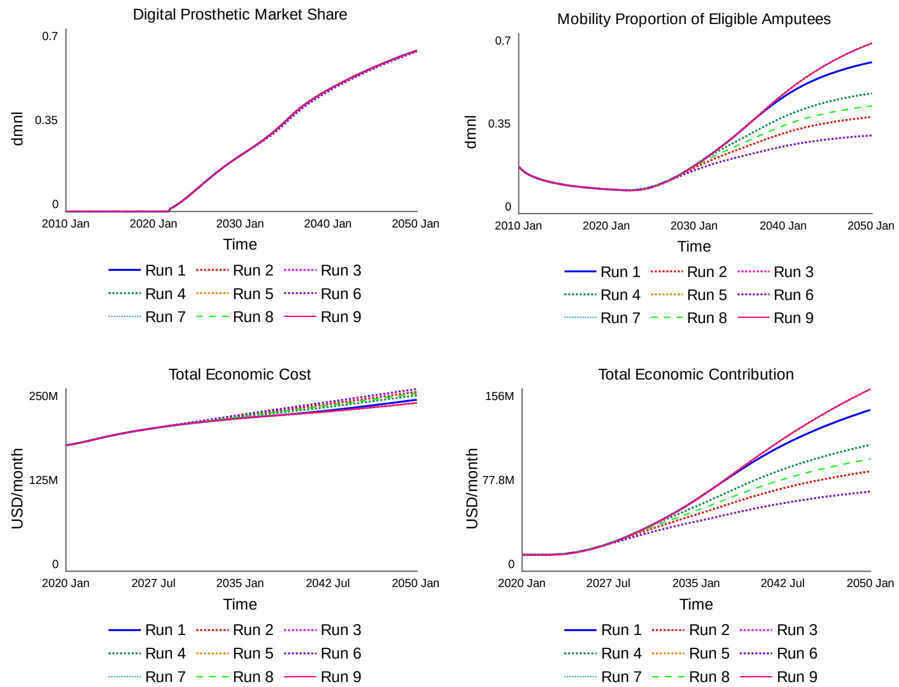


Figure B.0.4 Sensitivity Runs for Sensitivity of Clinics

Despite a large range of output in Mobility Proportion and Economic Contribution, the overall shape of development is maintained, and thus the results can be considered moderately sensitive (numerical). This parameter nevertheless could be a leverage point as it indicates the importance of building capacity for prosthetic fitting, which could yield much better outcomes for amputees as well as the economy at large.

Steepness PL on EA (uniform distribution 0.2 to 0.8)

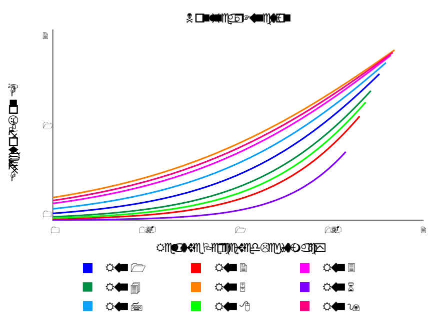


Figure B.0.5 Effect of Perceived Legitimacy on Entrepreneurial Activity

The Steepness of the effect of Perceived Legitimacy on Entrepreneurial Activity controls the rate of exponential growth of the effect variable. The higher the steepness, the faster the rate of growth.

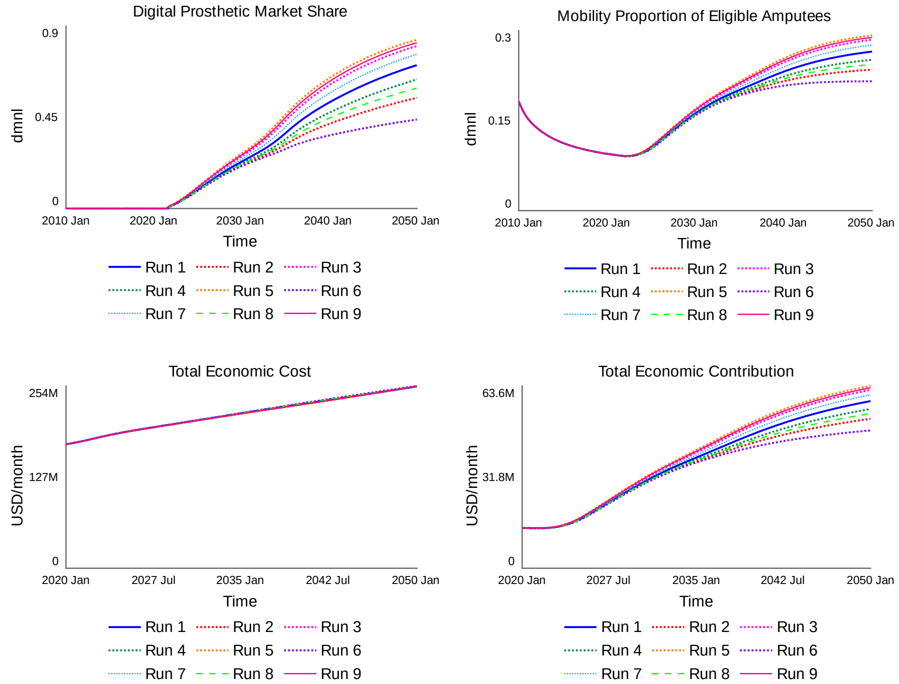


Figure B.0.6 Sensitivity Runs for Steepness Perceived Legitimacy on EA

A steeper effect on entrepreneurial activity increases the stock to a level higher than it otherwise would have been, and this impacts several feedback mechanisms that work to increase the market size of the digital prosthesis. Hence, we observe the sensitivity in market share. In turn, this influences the number of amputees that are successfully fitted with the prosthesis and thus can contribute to the economy. While such sensitivity indicates uncertainty with the parameter, this value was calibrated to fit the table function used in the original model (see Walrave & Raven, 2016a).

Steepness EA (uniform distribution 1 to 5)

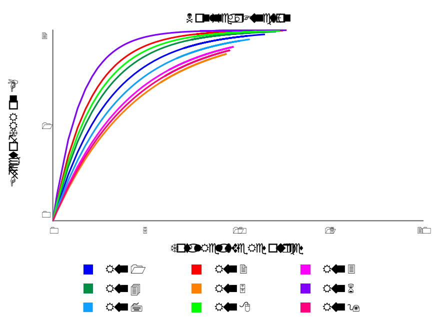


Figure B.0.7 Effect of Total Relative Resources on Entrepreneurial Activity

This parameter controls the rate at which the Effect of Total Relative Resources on Entrepreneurial Activity increases decreasingly. The faster the exponential decay, the higher the relative resources available for spurring the growth of Entrepreneurial Activity, which in turn increases market share, mobility proportion and economic contribution as explained above.

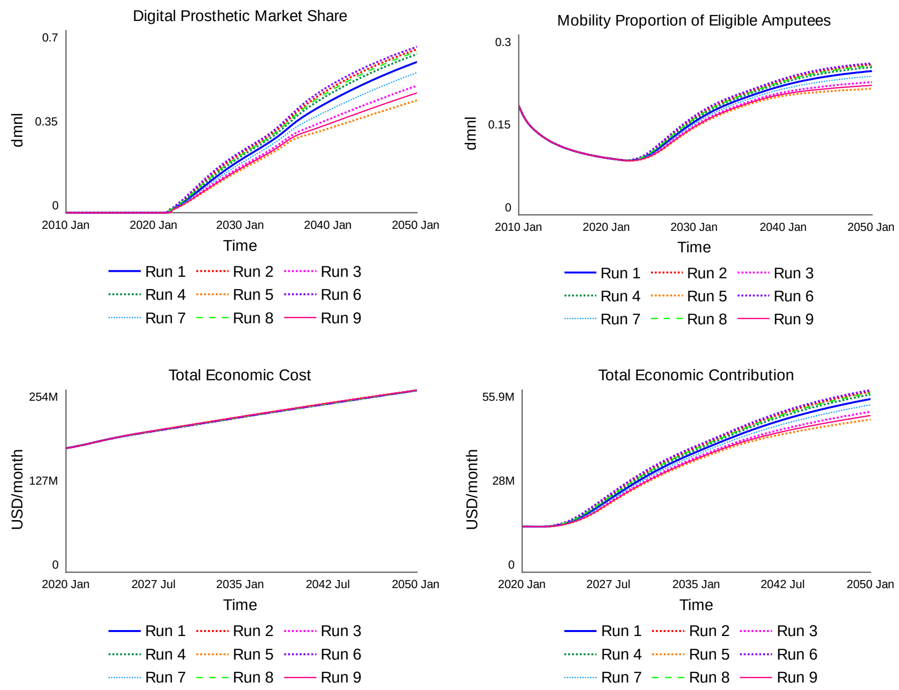


Figure B.0.8 Sensitivity Runs for Steepness Entrepreneurial Activity

This parameter value was assumed and thus points to some uncertainty in this structure. Afterall, this table function simplifies a more complex structure surrounding funding for entrepreneurial activity. Nevertheless, given that this subsystem is a conceptual model, and the shape of development is fundamentally retained, confidence in this parameter value can be maintained. For greater confidence, further modelling with more robust parameterisation should be conducted.

Steepness EA on MI (uniform distribution 0.2 to 0.8)

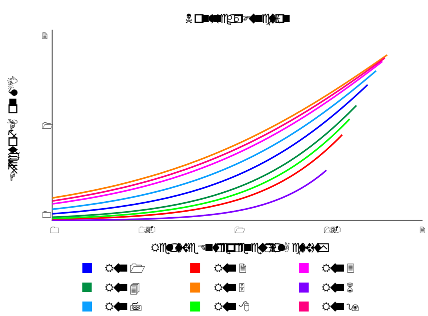


Figure B.0.9 Effect of Entrepreneurial Activity on Market Infrastructure

The Steepness of the effect of Entrepreneurial Activity on Market Infrastructure controls the rate of exponential growth of the effect variable. The higher the steepness, the faster the rate growth in the Market Infrastructure. When the Market Infrastructure increases to a level higher than it otherwise would have been, the market size increases directly and indirectly through reduced regime resistance and increased perceived legitimacy of digital technology. Hence, we observe sensitivity in Digital Prosthetic Market Share in Figure B.0.10. In turn, this increases more amputees getting prosthesis, thereby influencing the Mobility Proportion and Total Economic Contribution. Again, this value was calibrated to fit the table function used in the original model (see Walrave & Raven, 2016a).

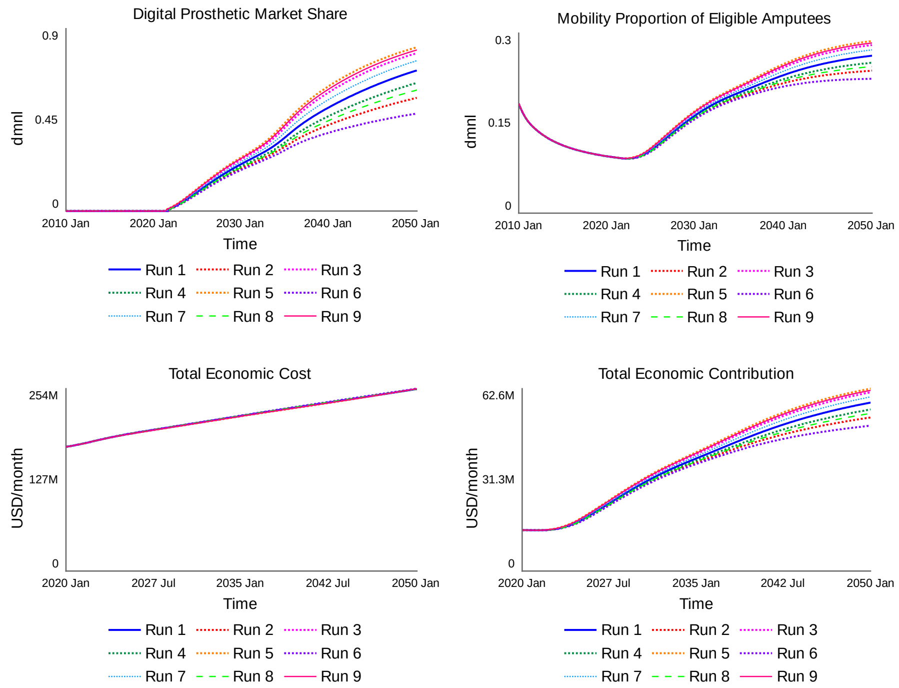


Figure B.0.10 Sensitivity Runs for Steepness EA on MI

Steepness MI (uniform distribution 1 to 5)

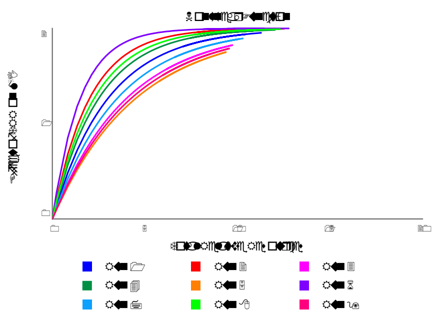


Figure B.0.11 Effect of Total Relative Resources on Market Infrastructure

This parameter controls the rate at which the Effect of Total Relative Resources on Market Infrastructure increases decreasingly. The faster the exponential decay, the higher the relative resources available for building Market Infrastructure, which in turn increases market share, mobility proportion and economic contribution as explained previously.

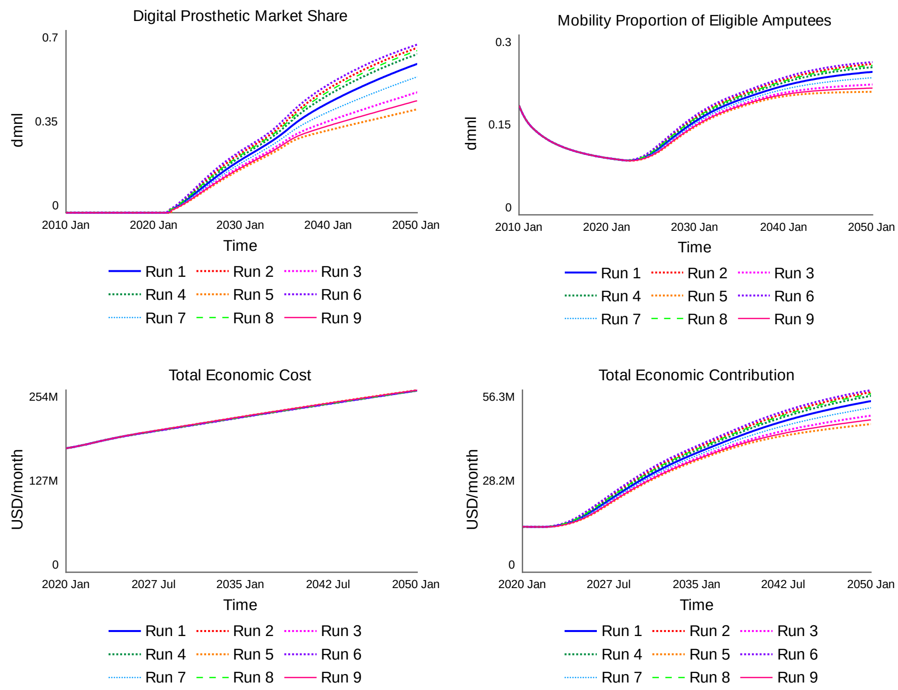


Figure B.0.12 Sensitivity Runs for Steepness of Market Infrastructure

Similarly, the table function associated with this parameter simplifies a more complex structure surrounding the funding for market infrastructure building. While further modelling could improve the sensitivity results, we can still assert confidence in this parameter as the shape of development is fundamentally retained.

Reference Values

Parameters typed as reference values refer to known values that have been obtained or calculated from available data. Typically, sensitivity resulting from these parameters do not diminish confidence in the model, but instead could point to leverage points in the system. In this model, five out 18 parameters were found to be moderately sensitive.

PAD-related Amputation Rate (uniform distribution halved to doubled)

Prior to discussing the sensitivity results, elaboration on the distribution is warranted given that the parameter is an arrayed dimension. For arrayed parameters, an adjustment converter was included in the model and multiplied with the parameter. The adjustment converter was put through the sensitivity analysis with a uniform distribution with the range 0.5 to 2, which at most halves and doubles the arrayed parameters in concert. In doing so, we avoid the case where the amputation rate is unrealistically lowered for one age group while the rate is increased for the other groups.

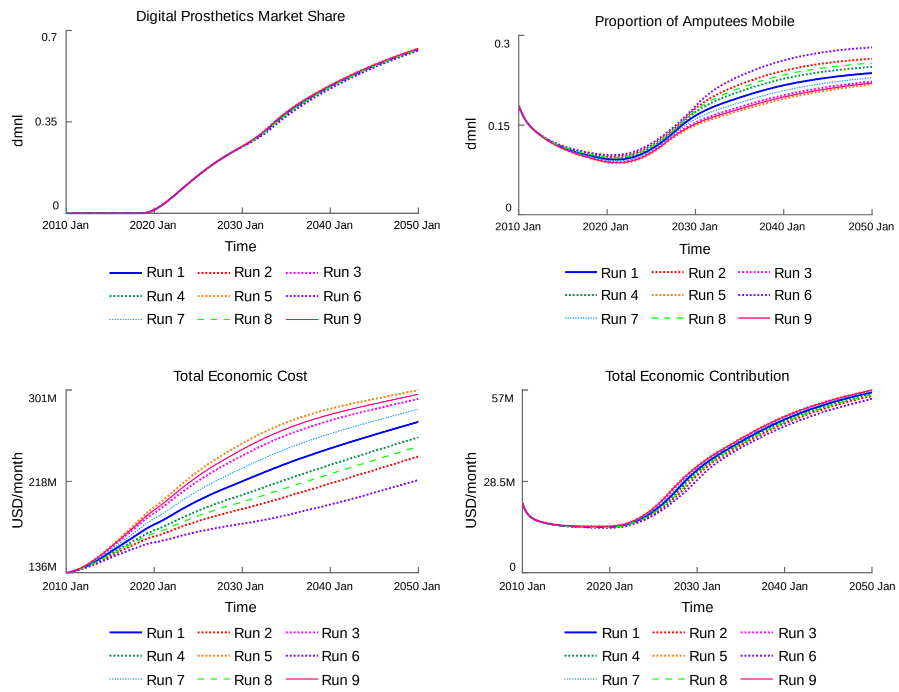


Figure B.0.13 Sensitivity Runs for PAD-related Amputation Rate

Here, we observe that the PAD-related Amputation Rate results in sensitivity for Mobility Proportion of Eligible Amputees, Total Economic Cost and Contribution. When the fractional rate increases, more people experience PAD-related Amputation, which increases the total number of amputees, thus decreasing the proportion of people who are mobile (higher denominator). While more people become amputees, the accessibility of prosthetic care does not increase proportionally, hence more people are left without mobility than with. Hence, we see that total economic cost increases disproportionately to the economic contribution. This sensitivity thus points to this parameter being a leverage point in the system: naturally, we should look to decrease the amputation rate to yield better outcomes.

Similar outcomes are observed in the *Reference PAD Incidence Rate*. A lower incidence rate improves Mobility Proportion, incurs a lower Total Economic Cost and slightly increases the Total Economic Contribution. Hence, this points to another leverage point in the system. The model has taken this into account and endogenously reduces this reference value through the Prevention Pressure (B1) feedback loop. However, the long delays involved in prevention programme slows down this potential. Hence, reducing the adjustment time by improving the effectiveness of the prevention programmes could be good policy leverage.

Reference Digital Clinics (uniform distribution 1 to 6)

The model is numerically sensitive to the parameter Reference Digital Clinics. Increasing the reference clinics, increases the fitting capacity. In turn, the prosthetic accessibility increases and accommodates more amputees to successfully enter the prosthetic fitting process. Hence, we observe sensitivity in the Mobility Proportion of Eligible Amputees. As more people are successfully fitted, more amputees can return to the workforce, which in turn increases the Economic Contribution. More successful digital fittings also increase the reputation of the digital technology, which influences the perceived legitimacy and thus the Market Share.

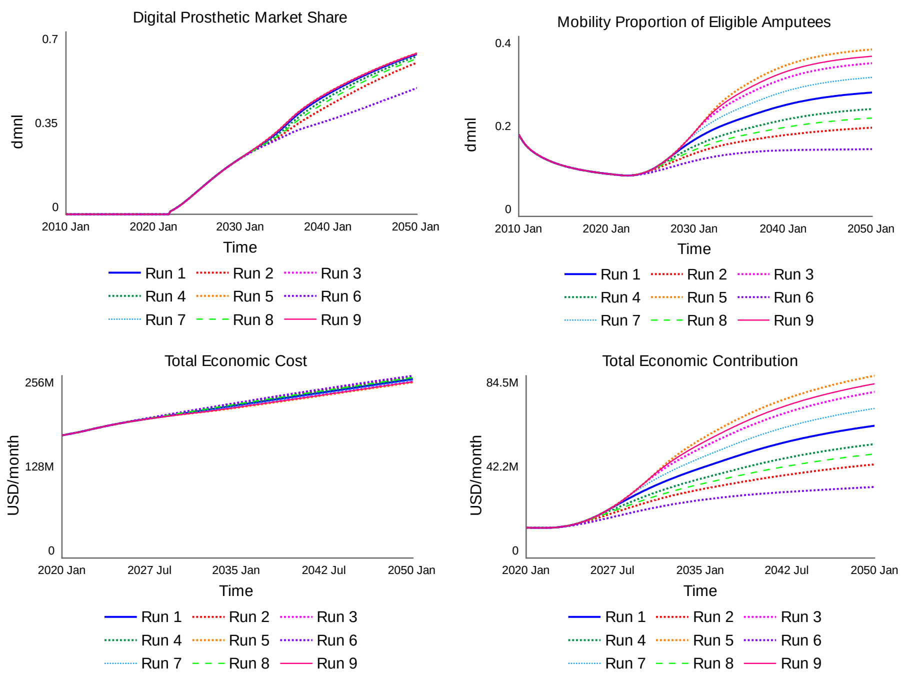


Figure B.0.14 Sensitivity Runs for Reference Digital Clinics

These results thus point to increasing Digital Clinics as a leverage point to increase the overall fitting capacity of the system. Two other related parameters, *Prosthetist per Clinic* and *Fitting Capacity per Prosthetist*, also experience similar sensitivity. This clearly emphasises the leverage strength of Fitting Capacity.

Assumed Values

Lastly, this subsection deals with uncertain parameters that take on assumed values based on reason. Sensitivity here could suggest the need for further modelling (as it is likely to be masking some important underlying structure) or more robust data collection. Here, I present the four out of 12 parameters that have resulted in sensitivity in the model.

