

European Master in System Dynamics
Master Thesis

**Taking Care of the Right Pressure: A Dynamic Theory of Health Care Work Pressure, Nurses Well-being
and Patient Satisfaction**

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Abstract

To hospitals it is of great importance to maintain and increase health care performance, especially with respect to patient satisfaction. Currently, work pressure is a crucial factor to a hospital's reputation, as well as to its employee's well-being and quality of care. System dynamics (SD) modeling is used to better understand the interaction among patient satisfaction and work pressure among nurses, based on literature review and a case study research of the nursing-cardiology unit of HNL Hospital. This area of research covers many already known causal relationships but leading authors point out a lack of dynamic implications and effects over time. This research addresses the complex causal feedback mechanisms responsible for changes in work pressure, employee well-being and patient satisfaction over a time span of ten years. Through an iterative process a quantitative SD model is built. The results suggest a fragile edge between a sustainable high workload and escalation, which might only appear after years of working under too much pressure. It proves to be most cost effective to provide more support in the work of nurses at earlier stages of symptoms of increased work pressure.

Keywords: Health care; System dynamics; Employee well-being; Patient satisfaction; Job Demands-Resources Theory

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Chapter 1. Introduction

1.1. Background

Patient satisfaction, defined as “an individual’s positive evaluation of distinct dimensions of health care” (Hutchinson, 1993, pp. 19, 21; Linder-Pelz, 1982, p. 578), is a long established performance measure for hospitals (Sitzia & Wood, 1997, p. 1831). Over the last ten years patient satisfaction has become of increasing importance in the health care system of the Netherlands. Health insurers negotiations with hospitals are becoming more dependent on indicators of patient satisfaction, and acquired accreditations of quality of care. As a result the health insurers currently hold pivotal roles in the distribution of health care thanks to their bargaining power (Porter & Teisberg, 2004, p. 7). This rise in bargaining power resulted from the transition of supply- to demand driven health care development (van de Ven, 1987, p. 256), and the adoption of a single universal health insurance scheme in 2006 (Bartholomé & Maarse, 2006, p. 10; Schäfer et al., 2010, pp. 167–184; Schut & van de Ven, 2011).

Patient satisfaction in itself is influenced by expectations (Hutchinson, 1993, p. 19), and described as “the margin between reality and desirability” (Sitzia & Wood, 1997; Van Maanen, 1984; Zastowny, Roghmann, & Hengst, 1983). The perceived quality of health care, the reality in this case study, is found to be mostly caused by the quality of service and employee satisfaction. Research on customer satisfaction has numerous studies that point out the positive effects of employee satisfaction and a focus on quality of service (Koys, 2001; Nishii, Lepak, & Schneider, 2008; Salanova, Agut, & Peiró, 2005; Schmit & Allscheid, 1995; Schneider & Reichers, 1983; Schneider, White, & Paul, 1998; Ulrich, Halbrook, Meder, Stuchlik, & Thorpe, 1991; Wiley, 1991). Moreover, research in health care also illustrates effects of employee well-being on patient satisfaction (Leiter, Harvie, & Frizzell, 1998; Newman, Maylor, & Chansarkar, 2001; Vahey, Aiken, Sloane, Clarke, & Vargis, 2004).

Nurses well-being is strongly related to their experienced work pressure and the care they can deliver. Research by Newman et al. (2001, p. 63) suggests that patient satisfaction is an important driver for nurses, and that patient dissatisfaction results in nurses dissatisfaction with their work. On a similar note, Tucker and Edmondson (2003, p. 60) found that nurses are gratified when they can continue providing patient care after working around a problem that prohibited it. The work load and quality of care that can be delivered is of concern among nurses in recent years; research from 2013 among nurses self-reported work circumstances in 12 EU countries concludes that often lack of time results in adverse events and important but unperformed tasks (Aiken, Sloane, Bruyneel, Van den Heede, & Sermeus, 2013). Moreover, research suggests that for hospital personnel it is hard to see opportunities for improvement in the problems they face, especially in the light of the high work load they experience (Tucker & Edmondson, 2003).