Weight of Perceived Legitimacy (uniform distribution 0.3 to 0.7)

The model is moderately sensitive (since the shape of the development is retained) to the weight of the effect of perceived legitimacy on entrepreneurial activity. Given the uncertainty in the parameter, the value was set to 0.5 to denote equal distribution between the weight of perceived legitimacy and funding. Here, we test values from 0.3 (low weightage) to 0.7 (high weightage). In general, a higher weight for Perceived Legitimacy results in a lower level of Entrepreneurial Activity, which feeds back to not only reduce the market infrastructure and market size, but also reduce the relative resources that further reduces the Entrepreneurial Activity. Hence, we observe sensitivity in the Market Share, which further impacts the Mobility Proportion and Economic Contribution.

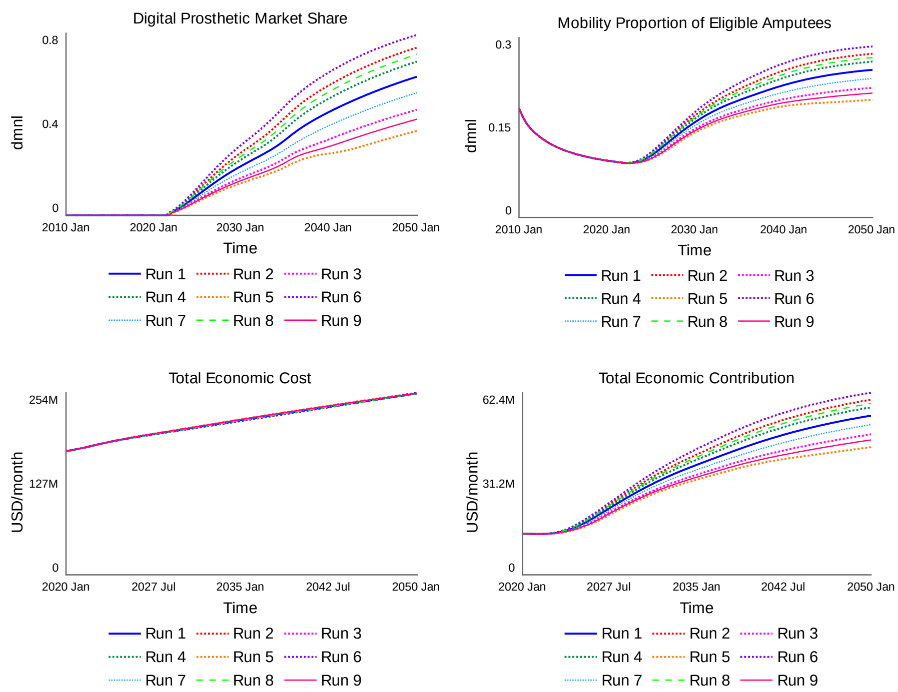


Figure B.0.15 Sensitivity Runs for Weight of Perceived Legitimacy

Given the conceptual nature of the market subsystem, this structure is an oversimplification of reality and thus results in such sensitivity. The confidence in this parameter should be improved with further modelling to capture the underlying system being masked.

Weight of Entrepreneurial Activity (uniform distribution 0.3 to 0.7)

As discussed in Chapter 3, under the behaviour sensitivity test section, this parameter generates behavioural sensitivity. Rather than repeating the discussion, I simply present the sensitivity runs of the KPIs in Figure B.0.16.

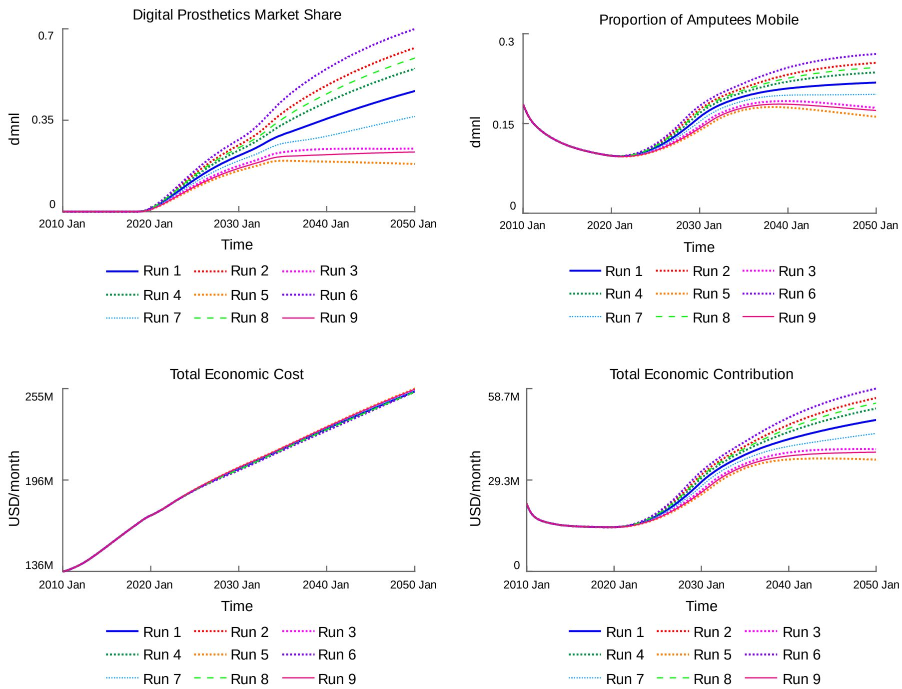


Figure B.0.16 Sensitivity Runs for Weight of Entrepreneurial Activity

Market Size Threshold (uniform distribution 0.025 to 0.075)

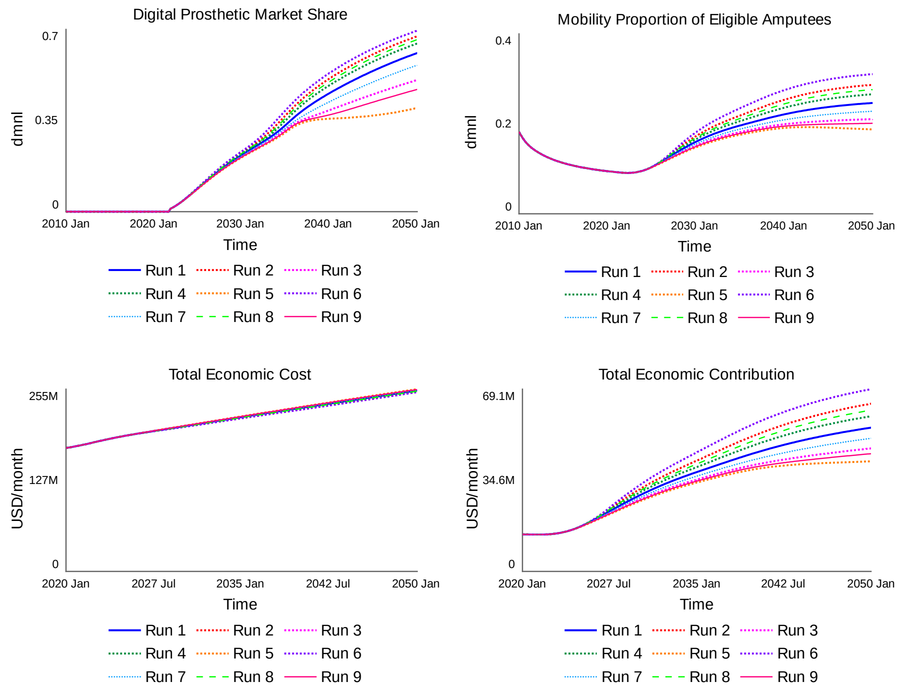


Figure B.0.17 Sensitivity Runs for Market Size Threshold

The model is sensitive to the Market Size Threshold parameter. This threshold determines the relative Market Size, which has multiple effects in the market subsystem: namely, effect on Total Relative Resource, Effect on Sailing Ship Effect, and Effect on Clinic

Size. Hence, naturally we expect sensitivity in the Digital Market Share. This threshold was assumed based on reason and should be made more robust through data collection.

Relative External Resources Size (uniform distribution 0 to 9)

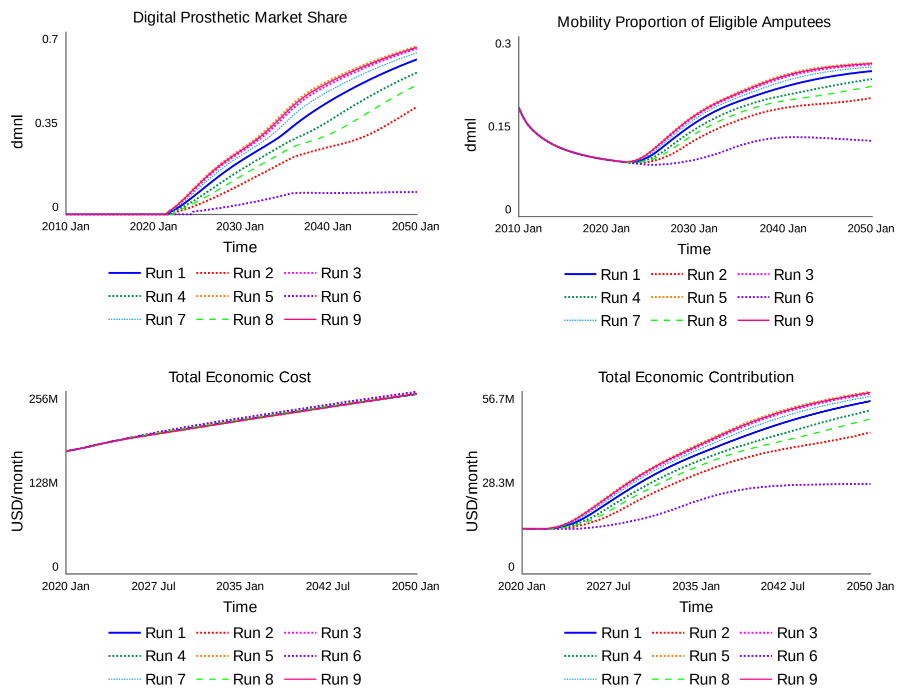


Figure B.0.18 Sensitivity Runs for Relative External Resources Size

Lastly, the model is very sensitive to the Relative External Resources Size. Uncertainty is to be expected here as this exogenous parameter is responsible for pushing the market subsystem out of steady state development. In general, the more the relative external resources, the stronger the feedback mechanisms in the subsystem, which work to increase the market share. As a result, the mobility proportion increases, and the economic outcomes improve. The results of this sensitivity analysis were mainly included to emphasise the leverage strength of this parameter, which has been used for policy experimentation.

C. Model Documentation

The model has 7 sectors, with one module in the root model. There are 303 (842) variables (array expansion in parenthesis). Of which, 21 (108) are Stocks; 57 (360) are Flows; 225 (374) are Converters. The model is quantified with 181 (586) Equations, 101 (148) Constants, and 5 (13) Graphicals. There are also 40 expanded macro variables.

Top-Level Prosthetic Care System

Table C.0.9 Documentation for Population Sector

Population Sector
Birth_Rate = Fertile_Female_Population*Total_Fertility_Rate/Time_to_Age["15_to_44"] UNITS: People/month DOCUMENT: This variable dynamically calculates the birth rate at any point in time, representing the births per month. It is calculated by multiplying the total fertile female population by the total fertility rate, and then divided by the fertile duration.
Effect_of_Amputation_on_Incidence = SMTH3(Indicated_Effect_of_Amputation_on_Incidence, Time_for_Prevention_to_take_effect) {DELAY CONVERTER} UNITS: dmnl DOCUMENT: This variable represented the delayed effect of PAD-related amputation rates on PAD incidence rate. It is modelled with a third-order information delay with the assumption that it goes through several delay processes, which includes prevention activity-planning and implementation.
Fertile_Female_Population = Total_Fertile_Population*Proportion_of_Female UNITS: people DOCUMENT: This variable dynamically calculates the total number of females in the United Kingdom who are of fertile age. It simply multiplies the proportion of females with the total fertile age population.
Indicated_Effect_of_Amputation_on_Incidence = Max_Effect_AoI/(1+ EXP(Steepness_AoI*("Perceived_PAD-related_Admission_Rate"//INIT("Perceived_PAD-related_Admission_Rate")-Inflection_AoI))) UNITS: dmnl DOCUMENT: This variable represents the effect of perceived PAD-related admission rate on PAD incidence rate. As the relative perceived admission rate from PAD-related amputation cases increases (current rate compared to initial), we expect pressure on the public health sector in stepping up PAD prevention activities to bring down the incidence rate.

The effect variable is analytically formulated as a inverse Sigmoid function (z-shaped). With this formulation, when the relative admission rate is 1, then the effect on incidence rate is 1 – meaning that it will be at its reference value. As the relative admission rate increases towards 2, indicating a prevention pressure, the effect decreases decreasingly towards 0. Whereas, as relative admission decreases towards 0 (situation easing), the effect increases decreasingly towards a maximum effect of 2. The assumption here is that if there is no prevention pressure, then the public health sector is likely to reallocate resources to other diseases.
Inflection_AoI = 1 UNITS: dmnl DOCUMENT: This parameter sets the inflection point of the Sigmoid curve for the Indicated Effect of Amputation on Incidence. The inflection point is set at (1,1) where relative value at 1 returns the reference PAD incidence rate.
"Initial_Non-PAD_Population"[Age_Cohort] = Initial_Total_Population-Initial_PAD_Population-Initial_Amputee_Population UNITS: People DOCUMENT: This variable calculates the Initial Non-Peripheral Arterial Disease (PAD) Population by subtracting the initial PAD and initial amputee populations from the initial total population.
Initial_PAD_Population[Under_15] = 0 Initial_PAD_Population["15_to_44"] = 0 Initial_PAD_Population["45_to_59"] = 285116 Initial_PAD_Population["60_to_79"] = 974435 Initial_PAD_Population[Above_80] = 555477 UNITS: People DOCUMENT: This constant parameter represents the total initial peripheral arterial disease (PAD) population for each age cohort in year 2010. The data was obtained from Global Burden of Disease Study filtered by cause "peripheral artery disease" (Global Burden of Disease Collaborative Network, 2020)
Initial_Total_Population[Under_15] = 11053185 Initial_Total_Population["15_to_44"] = 25466363 Initial_Total_Population["45_to_59"] = 12197752 Initial_Total_Population["60_to_79"] = 11187462 Initial_Total_Population[Above_80] = 2854694 UNITS: People

DOCUMENT: This constant parameter represents the total initial population for each age cohort in year 2010. The data was obtained from UK population estimates for that year (Office for National Statistics, 2015).
Max_Effect_AoI = 2 UNITS: dmnl DOCUMENT: This parameter sets the maximum effect at 2 for the Indicated Effect of Amputation on Incidence. It is assumed that the fractional PAD incidence rate would at worse double, and best reduce towards towards 0.
Mortality_Rate[Under_15] = GRAPH(TIME) Points: (0.0, 0.0000109), (12.0, 0.0000106), (24.0, 0.0000103), (36.0, 0.00001), (48.0, 0.0000097), (60.0, 0.0000094), (72.0, 0.0000091), (84.0, 0.0000088), (96.0, 0.0000086), (108.0, 0.0000083)… Mortality_Rate["15_to_44"] = GRAPH(TIME) Points: (0.0, 0.0000635), (12.0, 0.0000626), (24.0, 0.0000618), (36.0, 0.000061), (48.0, 0.0000603), (60.0, 0.0000596), (72.0, 0.000059), (84.0, 0.0000584), (96.0, 0.0000579), (108.0, 0.0000574)… Mortality_Rate["45_to_59"] = GRAPH(TIME) Points: (0.0, 0.0003067), (12.0, 0.0003017), (24.0, 0.0002975), (36.0, 0.0002942), (48.0, 0.0002908)… Mortality_Rate["60_to_79"] = GRAPH(TIME) Points: (0.0, 0.0017167), (12.0, 0.001675), (24.0, 0.0016417), (36.0, 0.0016167), (48.0, 0.0015917)… Mortality_Rate[Above_80] = GRAPH(TIME) Points: (0.0, 0.0166667), (12.0, 0.0165833), (24.0, 0.0165), (36.0, 0.0165), (48.0, 0.0164167), (60.0, 0.0163333), (72.0, 0.0163333), (84.0, 0.01625), (96.0, 0.0161667), (108.0, 0.0160833)… UNITS: dmnl/month DOCUMENT: This variable is the time-series data for mortality rates by age groups in the United Kingdom. The time-series is retrieved from population projections up to 2050 (Office for National Statistics, 2022c). The values have been adjusted from years to months.

Net_Migration_Rate[Under_15] = GRAPH(TIME)

Points: (0.0, 0.0000911), (12.0, 0.0000828), (24.0, 0.0000822), (36.0, 0.0001263), (48.0, 0.0001327), (60.0, 0.0001828), (72.0, 0.0001596), (84.0, 0.0001226), (96.0, 0.0000573), (108.0, 0.0001141)…

Net_Migration_Rate["15_to_44"] = GRAPH(TIME)

Points: (0.0, 0.00089), (12.0, 0.0007375), (24.0, 0.0006117), (36.0, 0.0007017), (48.0, 0.0011417), (60.0, 0.0011708), (72.0, 0.0009042), (84.0, 0.00089), (96.0, 0.0009467), (108.0, 0.0010758)…

Net_Migration_Rate["45_to_59"] = GRAPH(TIME)

Points: (0.0, 0.0000067), (12.0, 0.0000132), (24.0, 0.0000327), (36.0, 0.000052), (48.0, 0.0000709), (60.0, 0.0000576), (72.0, 0.000019), (84.0, 0.0000568), (96.0, -0.0000063), (108.0, 0.0000624)…

Net_Migration_Rate["60_to_79"] = GRAPH(TIME)

Points: (0.0, 0.0000313), (12.0, 0.0000078), (24.0, 0), (36.0, 0.0000077), (48.0, -0.0000076), (60.0, 0.0000301), (72.0, -0.0000373), (84.0, 0.000052), (96.0, -0.0000295), (108.0, -0.0000073)…

Net_Migration_Rate[Above_80] = GRAPH(TIME)

Points: (0.0, 0.0000381), (12.0, 0.0000381), (24.0, 0.0000381), (36.0, 0.0000381), (48.0, 0.0000381), (60.0, 0.0000381), (72.0, 0.0000381), (84.0, 0.0000381), (96.0, 0.0000381), (108.0, 0.0000381)…

UNITS: dmnl/month

DOCUMENT: This variable is the time-series data for net international migration into the United Kingdom. The time-series is a composite of estimated historical census data up to 2019 (Office for National Statistics, 2020) and population projections up to 2050 (Office for National Statistics, 2022a). The values have been adjusted from years to months.

Newborn_Mortality = GRAPH(TIME)

Points: (0.0, 0.000365), (12.0, 0.0003567), (24.0, 0.0003483), (36.0, 0.0003408), (48.0, 0.0003333), (60.0, 0.0003258), (72.0, 0.0003183), (84.0, 0.0003117), (96.0, 0.000305), (108.0, 0.0002983)…

UNITS: dmnl

DOCUMENT: This variable is the time-series data for the infant mortality rate in the United Kingdom. The time-series is retrieved from population projections up to 2050 (Office for National Statistics, 2022c).

"Non-PAD_Population"[Age_Cohort](t) = "Non-PAD_Population"[Age_Cohort](t - dt) + (Births[Age_Cohort] + NPAD_Migration[Age_Cohort] + NPAD_Aging_In[Age_Cohort] - NPAD_Aging_Out[Age_Cohort] - NPAD_Deaths[Age_Cohort] - NPAD_Amputation[Age_Cohort] - Peripheral_Arterial_Disease_Incidence[Age_Cohort]) * dt

INIT "Non-PAD_Population"[Age_Cohort] = "Initial_Non-PAD_Population"

UNITS: People

DOCUMENT: This stock represents the total non-amputee population who do not have peripheral arterial disease. It is accumulated by the inflows Births and net migration, and depleted by the outflows Deaths, PAD Incidence, and Amputation. The stock is arrayed by age cohorts. The initial value of the stock is simply the calculated Initial Non-PAD Population.

INFLOWS:

Births[Under_15] = Birth_Rate*(1-Newborn_Mortality)

Births["15_to_44"] = 0

Births["45_to_59"] = 0

Births["60_to_79"] = 0

Births[Above_80] = 0

UNITS: People/month

DOCUMENT: This inflow represents the number of successful births in the UK per month, and it accumulates the Non-PAD Population stock. The successful birth rates is determined by the total birth rates multiplied by the fraction of newborns that do not die, or rather survive.

NPAD_Migration[Age_Cohort] = "Non-PAD_Population"*Net_Migration_Rate

UNITS: People/month

DOCUMENT: This biflow represents the net migration for non-peripheral arterial disease population, that accumulates the population stock. The rate of net migration is determined by the the fractional net migration rate multiplied by the Non-PAD Population stock value.

NPAD_Aging_In[Under_15] = 0

NPAD_Aging_In["15_to_44"] = NPAD_Aging_Out[Under_15]

NPAD_Aging_In["45_to_59"] = NPAD_Aging_Out["15_to_44"]

NPAD_Aging_In["60_to_79"] = NPAD_Aging_Out["45_to_59"]

NPAD_Aging_In[Above_80] = NPAD_Aging_Out["60_to_79"]

UNITS: People/month

DOCUMENT: This inflow takes those who have aged out of the previous cohort and allows re-entry into the next appropriate age group.

OUTFLOWS:

NPAD_Aging_Out[Age_Cohort] = "Non-PAD_Population"//Time_to_Age

UNITS: People/month

DOCUMENT: This outflow represents the rate at which people age out of their respective cohort groups. This rate is determined by a simple first order adjustment, where the the total number of people in the population stock is divided by the residence time.

NPAD_Deaths[Age_Cohort] = "Non-PAD_Population"*Mortality_Rate

UNITS: People/month

DOCUMENT: This outflow represents the deaths for non-peripheral arterial disease population, that depletes the population stock. The rate is determined by the the mortality rate multiplied by the respective Non-PAD Population stock value.

NPAD_Amputation[Age_Cohort] = "Non-PAD_Population"*Traumatic_Amputation_Rate

UNITS: People/month

DOCUMENT: This outflow represents the amputation rates for non-peripheral arterial disease population, that depletes the population stock. The rate is determined solely by the traumatic amputation rate multiplied by the respective Non-PAD Population stock.

Peripheral_Arterial_Disease_Incidence[Age_Cohort] = "Non-PAD_Population"*PAD_Incidence_Rate

UNITS: People/month

DOCUMENT: This biflow represents the incidence rate for peripheral arterial disease (PAD); it depletes the non-PAD population stock and simultaneously accumulates the PAD population stock. The rate is determined by fractional PAD incidence rate multiplied with the Non-PAD population stock.

PAD_Incidence_Rate[Age_Cohort] = Reference_PAD_IR*Effect_of_Amputation_on_Incidence

UNITS: dmnl/month

DOCUMENT: This variable represents the monthly fractional incidence rate of peripheral arterial disease in the United Kingdom. It is determined by the reference fractional rate adjusted by the effect from PAD-related amputation admission rate.

PAD_Population[Age_Cohort](t) = PAD_Population[Age_Cohort](t - dt) + (Peripheral_Arterial_Disease_Incidence[Age_Cohort] + PAD_Migration[Age_Cohort] + PAD_Aging_In[Age_Cohort] - PAD_Amputation[Age_Cohort] - PAD_Deaths[Age_Cohort] - PAD_Aging_Out[Age_Cohort]) * dt

INIT PAD_Population[Age_Cohort] = Initial_PAD_Population

UNITS: People

DOCUMENT: This stock represents the total non-amputee population with peripheral arterial diseases population, and are at greater risk for amputation. It is accumulated by the inflows PAD Incidence and net migration, and depleted by the outflows Deaths and Amputation. The stock is arrayed by age cohorts. The initial value of the stock is simply the Initial Non-PAD Population obtained from data.

INFLOWS:

Peripheral_Arterial_Disease_Incidence[Age_Cohort] = "Non-PAD_Population"*PAD_Incidence_Rate

UNITS: People/month

DOCUMENT: This biflow represents the incidence rate for peripheral arterial disease (PAD); it depletes the non-PAD population stock and simultaneously accumulates the PAD population stock. The rate is determined by fractional PAD incidence rate multiplied with the Non-PAD population stock.

PAD_Migration[Under_15] = 0

PAD_Migration["15_to_44"] = 0

PAD_Migration["45_to_59"] = PAD_Population["45_to_59"]*Net_Migration_Rate["45_to_59"]

PAD_Migration["60_to_79"] = PAD_Population["60_to_79"]*Net_Migration_Rate["60_to_79"]

PAD_Migration[Above_80] = PAD_Population[Above_80]*Net_Migration_Rate[Above_80]

UNITS: People/month

DOCUMENT: This biflow represents the net migration for peripheral arterial disease population, that accumulates the population stock. The rate of net migration is determined by the the fractional net migration rate multiplied by the PAD Population stock value.

PAD_Aging_In[Under_15] = 0

PAD_Aging_In["15_to_44"] = 0

PAD_Aging_In["45_to_59"] = 0

PAD_Aging_In["60_to_79"] = PAD_Aging_Out["45_to_59"]

PAD_Aging_In[Above_80] = PAD_Aging_Out["60_to_79"]

UNITS: People/month DOCUMENT: This inflow takes those who have aged out of the previous cohort and allows re-entry into the next appropriate age group.
OUTFLOWS: PAD_Amputation[Age_Cohort] = PAD_Population*(Traumatic_Amputation_Rate+"PAD-related_Amputation_Rate") UNITS: People/month DOCUMENT: This outflow represents the amputation rates for peripheral arterial disease population, that depletes the population stock. The rate is determined by both the traumatic amputation rate and PAD-related amputation rate multiplied by the respective Non-PAD Population stock.
PAD_Deaths[Age_Cohort] = PAD_Population*Mortality_Rate*PAD_Relative_Mortality_Risk UNITS: People/month DOCUMENT: This outflow represents the deaths for peripheral arterial disease population, that depletes the population stock. The rate is determined by the the mortality rate multiplied by the respective PAD Population stock value, adjusted by a multiplier to take into account the relative mortality rate as a result of PAD.
PAD_Aging_Out[Age_Cohort] = PAD_Population//Time_to_Age UNITS: People/month DOCUMENT: This outflow represents the rate at which people age out of their respective cohort groups. This rate is determined by a simple first order adjustment, where the the total number of people in the population stock is divided by the residence time.
PAD_Relative_Mortality_Risk = 1.86 UNITS: dmnl DOCUMENT: This parameter represents the relative risk of death from all causes, or hazard ratio of persons diagnosed with peripheral arterial disease as compared to the rest of the population. Based on two separate studies, the average relative mortality risk was ascertained to be 1.86 across all stages of PAD (Diehm et al., 2009; Sartipy et al., 2018).
"PAD-related_Admission_Rate"[Age_Cohort] = PAD_Population*"PAD-related_Amputation_Rate" UNITS: People/month DOCUMENT: This variable dynamically calculates the PAD-related amputation admissions per month without taking into account traumatic injuries for each age cohort. It is calculated by multiplying the PAD Population with the fractional amputation rate.

"PAD-related_Amputation_Rate"[Under_15] = 0 "PAD-related_Amputation_Rate"["15_to_44"] = 0 "PAD-related_Amputation_Rate"["45_to_59"] = 0.00414/12 "PAD-related_Amputation_Rate"["60_to_79"] = 0.00278/12 "PAD-related_Amputation_Rate"[Above_80] = 0.00181/12 UNITS: dmnl/month DOCUMENT: This parameter represents the major lower limb amputation rate for patients with peripheral arterial disease. This number was calculated from a composite data set constructed from the UK's National Vascular Registry annual reports. It was calculated by dividing the estimated average (data points from year 2015 to 2020) PAD-related amputations for each age cohort (Healthcare Quality Improvement Partnership, 2015, 2016, 2018a, 2018b, 2019, 2020, 2021) with a reference number of people with PAD in each group (Global Burden of Disease Collaborative Network, 2020).
"Perceived_PAD-related_Admission_Rate" = SMTH3("Total_PAD-related_Admission_Rate", Time_to_Report, "Total_PAD-related_Admission_Rate") {DELAY CONVERTER} UNITS: People/month DOCUMENT: This variable represented the general perception of PAD-related admission rate. It is modelled with a third-order information delay with the assumption that it goes through several delay processes, which includes data collection, reporting, and dissemination.
Proportion_Major_Amputation = 0.1 UNITS: dmnl DOCUMENT: This parameter represents the proportion of lower limb amputation that are of major (above-ankle). The parameter was calibrated to 10% in order to attain an approximate proportion of traumatic amputation cases to 25% of all major lower limb amputations. This estimate was provided by expert opinion from ProsFit Technologies.
Proportion_of_Female = 0.584 UNITS: dmnl DOCUMENT: This parameter represents the proportion of females in the UK population. It is calculated as around 0.51 from population estimates (Office for National Statistics, 2015). However, the parameter was calibrated to a higher value to better fit the reference total population. This discrepancy can be explained by the fact that females have a lower mortality rate than males, which is not accounted for in this model.

Reference_PAD_IR[Under_15] = 0 Reference_PAD_IR["15_to_44"] = 0 Reference_PAD_IR["45_to_59"] = 28542/12197752/12 Reference_PAD_IR["60_to_79"] = 95697/11187462/12 Reference_PAD_IR[Above_80] = 27979/2854694/12 UNITS: dmnl/month DOCUMENT: This parameter is the reference peripheral arterial disease (PAD) fractional incidence rate for each age cohort in year 2010. It is calculated by taking the incidence estimate as a fraction of the prevalence estimate, divided by 12 months. The data was obtained from Global Burden of Disease Study filtered by cause "peripheral artery disease" (Global Burden of Disease Collaborative Network, 2020).
Steepness_AoI = 2 UNITS: dmnl DOCUMENT: This parameter controls the steepness of the curve or the rate of increase or decline of the Indicated Effect of Amputation on Incidence variable. The steepness is assumed to be 2, but can be calibrated to data if available.
Time_for_Prevention_to_take_effect = 10*12 UNITS: month DOCUMENT: This parameter represents the time taken for prevention activities to be implemented before there is an effect on the incidence rate. Here, it is assumed that the delay time is 10 years.
Time_to_Age[Under_15] = 15*12 Time_to_Age["15_to_44"] = 29*12 Time_to_Age["45_to_59"] = 14*12 Time_to_Age["60_to_79"] = 19*12 Time_to_Age[Above_80] = 0 UNITS: Months DOCUMENT: This parameter is the residence time for each age cohort. In other words, it represents the duration they will remain in the cohort before moving on to the next age cohort group. The residence time is multiplied by 12 for each value to convert the duration from years to months.
Time_to_Report = 36 UNITS: months

DOCUMENT: This parameter represents the time taken for the information to collected, reported and disseminated before reaching the wider public. Here, it is assumed that the information is updated with a three-year delay time.
Total_Fertile_Population = "Non-PAD_Population"["15_to_44"] + "Post-Op_Hospital_Care"["15_to_44"] + "Pre-Op_Hospital_Care"["15_to_44"] + "Recovery_(First_30_Days)"["15_to_44"] + SUM(Awaiting_Replacement["15_to_44", *]) + SUM(Definitive_Device["15_to_44",*]) + SUM(Eligible_for_Prosthesis["15_to_44",*]) + SUM(Full_Mobility["15_to_44",*]) + Ineligible_for_Prosthesis["15_to_44"] + SUM(Initial_Device["15_to_44",*]) + SUM(Limited_Mobility["15_to_44",*]) + SUM(Matured_Limb["15_to_44",*]) + PAD_Population["15_to_44"] {SUMMING CONVERTER} UNITS: people DOCUMENT: This summing converter dynamically calculates the total number of people in the age cohort 15-44 at any one point in time.
Total_Fertility_Rate = GRAPH(TIME) Points: (0.0, 1.930), (12.0, 1.920), (24.0, 1.930), (36.0, 1.840), (48.0, 1.830), (60.0, 1.820), (72.0, 1.810), (84.0, 1.750), (96.0, 1.690), (108.0, 1.650)… UNITS: dmnl DOCUMENT: This variable is the reference time-series for Total Fertility Rate in the United Kingdom. The time-series is a composite of estimated historical census data up to 2019 (Office for National Statistics, 2022b) and thereafter, population projections up to 2050 (Office for National Statistics, 2022a).
"Total_Non-PAD_Population" = SUM("Non-PAD_Population"[*]) {SUMMING CONVERTER} UNITS: people DOCUMENT: This variable dynamically sums the various age cohorts of the non-peripheral arterial disease population.
Total_PAD_Population = SUM(PAD_Population[*]) {SUMMING CONVERTER} UNITS: people DOCUMENT: This variable dynamically sums the various age cohorts of the peripheral arterial disease population.
"Total_PAD-related_Admission_Rate" = SUM("PAD-related_Admission_Rate") UNITS: People/month DOCUMENT: This converter simply sums up the PAD-related admission rate of the age cohort groups.

Trauma_Incidence[Under_15] = 0.0000566/12 Trauma_Incidence["15_to_44"] = 0.000105/12 Trauma_Incidence["45_to_59"] = 0.000197/12 Trauma_Incidence["60_to_79"] = 0.000453/12 Trauma_Incidence[Above_80] = 0.00241/12 UNITS: dmnl/month DOCUMENT: This parameter represents the average estimated traumatic injury incidence rate for each age cohort. The data was obtained from Global Burden of Disease Study filtered by cause "Injuries" and "Amputation of lower limb" (Global Burden of Disease Collaborative Network, 2020). The estimates from year 2010 to 2019 were averaged and adjusted to a monthly rate.
Traumatic_Amputation_Rate[Age_Cohort] = Trauma_Incidence*Proportion_Major_Amputation UNITS: dmnl/month DOCUMENT: This variable calculates the traumatic amputation rate for major lower limb cases by multiplied the trauma incidence rate with the proportion of which that are major amputation cases.

Table C.0.10 Documentation for Primary Care Sector

Primary Care Sector
Amputee_Relative_Mortality_Risk = 3.1 UNITS: dmnl DOCUMENT: This parameter represents the relative risk of death from all causes, or hazard ratio of persons with major lower limb amputation as compared to the rest of the population. The average relative mortality risk was ascertained to be between 2.9 and 3.3 after the third year (Ebskov, 1999).
Eligible_Fraction[Under_15] = 0.9 Eligible_Fraction["15_to_44"] = 0.9 Eligible_Fraction["45_to_59"] = 0.9 Eligible_Fraction["60_to_79"] = 0.9 Eligible_Fraction[Above_80] = 0.70 UNITS: dmnl DOCUMENT: This parameter represents the estimated fraction of people, based on age cohort, that typically are eligible for prosthesis. The numbers were estimated from expert opinion (correspondence with ProsFit Technologies).

"In-Patient_Duration" = 21.5/30

UNITS: months

DOCUMENT: This parameter represents the total in-patient stay duration for patients undergoing surgical amputation. This number was obtained from a composite data set constructed from the UK's National Vascular Registry annual reports. The data points available from year 2017 to 2020 was averaged (Healthcare Quality Improvement Partnership, 2018a, 2018b, 2019, 2020, 2021) and adjusted from days to months.

"In-Patient_Mortality_Rate" = 0.08

UNITS: dmnl/month

DOCUMENT: This parameter represents the in-patient mortality rate for patients undergoing surgical amputation. This number was obtained from a composite data set constructed from the UK's National Vascular Registry annual reports. The mortality rate data points available from year 2017 to 2020 was averaged (Healthcare Quality Improvement Partnership, 2018a, 2018b, 2019, 2020, 2021). Age-specific data was not available, and hence assumed to be the same across the board. Moreover, the mortality rate is assumed to be the same for PAD and non-PAD amputation cases.

Ineligible_for_Prosthesis[Age_Cohort](t) = Ineligible_for_Prosthesis[Age_Cohort](t - dt) + (To_Home_Care[Age_Cohort] + Ineligible_Aging_In[Age_Cohort] - Ineligible_Deaths[Age_Cohort] - Ineligible_Aging_Out[Age_Cohort]) * dt

INIT Ineligible_for_Prosthesis[Age_Cohort] = Initial_Ineligible_Population

UNITS: People

DOCUMENT: This stock represents the total amputees who are deemed ineligible for prosthesis for medical reasons. It is accumulated by the inflow To Home Care, and depleted by the outflow Ineligible Deaths. The stock is arrayed by age cohorts. The initial value of the stock is simply the calculated Initial Eligible Population.

INFLOWS:

To_Home_Care[Age_Cohort] = ("Recovery_(First_30_Days)"/Wound_Healing_Duration)*(1-Eligible_Fraction)

UNITS: People/month

DOCUMENT: This biflow represents the rate at which amputees are deemed ineligible for prosthesis and sent To Home Care permanently after recovering; it depletes the Recovery population stock and simultaneously accumulates the Ineligible for Prosthesis population stock. This rate is determined by the fraction of people who are ineligble for prosthesis multiplied by the total number of people recovering at any one point in time. This recovery rate is a first order adjustment, where the the total number of people in the Recovery stock is divided by the wound healing duration.

Ineligible_Aging_In[Under_15] = 0 Ineligible_Aging_In["15_to_44"] = Ineligible_Aging_Out[Under_15] Ineligible_Aging_In["45_to_59"] = Ineligible_Aging_Out["15_to_44"] Ineligible_Aging_In["60_to_79"] = Ineligible_Aging_Out["45_to_59"] Ineligible_Aging_In[Above_80] = Ineligible_Aging_Out["60_to_79"] UNITS: People/month DOCUMENT: This inflow takes those who have aged out of the previous cohort and allows re-entry into the next appropriate age group.
OUTFLOWS: Ineligible_Deaths[Age_Cohort] = Ineligible_for_Prosthesis*Mortality_Rate*Amputee_Relative_Mortality_Risk UNITS: People/month DOCUMENT: This outflow represents the deaths for the amputee population ineligible for prosthesis. The rate is determined by the fractional mortality rate multiplied by the respective population stock, adjusted by a multiplier to take into account the relative mortality rate as a result of amputation.
Ineligible_Aging_Out[Age_Cohort] = Ineligible_for_Prosthesis/Time_to_Age UNITS: People/month DOCUMENT: This outflow represents the rate at which people age out of their respective cohort groups. This rate is determined by a simple first order adjustment, where the the total number of people in the population stock is divided by the residence time.
Inital_Above_45_Population = Initial_Total_Population["45_to_59"] + Initial_Total_Population["60_to_79"] + Initial_Total_Population[Above_80] {SUMMING CONVERTER} UNITS: People DOCUMENT: This summing converter totals the number of people above 45 years of age in 2010 in the United Kingdom.
Initial_Amputee_Population[Under_15] = Traumatic_Amputation_Prevalence[Under_15]*Proportion_Major_Amputation Initial_Amputee_Population["15_to_44"] = Traumatic_Amputation_Prevalence["15_to_44"]*Proportion_Major_Amputation Initial_Amputee_Population["45_to_59"] = (Initial_Total_Population["45_to_59"]/Inital_Above_45_Population)*PAD_Amputation_Prevalence + Traumatic_Amputation_Prevalence["45_to_59"]*Proportion_Major_Amputation

Initial_Amputee_Population["60_to_79"] = (Initial_Total_Population["60_to_79"]/Inital_Above_45_Population)*PAD_Amputation_Prevalence + Traumatic_Amputation_Prevalence["60_to_79"]*Proportion_Major_Amputation Initial_Amputee_Population[Above_80] = (Initial_Total_Population[Above_80]/Inital_Above_45_Population)*PAD_Amputation_Prevalence + Traumatic_Amputation_Prevalence[Above_80]*Proportion_Major_Amputation UNITS: People DOCUMENT: This converter calculates the total initial amputee population of each age cohort in year 2010. In general, it is the sum of the total amputees from traumatic injuries and PAD for each age group. As for the PAD-amputees, the calculated total number of amputees is proportionally distributed to the respective age cohort.
Initial_Eligible_Population[Age_Cohort] = Initial_Amputee_Population*Eligible_Fraction UNITS: People DOCUMENT: This converter calculates the initial number of amputees who are eligible for prosthesis. This is calculated as the product of initial amputee population and the fraction of amputees who are typically deemed eligible.
Initial_Ineligible_Population[Age_Cohort] = Initial_Amputee_Population*(1-Eligible_Fraction) UNITS: People DOCUMENT: This converter calculates the initial number of amputees who are ineligible for prosthesis. This is calculated as the product of initial amputee population and the fraction of amputees who are typically deemed ineligible.
PAD_Amputation_Prevalence = PAD_Amputation_Prevalence_Rate*INIT(Reference_Total_Population) UNITS: People DOCUMENT: This converter calculates the prevalence of amputees from PAD-related amputations in year 2010 by multiplying the total population size in that year with the prevalence rate.
PAD_Amputation_Prevalence_Rate = 34/100000 UNITS: dmnl DOCUMENT: This parameter represents the prevalence rate for PAD-related amputations in year 2010. The data was obtained from Ahmad et al. (2016), which reported a prevalence rate of around 34 per 100,00 people in England. Here, this is extrapolated to the larger United Kingdom population.

"Post-Op_Hospital_Care"[Age_Cohort](t) = "Post-Op_Hospital_Care"[Age_Cohort](t - dt) + (Surgical_Amputation[Age_Cohort] + Readmission[Age_Cohort] - Discharge[Age_Cohort] - "Post-Op_Deaths"[Age_Cohort] - "Re-Amputation"[Age_Cohort]) * dt INIT "Post-Op_Hospital_Care"[Age_Cohort] = 0 UNITS: People DOCUMENT: This stock represents the total people in the post-operative stage of major lower limb amputation. It is accumulated by the inflows Surgical Amputation and Readmission, and depleted by the outflows Post-Op Deaths, Discharge and Re-Amputation. The stock is arrayed by age cohorts. The initial value for the stock is 0 with the assumption that there is no one in the primary care setting at the very start of the simulation.
INFLOWS: Surgical_Amputation[Age_Cohort] = "Pre-Op_Hospital_Care"/"Pre-Op_Stay" UNITS: People/month DOCUMENT: This biflow represents the Surgical Amputation rate; it depletes the Pre-Op population stock and simultaneously accumulates the Post-Op population stock. This rate is determined by a simple first order adjustment, where the the total number of people in the Pre-Op population stock is divided by the residence time (pre-op stay duration).
Readmission[Age_Cohort] = "Recovery_(First_30_Days)"*"Re-Admission_Rate" UNITS: People/month DOCUMENT: This biflow represents the readmission rate for amputees who have been discharged; it depletes the Recovery stock and simultaneously accumulates the Post-Op stock. The rate is determined by the fractional readmission rate multiplied with the Recovery stock.
OUTFLOWS: Discharge[Age_Cohort] = ("Post-Op_Hospital_Care"/"Post-Op_Stay") UNITS: People/month DOCUMENT: This biflow represents the Discharge rate; it depletes the Post-Op population stock and simultaneously accumulates the Recovery population stock. This rate is determined by a simple first order adjustment, where the the total number of people in the Post-Op population stock is divided by the residence time (post-op stay duration).
"Post-Op_Deaths"[Age_Cohort] = "Post-Op_Hospital_Care"*"In-Patient_Mortality_Rate" UNITS: People/month DOCUMENT: This outflow represents the post-operation deaths, that depletes the population stock. The rate is determined by the in-patient mortality rate multiplied by the respective Post-Op Hospital Care stock.

"Re-Amputation"[Age_Cohort] = "Post-Op_Hospital_Care"*"Re-Op_Rate" UNITS: People/month DOCUMENT: This biflow represents the re-amputation rate for post-op amputees; it depletes the Post-Op population stock and simultaneously accumulates the Pre-Op population stock. The rate is determined by the fractional re-operation rate multiplied with the Post-Op population stock.
"Post-Op_Stay" = 14.5/30 UNITS: months DOCUMENT: This parameter represents the post-operation stay duration for patients who underwent surgical amputation. This number was obtained from a composite data set constructed from the UK's National Vascular Registry annual reports. The data points available from year 2017 to 2020 was averaged (Healthcare Quality Improvement Partnership, 2018a, 2018b, 2019, 2020, 2021) and adjusted from days to months.
"Pre-Op_Hospital_Care"[Age_Cohort](t) = "Pre-Op_Hospital_Care"[Age_Cohort](t - dt) + ("Re-Amputation"[Age_Cohort] + Admission[Age_Cohort] - Surgical_Amputation[Age_Cohort] - "Pre-Op_Deaths"[Age_Cohort]) * dt INIT "Pre-Op_Hospital_Care"[Age_Cohort] = 0 UNITS: People DOCUMENT: This stock represents the total people admitted to hospital for major lower limb amputation, at the pre-operation stage. It is accumulated by the inflows Admission and Re-Amputation, and depleted by the outflows Pre-Op Deaths and Surgical Amputation. The stock is arrayed by age cohorts. The initial value for the stock is 0 with the assumption that there is no one in the primary care setting at the very start of the simulation.
INFLOWS: "Re-Amputation"[Age_Cohort] = "Post-Op_Hospital_Care"*"Re-Op_Rate" UNITS: People/month DOCUMENT: This biflow represents the re-amputation rate for post-op amputees; it depletes the Post-Op population stock and simultaneously accumulates the Pre-Op population stock. The rate is determined by the fractional re-operation rate multiplied with the Post-Op population stock.
Admission[Age_Cohort] = NPAD_Amputation[Age_Cohort]+ PAD_Amputation[Age_Cohort] UNITS: People/month DOCUMENT: This inflow represents the number of hopital admissions per month for major lower limb amputation, and it accumulates the Pre-Op Hospital Care stock. The admission rate is simply the sum of the Non-peripheral arterial diseases amputation cases and PAD amputation cases.

OUTFLOWS:

Surgical_Amputation[Age_Cohort] = "Pre-Op_Hospital_Care"/"Pre-Op_Stay"

UNITS: People/month

DOCUMENT: This biflow represents the Surgical Amputation rate; it depletes the Pre-Op population stock and simultaneously accumulates the Post-Op population stock. This rate is determined by a simple first order adjustment, where the the total number of people in the Pre-Op population stock is divided by the residence time (pre-op stay duration).

"Pre-Op_Deaths"[Age_Cohort] = "Pre-Op_Hospital_Care"*"In-Patient_Mortality_Rate"

UNITS: People/month

DOCUMENT: This outflow represents the pre-operation deaths, that depletes the population stock. The rate is determined by the in-patient mortality rate multiplied by the respective Pre-Op Hospital Care stock.

"Pre-Op_Stay" = "In-Patient_Duration"-"Post-Op_Stay"

UNITS: months

DOCUMENT: This converter calculates the pre-operation stay duration for patients undergoing surgical amputation. It is calculated by subtracting the Post-Op Stay from the total In-Patient Duration.

"Re-Admission_Rate" = 0.095

UNITS: dmnl/month

DOCUMENT: This parameter represents the fractional rate at which patients were re-admitted within the first 30 days after surgery. This number was obtained from a composite data set constructed from the UK's National Vascular Registry annual reports. The data points available from year 2017 to 2020 were averaged (Healthcare Quality Improvement Partnership, 2018a, 2018b, 2019, 2020, 2021).

"Re-Op_Rate" = 0.09

UNITS: dmnl/month

DOCUMENT: This parameter represents the fractional rate at which post-op patients return to theatre for re-amputation arising from complications. This number was obtained from a composite data set constructed from the UK's National Vascular Registry annual reports. The data points available from year 2017 to 2020 were averaged (Healthcare Quality Improvement Partnership, 2018a, 2018b, 2019, 2020, 2021).

"Recovery_(First_30_Days)"[Age_Cohort](t) = "Recovery_(First_30_Days)"[Age_Cohort](t - dt) + (Discharge[Age_Cohort] - Readmission[Age_Cohort] - Prosthesis_Referral[Age_Cohort] - To_Home_Care[Age_Cohort]) * dt INIT "Recovery_(First_30_Days)"[Age_Cohort] = 0 UNITS: People DOCUMENT: This stock represents the total people in the first 30 days of recovery after discharge. This is the critical period where patients might experience complications as well as the wound healing duration before being assessed and referred to a prosthetist. It is accumulated by the inflow Discharge, and depleted by the outflows Re-admission, Prosthesis Referral and To Home Care. The stock is arrayed by age cohorts. The initial value for the stock is 0 with the assumption that there is no one in the primary care setting at the very start of the simulation.
INFLOWS: Discharge[Age_Cohort] = ("Post-Op_Hospital_Care"/"Post-Op_Stay") UNITS: People/month DOCUMENT: This biflow represents the Discharge rate; it depletes the Post-Op population stock and simultaneously accumulates the Recovery population stock. This rate is determined by a simple first order adjustment, where the the total number of people in the Post-Op population stock is divided by the residence time (post-op stay duration).
OUTFLOWS: Readmission[Age_Cohort] = "Recovery_(First_30_Days)"*"Re-Admission_Rate" UNITS: People/month DOCUMENT: This biflow represents the readmission rate for amputees who have been discharged; it depletes the Recovery stock and simultaneously accumulates the Post-Op stock. The rate is determined by the fractional readmission rate multiplied with the Recovery stock.
Prosthesis_Referral[Age_Cohort] = ("Recovery_(First_30_Days)"/Wound_Healing_Duration)*Eligible_Fraction UNITS: People/month DOCUMENT: This outflow represents the rate at which amputees are deemed eligible for prosthesis and referred to a prosthetist. It depletes the Recovery population stock. The rate is determined by the fraction of people who are eligible for prosthesis multiplied by the total number of people recovering at any one point in time. This recovery rate is a first order adjustment, where the the total number of people in the Recovery stock is divided by the wound healing duration.

To_Home_Care[Age_Cohort] = ("Recovery_(First_30_Days)"/Wound_Healing_Duration)*(1-Eligible_Fraction) UNITS: People/month DOCUMENT: This biflow represents the rate at which amputees are deemed ineligible for prosthesis and sent To Home Care permanently after recovering; it depletes the Recovery population stock and simultaneously accumulates the Ineligible for Prosthesis population stock. This rate is determined by the fraction of people who are ineligble for prosthesis multiplied by the total number of people recovering at any one point in time. This recovery rate is a first order adjustment, where the the total number of people in the Recovery stock is divided by the wound healing duration.
Reference_Total_Population = GRAPH(TIME) Points: (0.0, 62759500.0), (12.0, 63285100.0), (24.0, 63705000.0), (36.0, 64105700.0), (48.0, 64596800.0), (60.0, 65110000.0), (72.0, 65648100.0), (84.0, 66040200.0), (96.0, 66435600.0), (108.0, 66796800.0)… UNITS: People DOCUMENT: This variable is the reference time-series for Total Population in the United Kingdom. The time-series is a composite of estimated historical census data up to 2019 (Office for National Statistics, 2021) and population projections up to 2050 (Office for National Statistics, 2022a).
Total_Admission_Rate = SUM(Admission[*]) {SUMMING CONVERTER} UNITS: People/month DOCUMENT: This summing converter totals the number of admissions irrespective of age groups at any one point in time.
Traumatic_Amputation_Prevalence[Under_15] = 4716 Traumatic_Amputation_Prevalence["15_to_44"] = 68727 Traumatic_Amputation_Prevalence["45_to_59"] = 71724 Traumatic_Amputation_Prevalence["60_to_79"] = 120616 Traumatic_Amputation_Prevalence[Above_80] = 89340 UNITS: People DOCUMENT: This parameter represents the prevalence of lower limb amputations (both major and minor) from traumatic injuries in year 2010 for each age cohort. The data was obtained from Global Burden of Disease Study filtered by cause "Injuries" and "Amputation of lower limb" (Global Burden of Disease Collaborative Network, 2020).

Wound_Healing_Duration = 1 UNITS: month DOCUMENT: This parameter represents the wound healing duration for patients who underwent surgical amputation. Based on the general timeline for prosthetic rehabilitation, amputees incision fully heals within the first month after surgery and receive an initial prosthetic evaluation (Rheinstein et al., 2021).

Table C.0.11 Documentation for Prosthetic Care Sector

Prosthetic Care Sector
Access_S1[Age_Cohort] = Initial_Population_with_Access*(1-Ref_EP_Dropout_Fraction[Traditional]) UNITS: People DOCUMENT: This converter calculates the remaining amputees who did not dropout in the first stage. It is calculated as the product of the initial population with access and the inverse of the reference eligible for prosthesis dropout fraction (retention fraction).
Access_S2[Age_Cohort] = Access_S1*(1-Ref_ID_Dropout_Fraction[Traditional]) UNITS: People DOCUMENT: This converter calculates the remaining amputees who did not dropout in the initial device stage. It is calculated as the product of the remaining amputee population in the initial device stage and the inverse of the reference initial device dropout fraction (retention fraction).
Access_S3[Age_Cohort] = Access_S2*(1-Ref_ML_Dropout_Fraction[Traditional]) UNITS: People DOCUMENT: This converter calculates the remaining amputees who did not dropout in the matured limb stage and moved on to the definitive device stage. It is calculated as the product of the remaining amputee population in the matured limb stage and the inverse of the reference matured limb dropout fraction (retention fraction).
Adjustment_Duration[Prosthesis_Type] = 3 UNITS: month DOCUMENT: This parameter represents the duration for amputees to adjust to their newly fitted prosthesis. Based on the general timeline for prosthetic rehabilitation, amputees continue to undergo rehabilitation after receiving the definitive device months (Rheinstein et al., 2021). In the timeline, the definitive device duration is 6 months and includes both delivery and rehabilitation. Hence, subtracting the delivery duration for traditional prosthesis from this timeline, gives us around 3 months of rehabilitation period before the patient exits prosthetic care and into holistic lifelong care (Rheinstein et al., 2021).

Awaiting_Replacement[Age_Cohort, Prosthesis_Type](t) = Awaiting_Replacement[Age_Cohort, Prosthesis_Type](t - dt) + (Prosthesis_Degradation[Age_Cohort, Prosthesis_Type] + AR_Aging_In[Age_Cohort, Prosthesis_Type] - Prosthesis_Replacement[Age_Cohort, Prosthesis_Type] - AR_Deaths[Age_Cohort, Prosthesis_Type] - AR_Aging_Out[Age_Cohort, Prosthesis_Type]) * dt INIT Awaiting_Replacement[Age_Cohort, Prosthesis_Type] = 0 UNITS: People DOCUMENT: This stock represents the total amputees who are awaiting the replacement of their degraded prosthesis and are thus temporarily made immobile. It is accumulated by the inflow Prosthesis Degradation, and depleted by the outflows AR Deaths and Prosthesis Replacement. The stock is arrayed by age cohorts and prosthesis type. The initial value for the stock is 0 with the assumption that there are no amputees in the midst of the fitting process at the very start of the simulation.
INFLOWS: Prosthesis_Degradation[Age_Cohort, Prosthesis_Type] = Full_Mobility/Prosthesis_Lifespan UNITS: People/month DOCUMENT: This biflow represents the Prosthesis Degradation rate; it depletes the Full Mobility stock and simultaneously accumulates the Awaiting Replacement stock. This rate is determined by a simple first order adjustment, where the the total number of people in the Full Mobility stock is divided by the residence time (prosthesis lifespan).
AR_Aging_In[Under_15, Digital] = 0 AR_Aging_In[Under_15, Traditional] = 0 AR_Aging_In["15_to_44", Digital] = AR_Aging_Out[Under_15,Digital] AR_Aging_In["15_to_44", Traditional] = AR_Aging_Out[Under_15,Traditional] AR_Aging_In["45_to_59", Digital] = AR_Aging_Out["15_to_44",Digital] AR_Aging_In["45_to_59", Traditional] = AR_Aging_Out["15_to_44",Traditional] AR_Aging_In["60_to_79", Digital] = AR_Aging_Out["45_to_59",Digital] AR_Aging_In["60_to_79", Traditional] = AR_Aging_Out["45_to_59",Traditional] AR_Aging_In[Above_80, Digital] = AR_Aging_Out["60_to_79",Digital] AR_Aging_In[Above_80, Traditional] = AR_Aging_Out["60_to_79",Traditional] UNITS: People/month DOCUMENT: This inflow takes those who have aged out of the previous cohort and allows re-entry into the next appropriate age group.

OUTFLOWS:

Prosthesis_Replacement[Age_Cohort, Prosthesis_Type] = Prosthetic_Accessibility[Prosthesis_Type]*Awaiting_Replacement/Desired_Appointment_Time

UNITS: People/month

DOCUMENT: This biflow represents the Prosthesis Replacement rate; it depletes the Awaiting Replacement stock and simultaneously accumulates the Matured Limb stock. The rate is determined by the fraction of people who have access to a prosthetist multiplied by the total number of people requiring a replacement at any one point in time.

AR_Deaths[Age_Cohort, Prosthesis_Type] = Awaiting_Replacement*Mortality_Rate[Age_Cohort]*Amputee_Relative_Mortality_Risk

UNITS: People/month

DOCUMENT: This outflow represents the deaths for the amputee population awaiting the replacement of their degraded prosthesis. The rate is determined by the fractional mortality rate multiplied by the respective population stock, adjusted by a multiplier to take into account the relative mortality rate as a result of amputation.

AR_Aging_Out[Age_Cohort, Prosthesis_Type] = Awaiting_Replacement//Time_to_Age[Age_Cohort]

UNITS: People/month

DOCUMENT: This outflow represents the rate at which people age out of their respective cohort groups. This rate is determined by a simple first order adjustment, where the the total number of people in the population stock is divided by the residence time.

Definitive_Device[Age_Cohort, Prosthesis_Type](t) = Definitive_Device[Age_Cohort, Prosthesis_Type](t - dt) + (Device_Delivery[Age_Cohort, Prosthesis_Type] - Successful_Fitting[Age_Cohort, Prosthesis_Type] - Unsuccessful_Fitting[Age_Cohort, Prosthesis_Type]) * dt

INIT Definitive_Device[Age_Cohort, Prosthesis_Type] = 0

UNITS: People

DOCUMENT: This stock represents the total amputees who has received a definitive device and are adjusting to the new prosthesis with rehabilitation. It is accumulated by the inflow Device Delivery and depleted by the outflows Successful Fitting and Unsuccessful Fitting. The stock is arrayed by age cohorts and prosthesis type. The initial value for the stock is 0 with the assumption that there are no amputees in the midst of the fitting process at the very start of the simulation.

INFLOWS: Device_Delivery[Age_Cohort, Prosthesis_Type] = Matured_Limb/Delivery_Duration[Prosthesis_Type] UNITS: People/month DOCUMENT: This biflow represents the rate at which amputees, whose limbs have matured, receive a definitive prosthesis device. It depletes the Matured Limb stock and simultaneously accumulates the Definitive Device stock. The rate is determined by a first order material delay, where the the total number of people in the Matured Limb stock is divided by the Delivery Duration.
OUTFLOWS: Successful_Fitting[Age_Cohort, Prosthesis_Type] = (Definitive_Device/Adjustment_Duration[Prosthesis_Type])*Success_Fraction[Prosthesis_Type] UNITS: People/month DOCUMENT: This biflow represents the rate at which amputees are successfully fitted with a prosthesis. It depletes the Definitive Device stock and simultaneously accumulates the Full Mobility stock. The rate is determined by the product of the success fraction and the total number of people who have adjusted to their new prosthesis device at any one point in time. This adjustment rate is a first order adjustment, where the the total number of people in the Definitive Device stock is divided by the adjustment duration.
Unsuccessful_Fitting[Age_Cohort, Prosthesis_Type] = (Definitive_Device/Adjustment_Duration[Prosthesis_Type])*(1-Success_Fraction[Prosthesis_Type]) UNITS: People/month DOCUMENT: This biflow represents the rate at which amputees are unsuccessfully fitted with a prosthesis, thus leading to abandonment of the definitive device. It depletes the Definitive Device stock and simultaneously accumulates the Limited Mobility stock. The rate is determined by the product of the total number of people who have adjusted to their new prosthesis device at any one point in time and the inverse of the success fraction. The adjustment rate is a first order adjustment, where the the total number of people in the Definitive Device stock is divided by the adjustment duration.
Delivery_Duration[Digital] = 0.25 Delivery_Duration[Traditional] = 1.5 UNITS: month DOCUMENT: This parameter represents the delivery duration for the definitive device to be manufactured and fitted on the amputees. Based on expert opinion from prosthetists, this delivery delay is estimated to be 1.5 months for traditional plaster-cast socket devices and a much shorter duration of 0.25 months for a 3D-printed digital device (correspondence with ProsFit).

Desired_Appointment_Time = 1 UNITS: month DOCUMENT: This parameter represents the desired time for an individual to make an appointment with a prosthetist in order to get fitted for a prosthesis or replace their degraded prosthesis. Here, the assumption is that people would want to get an appointment within the first month.
Effect_of_Fitting_Rate_on_Dropout = Initial_FRD*(EXP(-Perceived_Relative_Fitting_Rate/Steepness_FRD)) UNITS: dmnl DOCUMENT: This variable represents the effect of perceived Relative Fitting Rate on the reference Dropout Fraction. As the relative perceived successful fitting rate of the digital prosthesis increases, we expect more word of mouth dissemination of information. The assumption here is that as digital fittings experience more success, people are less likely to dropout since they might be motivated to see through the process and experience a similar success as others. The effect variable is analytically formulated as an exponential decay from 1 to 0. In other words, the effect decreases decreasingly from an initial value of 1 to 0, with a certain steepness. Hence, when the relative rate is 0, then the dropout fraction will be at it's normal or reference value. As the relative rate starts increasing, the dropout fraction will exponentially decay from its reference value towards 0.
Effect_of_Fitting_Rate_on_Readoption = MIN(Max_FRR, Initial_FRR*(EXP(Perceived_Relative_Fitting_Rate/Steepness_FRR))) UNITS: dmnl DOCUMENT: This variable represents the effect of perceived Relative Fitting Rate on the reference Readoption Fraction. As the relative perceived successful fitting rate of the digital prosthesis increases, we expect more word of mouth dissemination of information. The assumption here is that as digital fittings experience more success, people are more likely to readopt digital prosthesis since they might be motivated to try the digital process and experience a similar success as others. The effect variable is analytically formulated as an exponential growth from 1 to a maximum effect of 2. In other words, the effect increases increasingly from an initial value of 1 to 2, with a certain steepness. Hence, when the relative rate is 0, then the readoption fraction will be at it's normal or reference value. As the relative rate starts increasing, the dropout fraction will exponentially increase from its reference value towards a maximum of twice its value.

Eligible_for_Prosthesis[Age_Cohort, Prosthesis_Type](t) = Eligible_for_Prosthesis[Age_Cohort, Prosthesis_Type](t - dt) + (Prosthesis_Referred[Age_Cohort, Prosthesis_Type] - Fit_First_Prosthesis[Age_Cohort, Prosthesis_Type] - EP_Dropout[Age_Cohort, Prosthesis_Type]) * dt

INIT Eligible_for_Prosthesis[Age_Cohort, Prosthesis_Type] = 0

UNITS: People

DOCUMENT: This stock represents the total amputees who are eligible for a prosthesis and have entered the prosthetic care continuum. It is accumulated by the inflow Prosthesis Referred and depleted by the outflows Fit First Prosthesis and EP Dropout. The stock is arrayed by age cohorts and prosthesis type. The initial value for the stock is 0 with the assumption that there are no amputees in the midst of the fitting process at the very start of the simulation.

INFLOWS:

Prosthesis_Referred[Under_15, Digital] = Prosthesis_Referral[Under_15]*Market_Subsystem.Market_Share[Digital]

Prosthesis_Referred[Under_15, Traditional] = Prosthesis_Referral[Under_15]*Market_Subsystem.Market_Share[Traditional]

Prosthesis_Referred["15_to_44", Digital] = Prosthesis_Referral["15_to_44"]*Market_Subsystem.Market_Share[Digital]

Prosthesis_Referred["15_to_44", Traditional] = Prosthesis_Referral["15_to_44"]*Market_Subsystem.Market_Share[Traditional]

Prosthesis_Referred["45_to_59", Digital] = Prosthesis_Referral["45_to_59"]*Market_Subsystem.Market_Share[Digital]

Prosthesis_Referred["45_to_59", Traditional] = Prosthesis_Referral["45_to_59"]*Market_Subsystem.Market_Share[Traditional]

Prosthesis_Referred["60_to_79", Digital] = Prosthesis_Referral["60_to_79"]*Market_Subsystem.Market_Share[Digital]

Prosthesis_Referred["60_to_79", Traditional] = Prosthesis_Referral["60_to_79"]*Market_Subsystem.Market_Share[Traditional]

Prosthesis_Referred[Above_80, Digital] = Prosthesis_Referral[Above_80]*Market_Subsystem.Market_Share[Digital]

Prosthesis_Referred[Above_80, Traditional] = Prosthesis_Referral[Above_80]*Market_Subsystem.Market_Share[Traditional]

UNITS: People/month

DOCUMENT: This inflow represents the number of amputees who are deemed eligible and given a referral to prosthetic care, and it accumulates the Eligible for Prosthesis stock. The referred rate is simply the prosthesis referral rate that is redistributed to the respective prosthesis array dimension based on the market share of each prosthesis type. The market share is taken as the probability that an amputee will be referred to either a traditional or digital prosthetist.

OUTFLOWS:

Fit_First_Prosthesis[Age_Cohort, Prosthesis_Type] = Eligible_for_Prosthesis*Prosthetic_Accessibility[Prosthesis_Type]/Initial_Measurement_Duration[Prosthesis_Type]

UNITS: People/month

DOCUMENT: This biflow represents the rate at which amputees get measured and fitted with an initial fit first device. It depletes the Eligible for Prosthesis stock and simultaneously accumulates the Initial Device stock. The rate is determined by the product of the total number of people who would like to be fitted with an initial device at any one point in time and the prosthetic accessibility fraction. This initial measurement rate is a first order material delay, where the the total number of people in the Eligible for Prosthesis stock is divided by the Initial Measurement Duration.

EP_Dropout[Age_Cohort, Prosthesis_Type] = Eligible_for_Prosthesis*EP_Dropout_Fraction[Prosthesis_Type]/Time_to_Dropout

UNITS: People/month

DOCUMENT: This biflow represents the rate at which amputees who eligible for prosthesis dropout before the start of the fitting process. It depletes the Eligible for Prosthesis stock and simultaneously accumulates the Limited Mobility stock. The rate is simply a fraction of the total number of people in the Eligible for Prosthesis stock over a certain decision time to dropout.

EP_Dropout_Fraction[Digital] = Ref_EP_Dropout_Fraction[Digital]*Effect_of_Fitting_Rate_on_Dropout

EP_Dropout_Fraction[Traditional] = Ref_EP_Dropout_Fraction[Traditional]

UNITS: dmnl

DOCUMENT: This variable represents the fraction of people that on average decides to dropout from the prosthetic fitting process from the get-go, even before being fitted with an initial device. It is determined by the reference fraction adjusted by the effect from Perceived Relative Fitting Rate.

Fit_First_Duration[Prosthesis_Type] = 4

UNITS: month

DOCUMENT: This parameter represents the fit first duration for amputees. Based on the general timeline for prosthetic rehabilitation, amputees undergo gait training with an initial device for about 2 months and an additional 2 months while awaiting for the limb to mature and stabilise in volume (Rheinstein et al., 2021).

Fitting_Demand[Prosthesis_Type] = Prosthesis_To_Fit+Prosthesis_Reentry + Prosthesis_To_Replace

UNITS: People/month

DOCUMENT: This variable dynamically calculates the total demand for prosthesis fitting at any one point in time. It is simply the sum of the desired prosthesis to fit for new amputees, the desired prosthesis for rentrants, and the desired prosthesis for amputees who need to replace their device.

Full_Mobility[Under_15, Digital](t) = Full_Mobility[Under_15, Digital](t - dt) + (FM_Aging_In[Under_15, Digital] + Successful_Fitting[Under_15, Digital] - Prosthesis_Degradation[Under_15, Digital] - FM_Deaths[Under_15, Digital] - FM_Aging_Out[Under_15, Digital]) * dt

INIT Full_Mobility[Under_15, Digital] = 0

Full_Mobility[Under_15, Traditional](t) = Full_Mobility[Under_15, Traditional](t - dt) + (FM_Aging_In[Under_15, Traditional] + Successful_Fitting[Under_15, Traditional] - Prosthesis_Degradation[Under_15, Traditional] - FM_Deaths[Under_15, Traditional] - FM_Aging_Out[Under_15, Traditional]) * dt

INIT Full_Mobility[Under_15, Traditional] = Initial_Full_Mobility[Under_15]

UNITS: People

DOCUMENT: This stock represents the total amputees who are successfully fitted with a prosthesis and are thus fully mobile. It is accumulated by the inflow Successful Fitting, and depleted by the outflows FM Deaths and Prosthesis Degradation. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Full Mobility.

Full_Mobility["15_to_44", Digital](t) = Full_Mobility["15_to_44", Digital](t - dt) + (FM_Aging_In["15_to_44", Digital] + Successful_Fitting["15_to_44", Digital] - Prosthesis_Degradation["15_to_44", Digital] - FM_Deaths["15_to_44", Digital] - FM_Aging_Out["15_to_44", Digital]) * dt

INIT Full_Mobility["15_to_44", Digital] = 0

Full_Mobility["15_to_44", Traditional](t) = Full_Mobility["15_to_44", Traditional](t - dt) + (FM_Aging_In["15_to_44", Traditional] + Successful_Fitting["15_to_44", Traditional] - Prosthesis_Degradation["15_to_44", Traditional] - FM_Deaths["15_to_44", Traditional] - FM_Aging_Out["15_to_44", Traditional]) * dt

INIT Full_Mobility["15_to_44", Traditional] = Initial_Full_Mobility["15_to_44"]

UNITS: People

DOCUMENT: This stock represents the total amputees who are successfully fitted with a prosthesis and are thus fully mobile. It is accumulated by the inflow Successful Fitting, and depleted by the outflows FM Deaths and Prosthesis Degradation. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Full Mobility.

Full_Mobility["45_to_59", Digital](t) = Full_Mobility["45_to_59", Digital](t - dt) + (FM_Aging_In["45_to_59", Digital] + Successful_Fitting["45_to_59", Digital] - Prosthesis_Degradation["45_to_59", Digital] - FM_Deaths["45_to_59", Digital] - FM_Aging_Out["45_to_59", Digital]) * dt

INIT Full_Mobility["45_to_59", Digital] = 0

Full_Mobility["45_to_59", Traditional](t) = Full_Mobility["45_to_59", Traditional](t - dt) + (FM_Aging_In["45_to_59", Traditional] + Successful_Fitting["45_to_59", Traditional] - Prosthesis_Degradation["45_to_59", Traditional] - FM_Deaths["45_to_59", Traditional] - FM_Aging_Out["45_to_59", Traditional]) * dt

INIT Full_Mobility["45_to_59", Traditional] = Initial_Full_Mobility["45_to_59"]

UNITS: People

DOCUMENT: This stock represents the total amputees who are successfully fitted with a prosthesis and are thus fully mobile. It is accumulated by the inflow Successful Fitting, and depleted by the outflows FM Deaths and Prosthesis Degradation. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Full Mobility.

Full_Mobility["60_to_79", Digital](t) = Full_Mobility["60_to_79", Digital](t - dt) + (FM_Aging_In["60_to_79", Digital] + Successful_Fitting["60_to_79", Digital] - Prosthesis_Degradation["60_to_79", Digital] - FM_Deaths["60_to_79", Digital] - FM_Aging_Out["60_to_79", Digital]) * dt

INIT Full_Mobility["60_to_79", Digital] = 0

Full_Mobility["60_to_79", Traditional](t) = Full_Mobility["60_to_79", Traditional](t - dt) + (FM_Aging_In["60_to_79", Traditional] + Successful_Fitting["60_to_79", Traditional] - Prosthesis_Degradation["60_to_79", Traditional] - FM_Deaths["60_to_79", Traditional] - FM_Aging_Out["60_to_79", Traditional]) * dt

INIT Full_Mobility["60_to_79", Traditional] = Initial_Full_Mobility["60_to_79"]

UNITS: People

DOCUMENT: This stock represents the total amputees who are successfully fitted with a prosthesis and are thus fully mobile. It is accumulated by the inflow Successful Fitting, and depleted by the outflows FM Deaths and Prosthesis Degradation. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Full Mobility.

Full_Mobility[Above_80, Digital](t) = Full_Mobility[Above_80, Digital](t - dt) + (FM_Aging_In[Above_80, Digital] + Successful_Fitting[Above_80, Digital] - Prosthesis_Degradation[Above_80, Digital] - FM_Deaths[Above_80, Digital] - FM_Aging_Out[Above_80, Digital]) * dt

INIT Full_Mobility[Above_80, Digital] = 0

Full_Mobility[Above_80, Traditional](t) = Full_Mobility[Above_80, Traditional](t - dt) + (FM_Aging_In[Above_80, Traditional] + Successful_Fitting[Above_80, Traditional] - Prosthesis_Degradation[Above_80, Traditional] - FM_Deaths[Above_80, Traditional] - FM_Aging_Out[Above_80, Traditional]) * dt

INIT Full_Mobility[Above_80, Traditional] = Initial_Full_Mobility[Above_80]

UNITS: People

DOCUMENT: This stock represents the total amputees who are successfully fitted with a prosthesis and are thus fully mobile. It is accumulated by the inflow Successful Fitting, and depleted by the outflows FM Deaths and Prosthesis Degradation. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Full Mobility.

Full_Mobility_by_Type[Digital] = SUM(Full_Mobility[*,Digital])

Full_Mobility_by_Type[Traditional] = SUM(Full_Mobility[*, Traditional])

UNITS: People

DOCUMENT: This converter calculates the subtotals of amputees with full mobility by type of prosthesis.

ID_Dropout_Fraction[Digital] = Ref_ID_Dropout_Fraction[Digital]*Effect_of_Fitting_Rate_on_Dropout

ID_Dropout_Fraction[Traditional] = Ref_ID_Dropout_Fraction[Traditional]

UNITS: dmnl

DOCUMENT: This variable represents the fraction of people that on average decides to dropout from the Initial Device stage of the prosthetic fitting process. It is determined by the reference fraction adjusted by the effect from Perceived Relative Fitting Rate.

Initial_Accessibility = 0.5

UNITS: dmnl

DOCUMENT: This parameter represents the initial fraction of amputees in UK who have access to prosthetic care. This number is estimated to be 50% based on ProsFit's health economic model data set (C. Hutchison, 2021).

Initial_Device[Age_Cohort, Prosthesis_Type](t) = Initial_Device[Age_Cohort, Prosthesis_Type](t - dt) + (Fit_First_Prosthesis[Age_Cohort, Prosthesis_Type] - Maturation[Age_Cohort, Prosthesis_Type] - ID_Dropout[Age_Cohort, Prosthesis_Type]) * dt

INIT Initial_Device[Age_Cohort, Prosthesis_Type] = 0

UNITS: People

DOCUMENT: This stock represents the total amputees who have taken the initial measurements for their device and provided with a fit first device for gait training. It is accumulated by the inflow Fit First Prosthesis and depleted by the outflows Maturation and ID Dropout. The stock is arrayed by age cohorts and prosthesis type. The initial value for the stock is 0 with the assumption that there are no amputees in the midst of the fitting process at the very start of the simulation.

INFLOWS: Fit_First_Prosthesis[Age_Cohort, Prosthesis_Type] = Eligible_for_Prosthesis*Prosthetic_Accessibility[Prosthesis_Type]/Initial_Measurement_Duration[Prosthesis_Type] UNITS: People/month DOCUMENT: This biflow represents the rate at which amputees get measured and fitted with an initial fit first device. It depletes the Eligible for Prosthesis stock and simultaneously accumulates the Initial Device stock. The rate is determined by the product of the total number of people who would like to be fitted with an initial device at any one point in time and the prosthetic accessibility fraction. This initial measurement rate is a first order material delay, where the the total number of people in the Eligible for Prosthesis stock is divided by the Initial Measurement Duration.
OUTFLOWS: Maturation[Age_Cohort, Prosthesis_Type] = Initial_Device/Fit_First_Duration[Prosthesis_Type] UNITS: People/month DOCUMENT: This biflow represents the maturation rate of amputees limb, while they undergo rehabilitation with an initial fit first device. It depletes the Initial Device stock and simultaneously accumulates the Matured Limb stock. The rate is determined by a first order material delay, where the the total number of people in the Initial Device stock is divided by the Fit First Duration.
ID_Dropout[Age_Cohort, Prosthesis_Type] = ID_Dropout_Fraction[Prosthesis_Type]*Initial_Device/Time_to_Dropout UNITS: People/month DOCUMENT: This biflow represents the rate at which amputees dropout from the Initial Device stage of the fitting process. It depletes the Initial Device stock and simultaneously accumulates the Limited Mobility stock. The rate is simply a fraction of the total number of people in the Initial Device stock over a certain decision time to dropout.
Initial_FRD = 1 UNITS: dmnl DOCUMENT: This parameter sets the initial value for the effect of Fitting Rate on Dropout. Here, the initial effect is set at 1, so that the Dropout Fraction is initially set to its reference or normal value.
Initial_FRR = 1 UNITS: dmnl DOCUMENT: This parameter sets the initial value for the effect of Fitting Rate on Readoption. Here, the initial effect is set at 1, so that the Readoption Fraction is initially set to its reference or normal value.

Initial_Full_Mobility[Age_Cohort] = Access_S3*Success_Fraction[Traditional] UNITS: People DOCUMENT: This converter calculates the initial population who are successfully fitted with a prosthesis, thus achieving full mobility. It is calculated as the product of the remaining population who have moved on the definitive device stage and the success fraction.
Initial_Limited_Mobility[Age_Cohort] = Initial_Eligible_Population*(1-Initial_Accessibility) + Access_S3*(1-Success_Fraction[Traditional]) + Initial_LM1 + Initial_LM2 + Initial_LM3 UNITS: People DOCUMENT: This converter calculates the initial population who are not fitted with a prosthesis, thus experiencing limited mobility. It is calculated the sum of the various initial flow of people who have dropped out in the various stages, the initial eligible population without access, as well as the initial unsuccessfully fitted amputees.
Initial_LM1[Age_Cohort] = Initial_Population_with_Access*Ref_EP_Dropout_Fraction[Traditional] UNITS: People DOCUMENT: This converter calculates the initial flow of amputees who dropout from the Eligible for Prosthesis stage. It is simply the product of the initial population with access and the reference eligible for prosthesis dropout fraction.
Initial_LM2[Age_Cohort] = Access_S1*Ref_ID_Dropout_Fraction[Traditional] UNITS: People DOCUMENT: This converter calculates the initial flow of amputees who dropout from the Initial Device stage. It is simply the product of the remaining population in initial device stage and the reference initial device dropout fraction.
Initial_LM3[Age_Cohort] = Access_S2*Ref_ML_Dropout_Fraction[Traditional] UNITS: People DOCUMENT: This converter calculates the initial flow of amputees who dropout from the Matured Limb stage. It is simply the product of the remaining population in Matured Limb stage and the reference matured limb dropout fraction.
Initial_Measurement_Duration[Prosthesis_Type] = 0.5 UNITS: month DOCUMENT: This parameter represents the initial measurement duration for amputee. Based on the general timeline for prosthetic rehabilitation, amputees measure for a prosthesis after the incision fully heals about 8 weeks after surgery (Rheinstein et al., 2021). Expert opinion suggest that this measurement duration and initial device fitting is done in about 2 weeks or half a month (correspondence with ProsFit).

Initial_Population_with_Access[Age_Cohort] = Initial_Eligible_Population*Initial_Accessibility UNITS: People DOCUMENT: This converter calculates the initial amputee population who have had access to prosthetic care. It is simply the total initial eligible population multiplied by the accessibility fraction.
Insurance_Coverage_Cycle = 36 UNITS: months DOCUMENT: This parameter represents the average duration an amputee will take before deciding to restart the prosthesis fitting process. It is assumed that amputees would on average take 3 years for that decision since it is inline with the insurance coverage cycle. In the United Kingdom, the national health insurance covers the cost of prosthesis once every three years.
Limited_Mobility[Under_15, Digital](t) = Limited_Mobility[Under_15, Digital](t - dt) + (LM_Aging_In[Under_15, Digital] + EP_Dropout[Under_15, Digital] + ID_Dropout[Under_15, Digital] + Unsuccessful_Fitting[Under_15, Digital] + ML_Dropout[Under_15, Digital] + Failed_Readoption[Under_15, Digital] - LM_Deaths[Under_15, Digital] - LM_Aging_Out[Under_15, Digital] - Readoption[Under_15, Digital]) * dt INIT Limited_Mobility[Under_15, Digital] = 0 Limited_Mobility[Under_15, Traditional](t) = Limited_Mobility[Under_15, Traditional](t - dt) + (LM_Aging_In[Under_15, Traditional] + EP_Dropout[Under_15, Traditional] + ID_Dropout[Under_15, Traditional] + Unsuccessful_Fitting[Under_15, Traditional] + ML_Dropout[Under_15, Traditional] + Failed_Readoption[Under_15, Traditional] - LM_Deaths[Under_15, Traditional] - LM_Aging_Out[Under_15, Traditional] - Readoption[Under_15, Traditional]) * dt INIT Limited_Mobility[Under_15, Traditional] = Initial_Limited_Mobility[Under_15] UNITS: People DOCUMENT: This stock represents the total amputees who have dropped out of the prosthetic care continuum and thus experience limited mobility due to a lack of prosthesis. It is accumulated by the inflows Dropout Rate (various stages), Unsuccessful Fitting and Failed Readoption, and further depleted by the outflows LM Deaths and Prosthesis Re-adoption. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Limited Mobility.
Limited_Mobility["15_to_44", Digital](t) = Limited_Mobility["15_to_44", Digital](t - dt) + (LM_Aging_In["15_to_44", Digital] + EP_Dropout["15_to_44", Digital] + ID_Dropout["15_to_44", Digital] + Unsuccessful_Fitting["15_to_44", Digital] + ML_Dropout["15_to_44", Digital] + Failed_Readoption["15_to_44", Digital] - LM_Deaths["15_to_44", Digital] - LM_Aging_Out["15_to_44", Digital] - Readoption["15_to_44", Digital]) * dt INIT Limited_Mobility["15_to_44", Digital] = 0

Limited_Mobility["15_to_44", Traditional](t) = Limited_Mobility["15_to_44", Traditional](t - dt) + (LM_Aging_In["15_to_44", Traditional] + EP_Dropout["15_to_44", Traditional] + ID_Dropout["15_to_44", Traditional] + Unsuccessful_Fitting["15_to_44", Traditional] + ML_Dropout["15_to_44", Traditional] + Failed_Readoption["15_to_44", Traditional] - LM_Deaths["15_to_44", Traditional] - LM_Aging_Out["15_to_44", Traditional] - Readoption["15_to_44", Traditional]) * dt

INIT Limited_Mobility["15_to_44", Traditional] = Initial_Limited_Mobility["15_to_44"]

UNITS: People

DOCUMENT: This stock represents the total amputees who have dropped out of the prosthetic care continuum and thus experience limited mobility due to a lack of prosthesis. It is accumulated by the inflows Dropout Rate (various stages), Unsuccessful Fitting and Failed Readoption, and further depleted by the outflows LM Deaths and Prosthesis Re-adoption. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Limited Mobility.

Limited_Mobility["45_to_59", Digital](t) = Limited_Mobility["45_to_59", Digital](t - dt) + (LM_Aging_In["45_to_59", Digital] + EP_Dropout["45_to_59", Digital] + ID_Dropout["45_to_59", Digital] + Unsuccessful_Fitting["45_to_59", Digital] + ML_Dropout["45_to_59", Digital] + Failed_Readoption["45_to_59", Digital] - LM_Deaths["45_to_59", Digital] - LM_Aging_Out["45_to_59", Digital] - Readoption["45_to_59", Digital]) * dt

INIT Limited_Mobility["45_to_59", Digital] = 0

Limited_Mobility["45_to_59", Traditional](t) = Limited_Mobility["45_to_59", Traditional](t - dt) + (LM_Aging_In["45_to_59", Traditional] + EP_Dropout["45_to_59", Traditional] + ID_Dropout["45_to_59", Traditional] + Unsuccessful_Fitting["45_to_59", Traditional] + ML_Dropout["45_to_59", Traditional] + Failed_Readoption["45_to_59", Traditional] - LM_Deaths["45_to_59", Traditional] - LM_Aging_Out["45_to_59", Traditional] - Readoption["45_to_59", Traditional]) * dt

INIT Limited_Mobility["45_to_59", Traditional] = Initial_Limited_Mobility["45_to_59"]

UNITS: People

DOCUMENT: This stock represents the total amputees who have dropped out of the prosthetic care continuum and thus experience limited mobility due to a lack of prosthesis. It is accumulated by the inflows Dropout Rate (various stages), Unsuccessful Fitting and Failed Readoption, and further depleted by the outflows LM Deaths and Prosthesis Re-adoption. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Limited Mobility.

Limited_Mobility["60_to_79", Digital](t) = Limited_Mobility["60_to_79", Digital](t - dt) + (LM_Aging_In["60_to_79", Digital] + EP_Dropout["60_to_79", Digital] + ID_Dropout["60_to_79", Digital] + Unsuccessful_Fitting["60_to_79", Digital] + ML_Dropout["60_to_79", Digital] + Failed_Readoption["60_to_79", Digital] -

LM_Deaths["60_to_79", Digital] - LM_Aging_Out["60_to_79", Digital] - Readoption["60_to_79", Digital]) * dt INIT Limited_Mobility["60_to_79", Digital] = 0 Limited_Mobility["60_to_79", Traditional](t) = Limited_Mobility["60_to_79", Traditional](t - dt) + (LM_Aging_In["60_to_79", Traditional] + EP_Dropout["60_to_79", Traditional] + ID_Dropout["60_to_79", Traditional] + Unsuccessful_Fitting["60_to_79", Traditional] + ML_Dropout["60_to_79", Traditional] + Failed_Readoption["60_to_79", Traditional] - LM_Deaths["60_to_79", Traditional] - LM_Aging_Out["60_to_79", Traditional] - Readoption["60_to_79", Traditional]) * dt INIT Limited_Mobility["60_to_79", Traditional] = Initial_Limited_Mobility["60_to_79"] UNITS: People DOCUMENT: This stock represents the total amputees who have dropped out of the prosthetic care continuum and thus experience limited mobility due to a lack of prosthesis. It is accumulated by the inflows Dropout Rate (various stages), Unsuccessful Fitting and Failed Readoption, and further depleted by the outflows LM Deaths and Prosthesis Re-adoption. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Limited Mobility.
Limited_Mobility[Above_80, Digital](t) = Limited_Mobility[Above_80, Digital](t - dt) + (LM_Aging_In[Above_80, Digital] + EP_Dropout[Above_80, Digital] + ID_Dropout[Above_80, Digital] + Unsuccessful_Fitting[Above_80, Digital] + ML_Dropout[Above_80, Digital] + Failed_Readoption[Above_80, Digital] - LM_Deaths[Above_80, Digital] - LM_Aging_Out[Above_80, Digital] - Readoption[Above_80, Digital]) * dt INIT Limited_Mobility[Above_80, Digital] = 0 Limited_Mobility[Above_80, Traditional](t) = Limited_Mobility[Above_80, Traditional](t - dt) + (LM_Aging_In[Above_80, Traditional] + EP_Dropout[Above_80, Traditional] + ID_Dropout[Above_80, Traditional] + Unsuccessful_Fitting[Above_80, Traditional] + ML_Dropout[Above_80, Traditional] + Failed_Readoption[Above_80, Traditional] - LM_Deaths[Above_80, Traditional] - LM_Aging_Out[Above_80, Traditional] - Readoption[Above_80, Traditional]) * dt INIT Limited_Mobility[Above_80, Traditional] = Initial_Limited_Mobility[Above_80] UNITS: People DOCUMENT: This stock represents the total amputees who have dropped out of the prosthetic care continuum and thus experience limited mobility due to a lack of prosthesis. It is accumulated by the inflows Dropout Rate (various stages), Unsuccessful Fitting and Failed Readoption, and further depleted by the outflows LM Deaths and Prosthesis Re-adoption. The stock is arrayed by age cohorts and prosthesis type. The initial value for digital prosthesis is 0 simply because digital solutions started after 2010. The initial value for the traditional prosthesis is the calculated Initial Limited Mobility.

Limited_Mobility_by_Type[Digital] = SUM(Limited_Mobility[*,Digital])+ SUM(Awaiting_Replacement[*, Digital]) UNITS: People DOCUMENT: This converter calculates the subtotals of amputees with limited mobility by type of prosthesis.
Limited_Mobility_by_Type[Traditional] = SUM(Limited_Mobility[*,Traditional]) + SUM(Awaiting_Replacement[*, Traditional]) UNITS: People DOCUMENT: This converter calculates the subtotals of amputees with limited mobility by type of prosthesis.
Matured_Limb[Age_Cohort, Prosthesis_Type](t) = Matured_Limb[Age_Cohort, Prosthesis_Type](t - dt) + (Maturation[Age_Cohort, Prosthesis_Type] + Reentry[Age_Cohort, Prosthesis_Type] + Prosthesis_Replacement[Age_Cohort, Prosthesis_Type] - Device_Delivery[Age_Cohort, Prosthesis_Type] - ML_Dropout[Age_Cohort, Prosthesis_Type]) * dt INIT Matured_Limb[Age_Cohort, Prosthesis_Type] = 0 UNITS: People DOCUMENT: This stock represents the total amputees whose limb stump has matured and ready for a definitive device. It is accumulated by the inflows Maturation and Reentry (of amputees who have matured limbs and have decided to re-adopt a prosthesis) and further depleted by the outflows Device Delivery and ML Dropout. The stock is arrayed by age cohorts and prosthesis type. The initial value for the stock is 0 with the assumption that there are no amputees in the midst of the fitting process at the very start of the simulation.
INFLOWS: Maturation[Age_Cohort, Prosthesis_Type] = Initial_Device/Fit_First_Duration[Prosthesis_Type] UNITS: People/month DOCUMENT: This biflow represents the maturation rate of amputees limb, while they undergo rehabilitation with an initial fit first device. It depletes the Initial Device stock and simultaneously accumulates the Matured Limb stock. The rate is determined by a first order material delay, where the the total number of people in the Initial Device stock is divided by the Fit First Duration.

Reentry[Age_Cohort, Prosthesis_Type] = Subtotal_Readoptees[Age_Cohort]*Market_Subsystem.Market_Share[Prosthesis_Type]*Prosthetic_Accessibility[Prosthesis_Type]

UNITS: People/month

DOCUMENT: This inflow represents the rate at which matured amputees without a prosthesis have successfully re-entered the prosthesis fitting process. The rate is determined by the subtotal readoptees who are redistributed to the respective prosthesis array dimension based on the market share of each prosthesis type. The market share is taken as the probability that an amputee will be referred to either a traditional or digital prosthetist. Moreover, the Prosthetic Accessibility limits this rate by taking a fraction of people who are able to successfully gain access to a prosthetist.

Prosthesis_Replacement[Age_Cohort, Prosthesis_Type] = Prosthetic_Accessibility[Prosthesis_Type]*Awaiting_Replacement/Desired_Appointment_Time

UNITS: People/month

DOCUMENT: This biflow represents the Prosthesis Replacement rate; it depletes the Awaiting Replacement stock and simultaneously accumulates the Matured Limb stock. The rate is determined by the fraction of people who have access to a prosthetist multiplied by the total number of people requiring a replacement at any one point in time.

OUTFLOWS:

Device_Delivery[Age_Cohort, Prosthesis_Type] = Matured_Limb/Delivery_Duration[Prosthesis_Type]

UNITS: People/month

DOCUMENT: This biflow represents the rate at which amputees, whose limbs have matured, receive a definitive prosthesis device. It depletes the Matured Limb stock and simultaneously accumulates the Definitive Device stock. The rate is determined by a first order material delay, where the the total number of people in the Matured Limb stock is divided by the Delivery Duration.

ML_Dropout[Age_Cohort, Prosthesis_Type] = ML_Dropout_Fraction[Prosthesis_Type]*Matured_Limb/Time_to_Dropout

UNITS: People/month

DOCUMENT: This biflow represents the rate at which amputees dropout from the Matured Limb stage of the fitting process. It depletes the Matured Limb stock and simultaneously accumulates the Limited Mobility stock. The rate is simply a fraction of the total number of people in the Matured Limb stock over a certain decision time to dropout.

Max_FRR = 2

UNITS: dmnl

DOCUMENT: This parameter sets the maximum effect at 2. In this case, the maximum effect was set at 2 in order to limit the readoption fraction from exceeding 1.

ML_Dropout_Fraction[Digital] = Ref_ML_Dropout_Fraction[Digital]*Effect_of_Fitting_Rate_on_Dropout ML_Dropout_Fraction[Traditional] = Ref_ML_Dropout_Fraction[Traditional] UNITS: dmnl DOCUMENT: This variable represents the fraction of people that on average decides to dropout from the Matured Limb stage of the prosthetic fitting process. It is determined by the reference fraction adjusted by the effect from Perceived Relative Fitting Rate.
Mobility_Proportion[Prosthesis_Type] = Full_Mobility_by_Type//(Full_Mobility_by_Type+Limited_Mobility_by_Type) UNITS: dmnl DOCUMENT: This converter calculates the proportion of amputees who are fully mobile (by prosthesis type) as a fraction of the total amputee population who are deemed eligible for prosthesis. Note that it excludes those medically ineligible for prosthesis from the total amputee population.
Perceived_Relative_Fitting_Rate = SMTH3(Relative_Successful_Fitting_Rate_of_Digital, Time_to_Perceive_Fitting_Rate, 0) {DELAY CONVERTER} UNITS: dmnl DOCUMENT: This variable represented the general perception of the information about the relative successful fittings of the digital and traditional prosthesis type. It is modelled with a third-order information delay with the assumption that it goes through several delay processes, which includes data collection, reporting, and word of mouth dissemination.
Prosthesis_Lifespan = 36 UNITS: months DOCUMENT: This parameter represents the average lifespan of a prosthesis before it degrades and requires a complete replacement. On average, each device has a 3-year lifespan (C. Hutchison, 2021; Rheinstein et al., 2021).
Prosthesis_Reentry[Digital] = SUM(Subtotal_Readoptees)*Market_Subsystem.Market_Share[Digital] Prosthesis_Reentry[Traditional] = SUM(Subtotal_Readoptees)*Market_Subsystem.Market_Share[Traditional] UNITS: People/month DOCUMENT: This variable represents the desired rate at which amputees would like to renter the prosthetic care continuum. Here, the aggregated subtotal readoptees are redistributed into the prosthesis type array dimension based on the respective market share. The market share is taken as the probability that an amputee will choose either a traditional or digital prosthetist.

Prosthesis_To_Fit[Digital] = SUM(Eligible_for_Prosthesis[*,Digital])/Desired_Appointment_Time Prosthesis_To_Fit[Traditional] = SUM(Eligible_for_Prosthesis[*,Traditional])/Desired_Appointment_Time UNITS: People/month DOCUMENT: This variable represents the desired rate at which new prostheses are to be fitted. In other words, the number of people per month who would like to start the prosthesis fitting process. This rate is a first order adjustment, where the the total number of people Eligible for Prosthesis is divided by the Desired Appointment Time for meeting a prosthetist.
Prosthesis_To_Replace[Digital] = SUM(Awaiting_Replacement[*,Digital])/Desired_Appointment_Time Prosthesis_To_Replace[Traditional] = SUM(Awaiting_Replacement[*,Traditional])/Desired_Appointment_Time UNITS: People/month DOCUMENT: This variable represents the desired rate at which prostheses are to be replaced. In other words, the number of people per month who would like a replacement. This rate is a first order adjustment, where the the total number of people Awaiting Replacement is divided by the Desired Appointment Time for meeting a prosthetist.
Prosthetic_Accessibility[Prosthesis_Type] = MIN(1, Market_Subsystem.Fitting_Capacity//Fitting_Demand) UNITS: dmnl DOCUMENT: This variable represents the prosthetic accessibility for amputees desiring to be fitted with a new prosthesis. It refers to the ability of the existing fitting capacity to meet the demand. Hence, when fitting capacity is equal to fitting demand, the accessibility is 1, meaning 100% of all desired fittings can be accommodated. When the fraction is less than 1, it means that existing capacity can only meet a fraction of the demand. The equation includes a MIN function to limit this value from going above 1. So long as there is more capacity than demand, then prosthetists will still be able to meet 100% of all demand. Accessibility is conceptualised as a function of demand and capacity but does not take into account proximity. It is assumed that in the UK, all amputees have access to prosthetic healthcare in terms of physical location.
Readoption_Fraction[Prosthesis_Type] = Effect_of_Fitting_Rate_on_Readoption*Ref_Readoption_Fraction UNITS: dmnl DOCUMENT: This variable represents the fraction of people, who have previously abandoned a prosthesis, that on average decides to readopt it. It is determined by the reference fraction adjusted by the effect from Perceived Relative Fitting Rate.

Ref_EP_Dropout_Fraction[Prosthesis_Type] = 0.1 UNITS: dmnl DOCUMENT: This parameter represents the typical or normal fraction of people that on average decides to dropout from the prosthetic fitting process from the get-go, even before being fitted with an initial device. The reference value was estimated by prosthetists in the field based on their experience (correspondence with ProsFit Technologies).
Ref_ID_Dropout_Fraction[Prosthesis_Type] = 0.1 UNITS: dmnl DOCUMENT: This parameter represents the typical or normal fraction of people that on average decides to dropout from the Initial Device stage of the prosthetic fitting process. The reference value was estimated by prosthetists in the field based on their experience (correspondence with ProsFit Technologies).
Ref_ML_Dropout_Fraction[Prosthesis_Type] = 0.1 UNITS: dmnl DOCUMENT: This parameter represents the typical or normal fraction of people that on average decides to dropout from the Matured Limb stage of the prosthetic fitting process. The reference value was estimated by prosthetists in the field based on their experience (correspondence with ProsFit Technologies).
Ref_Readoption_Fraction[Prosthesis_Type] = 0.2 UNITS: dmnl DOCUMENT: This parameter represents the typical or normal fraction of people, who have previously abandoned a prosthesis, that on average decides to readopt it. The reference value was estimated by prosthetists in the field based on their experience (correspondence with ProsFit Technologies).
Relative_Mortality_Risk_Adjustment = 0.5 UNITS: dmnl DOCUMENT: This parameter represents the adjustment to Amputee Relative Mortality Risk as a result of prosthetic fitting. It has been acknowledged that prosthetic fitting is a statistically predictor of a lower mortality risk for amputees (Meshkin et al., 2021; Singh & Prasad, 2016). Based on the odds ratio found by Singh & Prasad (2016), amputees who have died are 2.6 times more likely to have not been fitted with a prosthesis than those who have. Although odds ratio and relative risks are not directly interchangeable, here, we make the extrapolation that Amputees who have been fitted with a prosthesis is half as likely to die than those without.

Relative_Successful_Fitting_Rate_of_Digital = SUM(Successful_Fitting[*,Digital])//SUM(Successful_Fitting[*,Traditional]) UNITS: dmnl DOCUMENT: This variable represents relative successful fitting rate of digital prosthesis as compared to the traditional prosthesis. The variable sums all the Successful Fitting rate by prosthesis type, and then takes the ratio of digital prosthesis to traditional. When digital successful fitting is equal to traditional successful fitting, the ratio is 1. When the ratio is less than 1, it means that there is more traditional fitting success as compared to digital. When the ratio is more than 1, it means that there is more digital fitting success than traditional.
Steepness_FRD = 1.5 UNITS: dmnl DOCUMENT: This parameter controls the steepness of the curve or the rate of increase or decline of the Effect of Fitting Rate on Dropout variable. The steepness is assumed to be 1.5, but can be calibrated to data if available.
Steepness_FRR = 6 UNITS: dmnl DOCUMENT: This parameter controls the steepness of the curve or the rate of increase or decline of the Effect of Fitting Rate on Readoption variable. The steepness is assumed to be 6, but can be calibrated to data if available.
Subtotal_Dropout_Rate[Prosthesis_Type] = SUM(EP_Dropout[*, Prosthesis_Type]) + SUM(ID_Dropout[*, Prosthesis_Type]) + SUM(ML_Dropout[*, Prosthesis_Type]) {SUMMING CONVERTER} UNITS: People/month DOCUMENT: This converter calculates the subtotal number of amputees who drop out from the fitting process at varying stages.
"Subtotal_Fitting_(Re)Entries"[Prosthesis_Type] = Subtotal_New_Fitting + Subtotal_Replacement + "Subtotal_Re-entry" UNITS: People/month DOCUMENT: This converter calculates the subtotal number of eligible amputees who successfully (re)enter the fitting process either for a new prosthesis, replacement or readoption.
Subtotal_New_Fitting[Prosthesis_Type] = SUM(Fit_First_Prosthesis[*,Prosthesis_Type]) UNITS: People/month DOCUMENT: This converter calculates the subtotal number of eligible amputees who successfully enter into the first stage of the fitting process.

"Subtotal_Re-entry"[Prosthesis_Type] = SUM(Reentry[*,Prosthesis_Type]) UNITS: People/month DOCUMENT: This converter calculates the subtotal number of amputees wanting to re-adopt a prosthesis who successfully re-enter the fitting process.
Subtotal_Readoptees[Age_Cohort] = SUM(Readoption[Age_Cohort,*]) UNITS: People/month DOCUMENT: This variable represents the desired rate at which matured amputees without a prosthesis would like to readopt a prosthesis. In other words, the number of people per month who would like to re-start the prosthesis fitting process. This rate is simply the sum of the Readoption rate by age cohorts. Amputees are re-aggregated (no longer differentiated by prosthesis type) since they have the choice to switch between prosthesis types.
Subtotal_Readoption_Rate[Prosthesis_Type] = SUM(Readoption[*, Prosthesis_Type]) {SUMMING CONVERTER} UNITS: People/month DOCUMENT: This converter calculates the subtotal number of amputees who wish to re-adopt a prosthesis and re-join the fitting process.
Subtotal_Replacement[Prosthesis_Type] = SUM(Prosthesis_Replacement[*,Prosthesis_Type]) UNITS: People/month DOCUMENT: This converter calculates the subtotal number of amputees who successfully enter the fitting process for replacing their degraded prosthesis.
Subtotal_Successful_Fitting_Rate[Prosthesis_Type] = SUM(Successful_Fitting[*,Prosthesis_Type]) UNITS: People/month DOCUMENT: This converter sums the Successful Fitting rate across the various age groups for each prosthetic types.
Success_Fraction[Digital] = 0.9 Success_Fraction[Traditional] = 0.5 UNITS: dmnl DOCUMENT: This parameter represents the fraction of people who have been fitted with a definitive device that would successfully adjust to it. The probability of success is related to the level of comfort or pain experienced by the amputee. According to expert opinion, digitally fitted prosthesis have a much higher success rate at 90% whereas traditional fitting yields only about 50% success (correspondence with ProsFit). The figure for traditional success rate is corroborated with literature, where two studies have observed a 43% (Kralovec et al., 2015) and 41.18% (Fajardo-Martos et al., 2018) successful fitting amongst their respective samples.

Time_to_Dropout = 1 UNITS: month DOCUMENT: This parameter represents the time taken for amputees to decide to drop out from the prosthetic fitting process. It is assumed that amputees would take 1 month to make the decision and drop out.
Time_to_Perceive_Fitting_Rate = 3*12 UNITS: months DOCUMENT: This parameter represents the time taken for the wider public to perceive the information about the relative successful fittings of the digital and traditional prosthesis type. This is assumed to be 3 years with the simple rationale that it often takes three years to form a pattern.
Total_Capacity = SUM(Market_Subsystem.Fitting_Capacity) UNITS: People/month DOCUMENT: This converter calculates the total fitting capacity at any one point in time. It is simply the sum of the traditional fitting capacity and the digital fitting capacity.
Total_Demand = SUM(Fitting_Demand) UNITS: People/month DOCUMENT: This converter calculates the total fitting demand at any one point in time. It is simply the sum of the traditional fitting demand and the digital fitting demand.
Total_Eligible_Amputee_Population = Total_Limited_Mobility+Total_Full_Mobility UNITS: People DOCUMENT: This converter calculates the total number of amputee population who are deemed eligible for a prosthesis. It is simply the sum of the total limited mobility population and the total full mobility population.
Total_Full_Mobility = SUM(Full_Mobility_by_Type) UNITS: People DOCUMENT: This converter sums the total amputees with full mobility, including both prosthesis types.
Total_Limited_Mobility = SUM(Limited_Mobility_by_Type) UNITS: People DOCUMENT: This converter sums the total amputees with limited mobility, including both prosthesis types.

Total_Mobility_Proportion = Total_Full_Mobility//Total_Eligible_Amputee_Population UNITS: dmnl DOCUMENT: This converter calculates the proportion of amputees who are fully mobile (both prosthesis type) as a fraction of the total amputee population who are deemed eligible for prosthesis. Note that it excludes those medically ineligible for prosthesis from the total amputee population.
Total_Readoptees = SUM(Subtotal_Readoption_Rate) UNITS: People/month DOCUMENT: This converter calculates the subtotal number of amputees who wish to re-adopt a prosthesis and re-join the fitting process.

Table C.0.12 Documentation for Health Economics Sector

Health Economics Sector
Amputee_Proportion = Total_Amputees//Total_Population UNITS: dmnl DOCUMENT: This variable dynamically calculates the proportion of amputees in the United Kingdom population. This is simply the total amputee population as a fraction of the total population.
Family_Costs[Not_Fitted] = 19845/12 Family_Costs[Traditional_Fit] = 13230/12 Family_Costs[Digital_Fit] = 8820/12 UNITS: USD/person/month DOCUMENT: This parameter represents the social cost borne by the families of amputees in the United Kingdom. According to ProsFit's health economic model data set, digitally fitted amputees incur the least social cost to their families (C. Hutchison, 2021). The assumption here is that digitally fitted amputees end up with better health and mobility outcomes, requiring less care work from the families and therefore less opportunity cost. The yearly cost is divided by 12 to obtain the monthly cost.
GDP_per_Capita = 44100/12 UNITS: USD/person/month DOCUMENT: This parameter represents the gross domestic product per capita of the United Kingdom. In ProsFit Health Economics Model, the GDP per capita is used as a proxy for the economic contribution of a working person (C. Hutchison, 2021). The model also standardises all monetary currencies for all countries to the US Dollar. The GDP per capita per annum was divided by 12 for a monthly rate.

Healthcare_Costs[Not_Fitted] = 7277/12 Healthcare_Costs[Traditional_Fit] = 6064/12 Healthcare_Costs[Digital_Fit] = 5336/12 UNITS: USD/person/month DOCUMENT: This parameter represents the healthcare cost associated with an amputee in the United Kingdom. According to ProsFit's health economic model data set, each type of amputee has differing healthcare costs, with digitally fitted amputees incurring the least healthcare costs (C. Hutchison, 2021). The assumption here is that digitally fitted amputees end up with better health outcomes. The yearly cost is divided by 12 to obtain the monthly cost.
Maintenance_Multiplier = 1.2 UNITS: dmnl DOCUMENT: This parameter represents the multiplier to the unit cost for taking into account the cost associated with maintenance for each prosthesis unit. The data was obtained from ProsFit's health economic model data set (C. Hutchison, 2021).
Overhead_Multiplier = 1/0.75 UNITS: dmnl DOCUMENT: This parameter represents the multiplier to the unit cost for taking into account the overhead cost associated with manufacturing each prosthesis unit. The data was estimated from ProsFit's health economic model data set, where direct unit cost account for about 75% of the total cost (C. Hutchison, 2021).
Proportion_of_FM_Employed = 0.8 UNITS: dmnl DOCUMENT: This parameter represents the proportion of amputees successfully fitted with a prosthesis who are actually employed. This number is estimated to be around 80% in the ProsFit's health economics model (C. Hutchison, 2021).
Social_Payments = 1191/12 UNITS: USD/person/month DOCUMENT: This parameter represents the cost of social payment per person per month in the United Kingdom, which paid to all amputees regardless of type. The annual social payment sum was obtained from ProsFit's health economic model data set, and divided by 12 for the monthly payment (C. Hutchison, 2021).

Subtotal_Prosthesis_Cost[Prosthesis_Type] = SUM(Successful_Fitting)*Unit_Cost*Overhead_Multiplier*Maintenance_Multiplier + SUM(Unsuccessful_Fitting)*Unit_Cost*Overhead_Multiplier UNITS: USD/month DOCUMENT: This variable dynamically calculates the subtotal prosthesis cost incurred for the total devices delivered. For successful fittings, the total devices is multiplied by the unit cost, overhead multiplier and maintenance multiplier. Whereas for unsuccessful fittings, there are no maintenance cost associated as the device is assumed to be abandoned soon after. The sum of the two products gives us the subtotal costs of each prosthesis type.
Total_Amputees = Total_Digital_Fit+Total_Traditional_Fit+Total_Not_Fitted UNITS: People DOCUMENT: This converter sums the total number of amputees in the United Kingdom at any point in time.
Total_Amputees_in_Primary_Care = SUM("Post-Op_Hospital_Care"[*]) + SUM("Pre-Op_Hospital_Care"[*]) + SUM("Recovery_(First_30_Days)"[*]) {SUMMING CONVERTER} UNITS: People DOCUMENT: This summing converter totals the number of amputees in primary care, meaning that they are either in pre-op, post-op or recovery, prior to being referred to a prosthetist.
Total_Amputees_in_Prosthetic_Care = SUM(Definitive_Device[*, *]) + SUM(Eligible_for_Prosthesis[*, *]) + SUM(Initial_Device[*, *]) + SUM(Matured_Limb[*, *]) {SUMMING CONVERTER} UNITS: People DOCUMENT: This summing converter totals the number of amputees in prosthetic care, meaning that they are either in one of the prosthesis fitting stages.
Total_Amputees_outside_of_Care = SUM(Awaiting_Replacement[*, *]) + SUM(Ineligible_for_Prosthesis[*]) + SUM(Limited_Mobility[*,*]) {SUMMING CONVERTER} UNITS: People DOCUMENT: This summing converter totals the number of amputees who are outside of primary or prosthetic care, and are not fitted with a prosthesis.
Total_Digital_Fit = SUM(Full_Mobility[*, Digital]) {SUMMING CONVERTER} UNITS: People DOCUMENT: This summing converter totals the number of amputees who are successfully fitted with a digital 3D-printed prosthesis.

Total_Economic_Contribution = GDP_per_Capita*Total_Employed_Amputees UNITS: USD/month DOCUMENT: This variable dynamically calculates the total economic contribution of amputees, particularly from fully mobile amputees who are participating in the workforce, It is calculated by multiplying the total employed amputees with the GDP per capita.
Total_Economic_Cost = Total_Unemployment_Cost+Total_Healthcare_Cost+Total_Family_Cost+Total_Social_Payment_Costs+Total_Prosthesis_Cost UNITS: USD/month DOCUMENT: This variable dynamically calculates the total economic cost incurred as a result of caring for the amputee population in the United Kingdom. It is sum of the various costs: unemployment, healthcare, family, social payout, prosthesis costs.
Total_Employed_Amputees = Proportion_of_FM_Employed*Total_Working_Age_FM UNITS: People DOCUMENT: This variable dynamically calculates the total number of fully mobile amputees who are employed. It simply multiplies the total working age population with the proportion who are employed.
Total_Family_Cost = Family_Costs[Not_Fitted]*Total_Not_Fitted+ Family_Costs[Traditional_Fit]*Total_Traditional_Fit + Family_Costs[Digital_Fit]*Total_Digital_Fit UNITS: USD/month DOCUMENT: This variable dynamically calculates the total social costs born by families of amputees. This is simply the sum of the various product of the amputee population by type and the respective family cost per person.
Total_Healthcare_Cost = Healthcare_Costs[Not_Fitted]*Total_Not_Fitted+ Healthcare_Costs[Traditional_Fit]*Total_Traditional_Fit + Healthcare_Costs[Digital_Fit]*Total_Digital_Fit UNITS: USD/month DOCUMENT: This variable dynamically calculates the total healthcare costs of amputees. This is simply the sum of the various product of the amputee population by type and the respective healthcare cost per person.

Total_Not_Fitted = Total_Amputees_outside_of_Care+Total_Amputees_in_Primary_Care+Total_Amputees_in_Prosthetic_Care UNITS: People DOCUMENT: This converter sums the total amputees who are either outside of care, in primary care or in prosthetic care. They represent the total amputees who are not fitted with a prosthesis (yet).
Total_Population = SUM("Non-PAD_Population"[*]) + SUM("Post-Op_Hospital_Care"[*]) + SUM("Pre-Op_Hospital_Care"[*]) + SUM("Recovery_(First_30_Days)"[*]) + SUM(Awaiting_Replacement[*, *]) + SUM(Definitive_Device[*, *]) + SUM(Eligible_for_Prosthesis[*, *]) + SUM(Full_Mobility[*, *]) + SUM(Ineligible_for_Prosthesis[*]) + SUM(Initial_Device[*, *]) + SUM(Limited_Mobility[*, *]) + SUM(Matured_Limb[*, *]) + SUM(PAD_Population[*]) {SUMMING CONVERTER} UNITS: people DOCUMENT: This summing converter totals the number of people in simulated the United Kingdom population.
Total_Prosthesis_Cost = SUM(Subtotal_Prosthesis_Cost) UNITS: USD/month DOCUMENT: This converter sums the total cost of providing a prosthesis, including both traditional and digital types.
Total_Prosthesis_Delivered[Prosthesis_Type] = SUM(Successful_Fitting)+SUM(Unsuccessful_Fitting) UNITS: People/month DOCUMENT: This variable dynamically calculates the total prosthesis device delivered regardless whether it was a successful fit or not. It is arrayed by prosthesis type.
Total_Social_Payment_Costs = Total_Amputees*Social_Payments UNITS: USD/month DOCUMENT: This variable dynamically calculates the total social payment costs paid out to amputees. This is simply the product of social payment per person and the total number of amputees.
Total_Traditional_Fit = SUM(Full_Mobility[*, Traditional]) {SUMMING CONVERTER} UNITS: People DOCUMENT: This summing converter totals the number of amputees who are successfully fitted with a traditional plaster-cast prosthesis.

Total_Unemployed_Amputees = Total_Working_Age_without_Mobility+ (1-Proportion_of_FM_Employed)*Total_Working_Age_FM UNITS: People DOCUMENT: This variable calculates the total number of amputees who are unemployed at any one point in time. It is the sum of the total working age amputees without mobility and the proportion of fully mobile amputees who are not employed.
Total_Unemployment_Cost = Total_Unemployed_Amputees*Unemployment_Payment UNITS: USD/month DOCUMENT: This variable dynamically calculates the total economic cost of making unemployment payments to amputees who are not employed. This is simply the product of the total unemployed amputees and the cost of unemployment payment per person.
Total_Working_Age_FM = SUM(Full_Mobility["15_to_44",*]) + SUM(Full_Mobility["45_to_59",*]) + SUM(Full_Mobility["60_to_79", *]) {SUMMING CONVERTER} UNITS: People DOCUMENT: This summing converter totals the number of fully mobile amputees who are capable to work. Fully mobile, here, means that they are successfully fitted with a prosthesis and is integrated back into society.
Total_Working_Age_without_Mobility = SUM(Awaiting_Replacement["15_to_44", *]) + SUM(Awaiting_Replacement["45_to_59", *]) + SUM(Awaiting_Replacement["60_to_79", *]) + SUM(Limited_Mobility["15_to_44",*]) + SUM(Limited_Mobility["45_to_59",*]) + SUM(Limited_Mobility["60_to_79",*]) + Ineligible_for_Prosthesis["15_to_44"] + Ineligible_for_Prosthesis["45_to_59"] + Ineligible_for_Prosthesis["60_to_79"] {SUMMING CONVERTER} UNITS: People DOCUMENT: This summing converter totals the number of amputees who are of working age, but do not have full mobility. This includes people who are ineligible for prosthesis, those who have dropped out of the prosthetic care continuum, and those who are awaiting replacement of their prosthesis after degradation.
Unemployment_Payment = 2381/12 UNITS: USD/person/month DOCUMENT: This parameter represents the cost of unemployment payment per person per month in the United Kingdom. The annual payment sum was obtained from ProsFit's health economic model data set, and divided by 12 for the monthly payment (C. Hutchison, 2021).

Unit_Cost[Digital] = 1573 Unit_Cost[Traditional] = 2186 UNITS: USD/person DOCUMENT: This parameter represents the unit cost of manufacturing a prosthesis by type. The data was obtained from ProsFit's health economic model data set (C. Hutchison, 2021).

Market Subsystem Module

Table C.0.13 Documentation for Innovation Diffusion Sector

Innovation Diffusion Sector
Market_Subsystem.Desired_Development = Innovation_Decay*Time_to_Develop_Innovation*Relative_Resources_for_R&D UNITS: dmnl DOCUMENT: This variable represents the desired innovation development rate. The base desired development rate is a function of the innovation decay rate and the average time taken for the development process, hence taking into account the delay time. The assumption here is that as the innovation becomes outdated, the industry at the very minimum seeks to maintain equilibrium replacement to prevent the technology from becoming obsolete. This base rate is then adjusted based on the relative resources available for research and development (R&D). When the R&D resources is at its normal level (1), then the desired development is at equilibrium replacement. When relative resources is more than 1, then the desired development is proportionally higher than the replacement rate. This means that there is room for new innovation to be developed. Similarly, if the relative resources is less than 1, then the desired development is proportionally reduced – meaning that there is insufficient resources to even maintain equilibrium replacement.
Market_Subsystem.Desired_Diffusion = Knowledge_Decay*Time_to_Diffuse_Knowledge*Relative_Resources_for_R&D UNITS: dmnl DOCUMENT: This variable represents the desired knowledge diffusion rate. The base desired diffusion rate is a function of the knowledge decay rate and the average time taken to diffuse new knowledge, hence taking into account the delay time. The assumption here is that as the knowledge decays, the industry at the very minimum seeks to maintain equilibrium replacement to prevent obscurity. This base rate is then adjusted based on the relative resources available for research and development (R&D). When the R&D resources is at its normal level (1), then the desired diffusion is at equilibrium replacement. When relative resources is more than 1, then the desired diffusion is proportionally higher than the replacement rate. This means that there is room for new knowledge to be diffused. Similarly, if the relative resources is less than 1, then the desired diffusion is proportionally reduced – meaning that there is insufficient resources to even maintain equilibrium replacement.

Market_Subsystem.GoS_Effectiveness_Factor = 0.25 UNITS: dmnl DOCUMENT: This parameter represents the Effectiveness Factor of the Guidance of Search function. It refers to the fraction of available resources for research and development that is subject to the influence of Guidance of Search. Here, Guidance of Search contributes up to 25% variability in the resources set for R&D, an assumption made in Walrave & Raven (2016a).
Market_Subsystem.Guidance_of_Search(t) = Guidance_of_Search(t - dt) + (Change_in_GoS) * dt INIT Market_Subsystem.Guidance_of_Search = Indicated_Guidance_of_Search UNITS: Dmnl DOCUMENT: This stock represents the level of Guidance of Search for the technological knowledge. The Guidance of Search function "refers to those activities within the innovation system that can positively affect the visibility and clarify of specific wants among technology users" (Hekkert et al., 2007, p. 423). It acts as a priority setting indicator for allocating resources to R&D based on technological prominence (Walrave & Raven, 2016a). The stock varies between 0 and 1, where 0 means the lowest level and 1 is the maximum level of Guidance of Search. The initial value of the stock is set at its indicated value.
INFLOWS: Market_Subsystem.Change_in_GoS = (Indicated_Guidance_of_Search-Guidance_of_Search)/Time_to_Adjust_GoS UNITS: dmnl/month DOCUMENT: This inflow represents the rate of change in the Guidance of Search level. It is formulated as a first order adjustment, where the Guidance of Search adjusts to its indicated level with a certain adjustment time.
Market_Subsystem.Indicated_Guidance_of_Search = Innovation_Developed*Knowledge_Diffused UNITS: dmnl DOCUMENT: This variable represents the indicated level of the Guidance of Search prior to the delay adjustment. The indicated value is determined by the product of Innovation Developed and Knowledge Diffused. The product of the two "reflect the status" of the current innovation knowledge that is circulating amongst relevant actors (Walrave & Raven, 2016a, p. 7). A reduction in any of the two would proportionally reduce the "visibility and clarity" of the state of the art (Hekkert et al., 2007, p. 423).

Market_Subsystem.Innovation_Developed(t) = Innovation_Developed(t - dt) + (Innovation_Development - Innovation_Decay) * dt

INIT Market_Subsystem.Innovation_Developed = 0.001

UNITS: Dmnl

DOCUMENT: This stock represents the level of innovation developed, or the "current state-of-the-art, with respect to technological knowledge developed" (Walrave & Raven, 2016a, p. 4). The stock varies between 0, denoting "no knowledge" or the lowest level of innovation developed, and 1, denoting "a nearly, for that moment in time, 'complete' understanding of the technology" (Walrave & Raven, 2016a, p. 4).

The initial value of the stock is set at 0.001, in order to kick it out of the unstable equilibrium point and allow for exponential growth.

INFLOWS:

Market_Subsystem.Innovation_Development = Desired_Development/Time_to_Develop_Innovation*MAX(0, 1-Innovation_Developed)

UNITS: Per Month

DOCUMENT: This inflow represents the innovation development rate. The rate is determined by a first order adjustment, where the desired rate is divided by the delay time. This delay adjusted rate is further controlled by the current Innovation Developed level. As the innovation reaches its maximum potential (innovation level = 1), the equation '1 - Innovation Developed' enforces "a S-shaped growth curve, typical for technological development" that makes the development of new innovation to be progressively more difficult (Schilling & Esmundo, 2009; Walrave & Raven, 2016a, p. 4). In essence, it prevents the stock from increasing beyond the maximum level. The MAX function prevents the inflow from going below 0.

OUTFLOWS:

Market_Subsystem.Innovation_Decay = Innovation_Developed/Time_to_Decay

UNITS: Per Month

DOCUMENT: This outflow represents the innovation decay rate since technological knowledge may become outdated over time, especially with the development of new innovation. The decay rate is simply a first order adjustment where the innovation decays with a certain adjustment time (time to decay).

Market_Subsystem.Knowledge_Diffused(t) = Knowledge_Diffused(t - dt) + (Knowledge_Diffusion - Knowledge_Decay) * dt INIT Market_Subsystem.Knowledge_Diffused = 0.001 UNITS: Dmnl DOCUMENT: This stock represents the level of technological knowledge diffused amongst relevant parties. The stock varies between 0, denoting no diffusion of knowledge and 1, denoting "that nearly all currently available technological knowledge is diffused" (Walrave & Raven, 2016a, p. 6). The initial value of the stock is set at 0.001, in order to kick it out of the unstable equilibrium point and allow for exponential growth.
INFLOWS: Market_Subsystem.Knowledge_Diffusion = Desired_Diffusion/Time_to_Diffuse_Knowledge*MAX(0, 1-Knowledge_Diffused) UNITS: dmnl/month DOCUMENT: This inflow represents the knowledge diffusion rate. The rate is determined by a first order adjustment, where the desired rate is divided by the delay time. This delay-adjusted rate is further controlled by the current Knowledge Diffused level. As the Knowledge Diffused reaches its maximum potential (1), the equation '1 - Knowledge Diffused' enforces "a S-shaped growth curve" that makes diffusion to be progressively more difficult (Walrave & Raven, 2016a, p. 6). In essence, it prevents the stock from increasing beyond the maximum level. The MAX function prevents the inflow from going below 0.
OUTFLOWS: Market_Subsystem.Knowledge_Decay = (Knowledge_Diffused/Time_to_Decay) + (Knowledge_Diffused*New_Innovation_Proportion) UNITS: dmnl/month DOCUMENT: This outflow represents the technological knowledge decay rate since diffused knowledge may become outdated over time with the development of new innovation. The decay rate is a sum of a first order adjustment where the level of Knowledge Diffused decays over a certain adjustment time (time to decay) and the fraction of the knowledge diffused that is made obsolete by new innovation. This formulation ensures that the level of knowledge diffused decreases pro-rata to the new innovation that is developed (Walrave & Raven, 2016a, p. 6).
Market_Subsystem.New_Innovation_Proportion = Innovation_Development/Innovation_Developed UNITS: dmnl/month DOCUMENT: This variable calculates the ratio of the innovation development rate to the current state of the innovation. This gives a proportion of the new to old innovation level, which then gives us the pro-rate knowledge that has become obsolete.

Market_Subsystem.Relative_Internal_Resources = Relative_MS^Sensitivity_of_Resources_to_MS UNITS: dmnl DOCUMENT: This variable represents the relative change in Internal Resource with respect to a certain sensitivity to changes in Relative Market Size. This is calculated by taking the Sensitivity of Resources as an exponent of the Relative Market Size.
Market_Subsystem.Relative_Resources_for_R&D = Total_Relative_Resources*(1-GoS_Effectiveness_Factor) + Total_Relative_Resources*GoS_Effectiveness_Factor*Guidance_of_Search UNITS: dmnl DOCUMENT: This variable represents the relative resources available for research and development (R&D). It is the Total Relative Resources adjusted by the Guidance of Search level. The Effectiveness Factor determines the percentage of the Total Relative Resources that is influenced by the Guidance of Search (GoS). This percentage varies proportionally to the level of GoS. When the GoS is at its lowest (0), then the relative resources allocated to R&D will be at its fixed level (in this case, 75% of the total relative resources). When the GoS is at its maximum (1), then the relative resources for R&D will be the total relative resources (100%). For values of GoS between 0 and 1, the relative resources varies proportionally.
Market_Subsystem.Sensitivity_of_Resources_to_MS = 1 UNITS: dmnl DOCUMENT: This parameter determines the sensitivity of Relative Internal Resources to changes in Relative Market Size. In this model, it is assumed that Internal Resources is sensitive and responds proportionally to changes in Market Size.
Market_Subsystem.Time_to_Adjust_GoS = 3 UNITS: month DOCUMENT: This parameter represents the adjustment time for the Guidance of Search to update. Here, the adjustment time of 3 months, set by Walrave & Raven (2016a), was kept.
Market_Subsystem.Time_to_Decay = 60 UNITS: month DOCUMENT: This parameter represents the residence time of any innovation developed or diffused, or the time taken for knowledge to decay. Here, the decay time of 60 months, set by Walrave & Raven (2016a), was kept.
Market_Subsystem.Time_to_Develop_Innovation = 12 UNITS: month DOCUMENT: This parameter represents the delay time for the development of new innovation. Here, the average delay time is assumed to be a year.

Market_Subsystem.Time_to_Diffuse_Knowledge = 12 UNITS: month DOCUMENT: This parameter represents the delay time for the diffusion of new technological knowledge. Here, the average delay time is assumed to be a year.
Market_Subsystem.Time_to_Mobilise_Resources = 6 UNITS: month DOCUMENT: This parameter represents the delay time for the mobilising resources. Here, the adjustment time of 6 months, set by Walrave & Raven (2016a), was kept.
Market_Subsystem.Total_Relative_Resources = SMTH1(Relative_Internal_Resources+Adjusted_Relative_External_Resources, Time_to_Mobilise_Resources) {DELAY CONVERTER} UNITS: dmnl DOCUMENT: This variable represents the Total Relative Resources available to the technological innovation system. It is the sum of the relative external and relative internal resources, adjusted by a delay time to mobilise resources. This delay process is captured by the SMTH1 function that introduces a first order delay adjustment.

Table C.0.14 Documentation for Market Formation Sector

Market Formation Sector
Market_Subsystem.Adjusted_Relative_External_Resources = (1-Variable_Input_Fraction)*Relative_External_Resources + Variable_Input_Fraction*Relative_External_Resources*Entrepreneurial_Activity UNITS: dmnl DOCUMENT: This variable represents the Adjusted Relative External Resources that is actually pumped into the innovation system, by external funders. Although exogenous, Relative External Resources is influenced by the Entrepreneurial Activity level by some extent. The Variable Input Fraction determines the percentage of the resources that is dependent on the Entrepreneurial Activity. When Activity is at its lowest (0), then the relative resources will be at its fixed level (inverse of variable fraction). When the Activity is at its maximum (1), then there will be no adjustment to the Relative External Resources. For values of EA between 0 and 1, the variable portion of the relative external resources varies proportionally.

Market_Subsystem.Clinics[Digital] = Ref_Digital_Clinics*Effect_of_MS_on_Clinics Market_Subsystem.Clinics[Traditional] = 35 UNITS: clinic DOCUMENT: This variable represents the number of prosthetic clinics at any one point in time. For the traditional clinics, the number is held constant at 35 – it includes both the public-funded NHS clinics and private clinics (Amputation Foundation, 2022). For the digital clinics, the reference number of clinics endogenously changes with the relative Market Size.
Market_Subsystem.Clinics_Sensitivity_SWITCH = 0 UNITS: dmnl DOCUMENT: This parameter represents the experimental switch for changing the sensitivity of Clinics to Market Size according to different scenarios.
Market_Subsystem.Digital_Fitting_Reputation = Limit_DFR/(1+EXP((Inflection_DFR-.Perceived_Relative_Fitting_Rate)/Steepness_DFR)) UNITS: dmnl DOCUMENT: This variable represents the Reputation of Digital Fitting that dependent on the perceived relative fitting rate of the digital prosthesis as compared to the traditional one. The reputation level can vary from 0 to 1 and is analytically formulated as a Sigmoid function (s-shape curve). When the perceived ratio is 0, then we can expect reputation formed to be non-existent (0). However, as the ratio increases towards 1, we can expect the reputation of digital fitting to increase increasingly towards the mid-point (0.5), indicating a someone neutral reputation position. As the ratio increases above 1, then the reputation increases decreasingly towards the maximum of 1.
Market_Subsystem.Duration_RER = 180 UNITS: month DOCUMENT: This parameter sets how long the external resources will be pumped into the system.

Market_Subsystem.Effect_of_EA_on_MI = MIN(2, Limit_EA_on_MI/(1+EXP((Inflection_EA_on_MI-Entrepreneurial_Activity//Ref_EA)/Steepness_EA_on_MI))) UNITS: dmnl DOCUMENT: This variable represents the Effect of entrepreneurial activity on market infrastructure. According Walrave & Raven (2016a, p. 12), the relationship between the two is one of exponential growth curve, where the "influence of entrepreneurs on the formation processes of [market infrastructure] becomes increasingly large as Entrepreneurial activity increases – reflecting the need for a certain critical mass before substantial influence can be exercise." The table function provided by the authors was replicated here with an analytical formulation. To best control the curvature and end points of the exponential growth function, a Sigmoid curve was formulated such that the inflection point ends at the desired end point (2,2). In doing so, we are able to obtain an increasing increasingly curve from (~0,0) to (2,2) with a steepness that can be calibrated.
Market_Subsystem.Effect_of_MS_on_Clinics = SMTH1(Relative_MS^Sensitivity_of_Clinics_to_Market_Size, Time_to_Adjust_Clinics) {DELAY CONVERTER} UNITS: dmnl DOCUMENT: This variable represents the relative change in Digital Clinics with respect to a certain sensitivity to changes in Relative Market Size. This relative change is calculated by taking the Sensitivity of Clinics as an exponent of the Relative Market Size. The relative change is further delayed with a SMTH function to take into account the time taken to set up or tear down clinics.
Market_Subsystem.Effect_of_MS_on_SSE = Maximum_Effect_MS*EXP(-(Relative_MS-Mean_Position_MS)^2/(2*Spread_MS^2)) UNITS: dmnl DOCUMENT: This variable represents the effect of Relative Market Size on the Maximum Sailing Ship Effect. As the relative market size of the digital prosthesis industry increases beyond a threshold, we expect a sailing ship effect, or a response from the incumbent traditional prosthesis regime to step up their competitiveness. However, "the sailing ship effect is not likely to last indefinitely" and is expected to wane after the market size exceed a certain size (Walrave & Raven, 2016a, p. 16) Accordingly, the effect variable is analytically formulated as a normal distribution around a certain mean position. At the mean position, the effect is at the maximum height (1). The distribution around the mean is controlled by the spread. With this normal distribution, the effect increases towards the maximum as the relative market size increases towards 5 (corresponding to 25% market size). Beyond which, the effect decreases towards 0. The distribution references the table function provided in Walrave & Raven (2016a, p. 18)

Market_Subsystem.Effect_of_PL_on_EA = MIN(2, Limit_PL_on_EA/(1+EXP((Inflection_PL_on_EA-Perceived_Legitimacy//Ref_PL)/Steepness_PL_on_EA))) UNITS: dmnl DOCUMENT: This variable represents the Effect of perceived legitimacy on entrepreneurial activity. According Walrave & Raven (2016a, p. 9), the relationship between the two is one of exponential growth curve due to the "band-wagon effect" (Geels, 2005). Particularly, as more entrepreneurial activity installs more infrastructure and thus increases the the perceived legitimacy of the technological system, we expect even more entrepreneurs to be interested and join the activity. The table function provided by the authors was replicated here with an analytical formulation. To best control the curvature and end points of the exponential growth function, a Sigmoid curve was formulated such that the inflection point ends at the desired end point (2,2). In doing so, we are able to obtain an increasing increasingly curve from (~0,0) to (2,2) with a steepness that can be calibrated.
Market_Subsystem.Effect_of_TRR_on_EA = Limit_EA*(1-EXP(-Total_Relative_Resources/Steepness_EA)) UNITS: dmnl DOCUMENT: This variable represents the effect of total relative resources on entrepreneurial activity. External actors, be it government agencies or other private investors, could be backing entrepreneurs such that the perceived entrepreneurial risks are reduced (Suurs, 2009; Walrave & Raven, 2016a). Hence when total relative resources increases, we assume that funding for entrepreneurs increases. Here, the effect of total relative resources is formulated as a nonlinear function that increases decreasingly. As funding increases beyond the normal, we can expect entrepreneurial interest to increase quickly before increasing decreasingly to the maximum as more and more resources is pumped in.
Market_Subsystem.Effect_of_TRR_on_MI = Limit_MI*(1-EXP(-Total_Relative_Resources/Steepness_MI)) UNITS: dmnl DOCUMENT: This variable represents the effect of total relative resources on market infrastructure. According to Walrave & Raven (2016a, p. 12), "other actors can also stimulate development" of market infrastructure. Funding for market development can come from other such actors like government institutions that could build the necessary infrastructure for market formation (Suurs, 2009). Here, the effect of total relative resources is formulated as a nonlinear function that increases decreasingly. As funding increases beyond the normal, we can expect market infrastructure to expand quickly. However, as more and more money is pumped in, we expect a diminishing returns in investment, thus tailoring off to a maximum effect.

Market_Subsystem.Entrepreneurial_Activity(t) = Entrepreneurial_Activity(t - dt) + (Change_in_EA) * dt

INIT Market_Subsystem.Entrepreneurial_Activity = 0

UNITS: dmnl

DOCUMENT: This stock represents the level of entrepreneurial activities in the digital prosthetic industry. The stock varies between 0 (no activity) and 1 (full activity). The initial value of the stock is set at 0.

INFLOWS:

Market_Subsystem.Change_in_EA = (Indicated_Entrepreneurial_Activity-Entrepreneurial_Activity)/Time_to_Adjust_EA

UNITS: Per Month

DOCUMENT: This inflow represents the rate of change in the Entrepreneurial Activity stock. It is formulated as a first order adjustment, where the Entrepreneurial Activity adjusts to its indicated level with a certain adjustment time.

Market_Subsystem.External_Resource_Size_SWITCH = 0

UNITS: dmnl

DOCUMENT: This parameter represents the experimental switch for changing the size of the relative external resources according to different scenarios.

Market_Subsystem.Fitting_Capacity[Prosthesis_Type] = Prosthetist_per_clinic*Clinics*Fitting_Capacity_per_Prosthetist

UNITS: People/month

DOCUMENT: This variable represents the Fitting Capacity or the number of amputees that can be seen by a prosthetist and fitted with a prosthesis per month. It is a function of the number of clinics available at any one point in time, multiplied with the average number of prosthetist per clinic, and the fitting capacity per prosthetist.

Market_Subsystem.Fitting_Capacity_per_Prosthetist[Digital] = 288/12

Market_Subsystem.Fitting_Capacity_per_Prosthetist[Traditional] = 58/12

UNITS: people/prosthetist/month

DOCUMENT: This parameter represents the average number of amputees that a prosthetist can fit in each month. The value is obtained from ProsFit's health economic model data set (C. Hutchison, 2021) and divided by 12 to convert the value from years to months.

Market_Subsystem.Indicated_Entrepreneurial_Activity = Ref_EA*(Effect_of_PL_on_EA*Weight_of_PL+Effect_of_TRR_on_EA*(1-Weight_of_PL))

UNITS: dmnl

DOCUMENT: This variable represents the indicated entrepreneurial activity level of the digital prosthetic industry. The indicated activity is formulated as additive effects of Perceived Legitimacy

and Total Relative Resources on the Reference Entrepreneurial Activity level, governed by the respective weight of each effect. According to Walrave & Raven (2016a), resources available for stimulating entrepreneurial activity has an independent effect on activity. Hence, the variable is formulated as additive effects rather than multiplicative.
Market_Subsystem.Indicated_Legitimacy = (Knowledge_Diffused*Innovation_Developed)*Weight_of_Innovation_Diffusion + Digital_Fitting_Reputation*Weight_of_Reputation + (1-Regime_Resistance)*Weight_of_Resistance + Market_Infrastructure*Weight_of_Infrastructure UNITS: dmnl DOCUMENT: This variable represents the indicated legitimacy of the digital prosthetic industry. The indicated legitimacy is a function of "both technological legitimacy and market legitimacy" (Walrave & Raven, 2016a, p. 8). Digital Fitting Reputation and Innovation Diffusion represent the technological legitimacy, where they positively influence the indicated legitimacy. Market legitimacy is represented by Market Infrastructure and Regime Resistance. While Market Infrastructure positively influences legitimacy, Regime Resistance negatively influences legitimacy. Legitimacy is formulated as additive functions with a respective weight for each in order to ensure limit the range between 0 (no legitimacy) to 1 (full legitimacy).
Market_Subsystem.Indicated_Market_Infrastructure = Ref_MI*(Effect_of_EA_on_MI*Weight_of_EA+Effect_of_TRR_on_MI*(1-Weight_of_EA)) UNITS: dmnl DOCUMENT: This variable represents the indicated market infrastructure level of the digital prosthetic industry. The indicated infrastructure is formulated as additive effects of Entrepreneurial Activity and Total Relative Resources on the Reference Market Infrastructure level, governed by the respective weight of each effect. According to Walrave & Raven (2016a), market infrastructure development is only partially determined by entrepreneurial interest; the other part of the key is the effect of funding for market development that could be supported by other actors like the government. Hence, the variable is formulated as additive effects rather than multiplicative.
Market_Subsystem.Indicated_Market_Size = Market_Infrastructure*Entrepreneurial_Activity UNITS: dmnl DOCUMENT: This variable represents the indicated Market Size prior to the delay adjustment. The indicated value is determined by the product of Entrepreneurial Activity and Market Infrastructure. While Market Size growths with the Entrepreneurial Activity with a delay, the market "can only truly develop when innovation system actors successfully navigate" the Market Infrastructure (Walrave & Raven, 2016a, p. 13).

Market_Subsystem.Indicated_Resistance = MIN(1, (1-Market_Infrastructure) + Sailing_Ship_Effect) UNITS: dmnl DOCUMENT: This variable represents the indicated resistance of the incumbent traditional prosthetic industry. The indicated resistance is partially determined by the inverse of the market infrastructure. The assumption here is that the effective resistance is simply the remaining percentage of market infrastructure potential that has been prevented from being reached. The other part of resistance comes from sailing ship effect that kicks in to increase the competitiveness of the incumbent. The MIN function is added for robustness to ensure that the resistance can never increase beyond 1.
Market_Subsystem.Inflection_DFR = 1 UNITS: dmnl DOCUMENT: This parameter sets the inflection point of the Sigmoid curve for the Digital Fitting Reputation. The inflection point is set at 1 (i.e. when the perceived relative fitting rate is at 1).
Market_Subsystem.Inflection_EA_on_MI = 2 UNITS: dmnl DOCUMENT: This parameter sets the inflection point of the Sigmoid curve for the Effect of entrepreneurial activity on market infrastructure. The inflection point is set at 2 so that the curve only increases increasingly for the range of relative entrepreneurial activity 0 to 2.
Market_Subsystem.Inflection_PL_on_EA = 2 UNITS: dmnl DOCUMENT: This parameter sets the inflection point of the Sigmoid curve for the Effect of perceived legitimacy on entrepreneurial activity. The inflection point is set at 2 so that the curve only increases increasingly for the range of relative entrepreneurial activity 0 to 2.
Market_Subsystem.Limit_DFR = 1 UNITS: dmnl DOCUMENT: This parameter sets the limit of the Sigmoid curve for the Digital Fitting Reputation, which prevents it from growing above 1.
Market_Subsystem.Limit_EA = 2 UNITS: dmnl DOCUMENT: This parameter sets the limit that the exponential decay function approaches, thereby controlling the maximum effect at 2. The maximum is set as such in order to prevent entrepreneurial activity from exceeding beyond 1.

Market_Subsystem.Limit_EA_on_MI = 4 UNITS: dmnl DOCUMENT: This parameter sets the limit that is approached by the Sigmoid curve for the Effect of entrepreneurial activity on market infrastructure. By doubling the limit, then we can set the inflection point at (2,2), the desired end point for the exponential curve part of the Sigmoid function.
Market_Subsystem.Limit_MI = 2 UNITS: dmnl DOCUMENT: This parameter sets the limit that the exponential decay function approaches, thereby controlling the maximum effect at 2. The maximum is set as such in order to prevent market infrastructure from exceeding beyond 1.
Market_Subsystem.Limit_PL_on_EA = 4 UNITS: dmnl DOCUMENT: This parameter sets the limit that is approached by the Sigmoid curve for the Effect of perceived legitimacy on entrepreneurial activity. By doubling the limit, then we can set the inflection point at (2,2), the desired end point for the exponential curve part of the Sigmoid function.
Market_Subsystem.Market_Infrastructure(t) = Market_Infrastructure(t - dt) + (Change_in_MI) * dt INIT Market_Subsystem.Market_Infrastructure = Indicated_Market_Infrastructure UNITS: dmnl DOCUMENT: This stock represents the Market Infrastructure of the digital prosthetic industry. The stock varies between 0 (no infrastructure developed) and 1 (full market infrastructure). The initial value of the stock is set at its indicated value.
INFLOWS: Market_Subsystem.Change_in_MI = (Indicated_Market_Infrastructure - Market_Infrastructure)/Time_to_Adjust_MI UNITS: Per Month DOCUMENT: This inflow represents the rate of change in the Market Infrastructure. It is formulated as a first order adjustment, where the Market Infrastructure adjusts to its indicated level with a certain adjustment time.
Market_Subsystem.Market_Share[Digital] = Market_Size Market_Subsystem.Market_Share[Traditional] = 1-Market_Size UNITS: dmnl DOCUMENT: This variable represents the respective Market Shares of the digital and traditional prosthetic industry. The digital market share is assumed to be directly proportional to the

Market Size, which is taken as percentage between 0 to 1. The traditional market size is simply the inverse of the digital market share.
Market_Subsystem.Market_Size(t) = Market_Size(t - dt) + (Change_in_MS) * dt INIT Market_Subsystem.Market_Size = 0 UNITS: dmnl DOCUMENT: This stock represents the Market Size of the digital prosthetic industry. The stock varies between 0 and 1, where 0 means the industry failed to capture any prosthetic market, and 1 indicates 100% of the prosthetic market is captured by the digital industry. The initial value of the stock is set at 0.
INFLOWS: Market_Subsystem.Change_in_MS = (Indicated_Market_Size-Market_Size)/Time_to_Adjust_MS UNITS: Per Month DOCUMENT: This inflow represents the rate of change in the Market Size. It is formulated as a first order adjustment, where the Market Size adjusts to its indicated level with a certain adjustment time.
Market_Subsystem.Maximum_Effect_MS = 1 UNITS: dmnl DOCUMENT: This parameter sets the Maximum Effect of MS on the Maximum SSE. The maximum effect is 1, indicating that at the normal or mean position, the sailing ship effect will be at its maximum.
Market_Subsystem.Maximum_SSE = 0.25 UNITS: dmnl DOCUMENT: This parameter represents the maximum Sailing Ship Effect. Here, the maximum effect of 0.25, set by Walrave & Raven (2016a), was kept.
Market_Subsystem.Mean_Position_MS = 5 UNITS: dmnl DOCUMENT: This parameter sets the normal or mean position of the relative market size. Here, the maximum effect will occur when the relative size is 5. This value was chosen as it corresponds to 0.25 (5 times the threshold), which is the threshold size before the sailing ship wanes according to Walrave & Raven (2016a).

Market_Subsystem.MS_Threshold = 0.05 UNITS: dmnl DOCUMENT: This parameter represents the Market Size Threshold that acts as the reference value for the Relative Market Size. Here, the threshold is set at 0.05, meaning that the minimum viability of the digital technology industry is 5%. The assumption here is that below 5% the industry is still in the red and is not profiting enough for long-term viability.
Market_Subsystem.Perceived_Legitimacy(t) = Perceived_Legitimacy(t - dt) + (Change_in_PL) * dt INIT Market_Subsystem.Perceived_Legitimacy = Indicated_Legitimacy UNITS: dmnl DOCUMENT: This stock represents the Perceived Legitimacy of system actors towards the digital prosthetic industry. The stock varies between 0 and 1, where 0 indicates a complete lack of legitimacy, and 1 indicates a very high level of legitimacy. The initial value of the stock is set at its indicated value.
INFLOWS: Market_Subsystem.Change_in_PL = (Indicated_Legitimacy-Perceived_Legitimacy)/Time_to_Perceive_Legitimacy UNITS: Per Month DOCUMENT: This inflow represents the rate of change in the Perceived Legitimacy. It is formulated as a first order adjustment, where the Perceived Legitimacy adjusts to its indicated level with a certain adjustment time.
Market_Subsystem.Prosthetist_per_clinic = 2 UNITS: prosthetist/clinic DOCUMENT: This parameter represents the average number of prosthetist in each clinic. The value is obtained from ProsFit's health economic model data set (C. Hutchison, 2021).
Market_Subsystem.Ref_Digital_Clinics = 3 UNITS: clinic DOCUMENT: This parameter represents the reference number of digital clinics in the United Kingdom. This number is calibrated to 3 based on the projected number of digital clinics in the future based on ProsFit's health economic model data set (C. Hutchison, 2021).
Market_Subsystem.Ref_EA = 0.5 UNITS: dmnl DOCUMENT: The reference Entrepreneurial Activity is set at 0.5, the mid value of the stock which ranges from 0 to 1.

Market_Subsystem.Ref_MI = 0.5

UNITS: dmnl

DOCUMENT: The reference market infrastructure is set at 0.5, the mid value of the stock which ranges from 0 to 1.

Market_Subsystem.Ref_PL = 0.5

UNITS: dmnl

DOCUMENT: The reference Perceived Legitimacy is set at 0.5, the mid value of the stock which ranges from 0 to 1.

Market_Subsystem.Regime_Resistance(t) = Regime_Resistance(t - dt) + (Change_in_RR) * dt

INIT Market_Subsystem.Regime_Resistance = 1

UNITS: dmnl

DOCUMENT: This stock represents the Regime Resistance of the incumbent traditional prosthetic industry, then campaigns to counter the growth of the digital market. The stock varies between 0 and 1, where 0 means there is no resistance, and 1 implies a severe resistance that suppresses the digital industry. The initial value of the stock is set to 1.

INFLOWS:

Market_Subsystem.Change_in_RR = (MIN(Indicated_Resistance, 1) - Regime_Resistance)/Time_to_Adjust_RR

UNITS: Per Month

DOCUMENT: This inflow represents the rate of change in the Regime Resistance. It is formulated as a first order adjustment, where the Regime Resistance adjusts to its indicated level with a certain adjustment time.

Market_Subsystem.Relative_External_Resources = IF TIME>=Timing_RER AND TIME<Timing_RER+Duration_RER THEN RER_Size ELSE 0

UNITS: dmnl

DOCUMENT: This variable represents the Relative External Resources that is being pumped into the system at any one point in time. The equation sets External Funding to be temporary. The amount is only starts to be pumped from the Timing set and for a certain Duration before returning back to 0.

Market_Subsystem.Relative_MS = Market_Size//MS_Threshold

UNITS: dmnl

DOCUMENT: This variable calculates the Relative Market Size, the ratio of the current Market Size relative to the Threshold. When the ratio is 1, it means that the Market Size is at the threshold level. If the ratio is less than 1, it means that the market size is not viable. And if the ratio is more than 1, then it indicates that relative market size is above the viability threshold.

Market_Subsystem.Relative_Weight_of_Reputation = 0.6 UNITS: dmnl DOCUMENT: This parameter represents the relative weight distribution of Reputation to Innovation Distribution. Here, it is assumed that Reputation has a slightly higher weight (60%) than Innovation Diffusion (40%) as investors react more favourably to proven success of the technology rather than its potential.
Market_Subsystem.Relative_Weight_of_Resistance = 0.6 UNITS: dmnl DOCUMENT: This parameter represents the relative weight distribution of Resistance to Market Infrastructure. Here, it is assumed that Resistance has a slightly higher weight (60%) than Market Infrastructure (40%) as investors tend to react more strongly to possible negative repercussion from competition.
Market_Subsystem.RER_Size = (1-External_Resource_Size_SWITCH)*1 + External_Resource_Size_SWITCH*5 UNITS: dmnl DOCUMENT: This parameter sets the size of the relative external resources. This number changes based on the SWITCH for different scenarios. When the switch is turned on, the size of external resources is 5 times the normal. When the switch is turned off, the size of external resources is set to 1, denoted the normal size.
Market_Subsystem.Sailing_Ship_Effect = Maximum_SSE*Effect_of_MS_on_SSE UNITS: dmnl DOCUMENT: This variable dynamically calculates the Sailing Ship Effect. The maximum effect is endogenously adjusted with changes in the relative Market Size.
Market_Subsystem.Sensitivity_of_Clinics_to_Market_Size = (1-Clinics_Sensitivity_SWITCH)*0.5 + Clinics_Sensitivity_SWITCH*1 UNITS: dmnl DOCUMENT: This parameter determines the sensitivity of Digital Clinics to changes in Relative Market Size. When the SWITCH is turned on, then the clinics is sensitive to changes in Market Size and adjusts proportionally. When the SWITCH is turned off, then the clinics is not as sensitive to changes in Market Size and adjusts less than proportionally.
Market_Subsystem.Spread_MS = 0.25 UNITS: dmnl DOCUMENT: This parameter sets the dispersion around the mean in the normal distribution. This value was calibrated to fit the table function provided by Walrave & Raven (Walrave & Raven, 2016a, p. 18), where the values are distributed between 0 and 0.3 market size.

Market_Subsystem.Steepness_DFR = 0.2

UNITS: dmnl

DOCUMENT: This parameter controls the steepness of the curve or the rate of increase or decline of the Digital Fitting Reputation. The steepness is assumed to 0.2, which can be further calibrated with data collection.

Market_Subsystem.Steepness_EA = 2.5

UNITS: dmnl

DOCUMENT: This parameter controls the steepness of the curve or the rate of increase or decline of the Effect of total relative resources on entrepreneurial activity. The steepness is assumed to be 2.5, and can be calibrated with more robust data collection.

Market_Subsystem.Steepness_EA_on_MI = 0.4

UNITS: dmnl

DOCUMENT: This parameter controls the steepness of the curve or the rate of increase or decline of the Effect of entrepreneurial activity on market infrastructure. The steepness is set to 0.4 to fit the table function provided by Walrave & Raven (2016a, p. 12).

Market_Subsystem.Steepness_MI = 2.5

UNITS: dmnl

DOCUMENT: This parameter controls the steepness of the curve or the rate of increase or decline of the Effect of total relative resources on market infrastructure. The steepness is assumed to be 2.5, and can be calibrated with more robust data collection.

Market_Subsystem.Steepness_PL_on_EA = 0.4

UNITS: dmnl

DOCUMENT: This parameter controls the steepness of the curve or the rate of increase or decline of the Effect of perceived legitimacy on entrepreneurial activity. The steepness is set to 0.4 to fit the table function provided by Walrave & Raven (2016a, p. 12)

Market_Subsystem.Time_to_Adjust_Clinics = 24

UNITS: months

DOCUMENT: This parameter represents the delay time to adjust clinics. Here, it is assumed to be 24 months to set up clinics.

Market_Subsystem.Time_to_Adjust_EA = 12

UNITS: month

DOCUMENT: This parameter represents the adjustment time for a change in the entrepreneurial activity. Here, the adjustment time of 12 months, set by Walrave & Raven (2016a), was kept.

Market_Subsystem.Time_to_Adjust_MI = 60 UNITS: month DOCUMENT: This parameter represents the adjustment time for a change in the market infrastructure. Here, the adjustment time of 60 months, set by Walrave & Raven (2016a), was kept.
Market_Subsystem.Time_to_Adjust_MS = 24 UNITS: month DOCUMENT: This parameter represents the adjustment time for a change in the market size. Here, the adjustment time of 24 months, set by Walrave & Raven (2016a), was kept.
Market_Subsystem.Time_to_Adjust_RR = 12 UNITS: month DOCUMENT: This parameter represents the adjustment time for a change in the Regime Resistance. Here, the adjustment time of 12 months, set by Walrave & Raven (2016a), was kept.
Market_Subsystem.Time_to_Perceive_Legitimacy = 12 UNITS: month DOCUMENT: This parameter represents the adjustment time for a change in perceived legitimacy of digital technology. Here, the adjustment time of 12 months, set by Walrave & Raven (2016a), was kept.
Market_Subsystem.Timing_RER = 96 UNITS: month DOCUMENT: This parameter sets the start time for the external resources to be pumped into the system.
Market_Subsystem.Variable_Input_Fraction = 0.25 UNITS: dmnl DOCUMENT: This parameter represents the Variable portion of the Relative External Resources. It refers to the fraction of resources that is subject to the influence of Entrepreneurial Activity, which is assumed to be 25% by Walrave & Raven (2016a).
Market_Subsystem.Weight_of_EA = 0.4 UNITS: dmnl DOCUMENT: This parameter represents the weight of Entrepreneurial Activity. Here, it is assumed to be 0.4, meaning that slightly less weight is placed on entrepreneurial interest than on the effect of funding for market development.

Market_Subsystem.Weight_of_Infrastructure = (1-Weight_of_Technological_Legitimacy)*(1-Relative_Weight_of_Resistance) UNITS: dmnl DOCUMENT: This converter calculates the weight of the Infrastructure. It is simply the product of the inverse of the weight of technological legitimacy and the inverse of the relative weight of resistance.
Market_Subsystem.Weight_of_Innovation_Diffusion = Weight_of_Technological_Legitimacy*(1-Relative_Weight_of_Reputation) UNITS: dmnl DOCUMENT: This converter calculates the weight of the Innovation Diffusion. It is simply the product of the weight of technological legitimacy and the inverse of the relative weight of reputation.
Market_Subsystem.Weight_of_PL = 0.5 UNITS: dmnl DOCUMENT: This parameter represents the weight of Perceived Legitimacy. Here, both perceived legitimacy and effect of total relative resources are assumed to have equal weight distribution.
Market_Subsystem.Weight_of_Reputation = Weight_of_Technological_Legitimacy*Relative_Weight_of_Reputation UNITS: dmnl DOCUMENT: This converter calculates the weight of the Reputation. It is simply the product of the weight of technological legitimacy and the relative weight of reputation.
Market_Subsystem.Weight_of_Resistance = (1-Weight_of_Technological_Legitimacy)*Relative_Weight_of_Resistance UNITS: dmnl DOCUMENT: This converter calculates the weight of the Resistance. It is simply the product of the inverse of the weight of technological legitimacy and the relative weight of resistance.
Market_Subsystem.Weight_of_Technological_Legitimacy = 0.5 UNITS: dmnl DOCUMENT: This parameter represents the relative Weight of Technological Legitimacy to Market Legitimacy. Here, the distribution of weight is assumed to be equal between the two types. "Technological Legitimacy" is conceptualised as functions of innovation diffusion and reputation of digital fittings, while "Market Legitimacy" is conceptualised as function of Market Infrastructure and Regime Resistance (Walrave & Raven, 2016a, p. 8).