One way of considering employee well-being is by the balance between the job’s demands and resources (JD-R model; Bakker & Demerouti, 2007). In short, the JD-R model considers physical, psychological, social, and organizational aspects; of which demands are defined as any of those that require physical, cognitive, or emotional effort or skills; and resources are defined as functional in achieving work goals, reducing the development of job demands, and stimulating personal growth, learning, and development (Bakker & Demerouti, 2007, p. 312). Effects on employee well-being -all of which can be separately considered as either resource or demand- are numerous: age, experience, morale, work-life balance, emotionally demanding interactions with clients, high work pressure, autonomy, physical demands, to name a few that might play a role at the group level of a nursing unit (Bakker & Demerouti, 2014, p. 9; Kristekova, Jurisch, Schermann, & Krcmar, 2012).

1.2. Problem statement

Patient satisfaction, employee well-being, and work pressure are thoroughly researched by means of qualitative studies and inferential statistical analysis (Bakker & Demerouti, 2007; Sitzia & Wood, 1997; Sonnentag, 2015; Sonnentag & Frese, 2003; Wright & Cropanzano, 2000). Recently, there is a call for more complex, long-term, predictions, which explicitly incorporates the role of time and feedback processes (Bakker, 2015; Ilies, Aw, & Pluut, 2015; Ilies, Pluut, & Aw, 2015). However, an integrated overview of how

the current work-pressure developed due to their complex causal feedback mechanisms in the health care system and among nurses is lacking. This thesis main research objective is to gather insight in how work pressure, employee well-being and patient satisfaction affect each other over a time-span of 120 months. A side objective is to explain the developments of work pressure, employee well-being and patient satisfaction in a case study over a 60 months period from January 2012 till December 2016. Hence, the central research question of this thesis is: how are changes in patient satisfaction related to employee well-being and work pressure over a time period of 120 months? For answering the central research question the following sub questions are formulated:

1. What are the causal effects among work pressure, employee well-being, and patient satisfaction?
2. What are the feedback loops resulting from the causal effects among work pressure, employee well-being, and patient satisfaction?
3. What is the dynamic behavior resulting from the feedback loops among work pressure, employee well-being, and patient satisfaction?

The case of this study is a nursing-cardiology unit at a hospital in the Netherlands (referred to as HNL). The following sub questions are formulated for HNL

4. What affects the dynamics of work pressure, employee well-being, and patient satisfaction on the cardiology department of HNL?
5. What are future threats regarding the dynamics of work pressure, employee well-being, and patient satisfaction on the cardiology department of HNL?
6. What are future opportunities regarding the dynamics of work pressure, employee well-being, and patient satisfaction on the cardiology department of HNL?

1.3. Case study: HNL nursing-cardiology unit

For the last five years, the nursing-cardiology unit of HNL has provided care for on average 3500 patients each year. Patients are diagnosed with various heart-related diseases and the majority of the nurses are trained in using telemetric devices for monitoring. The last two years the nurses and the units managing team are increasingly more dissatisfied with the quality of care. Nurses would like to deliver a better quality of care but feel they cannot due to higher levels of work pressure. It is inconclusive what this work pressure consists of and what leads to this increasing dissatisfaction.

1.4. Scientific and social relevance

In the latest contributions in the field of employee well-being, Bakker (2015, p. 840) proposes the perspective of loss and gain cycles, hypothesizing an endogenous dynamic effect responsible for employee well-being and job performance (Bakker & Demerouti, 2014, p. 47). Next to that, Cropanzano and Dasborough (2015, p. 845) describe the dynamic aspect of well-being in the context of affective climates that can exist on the group level (Weick & Quinn, 1999). Those affective climates can be seen as either job resources or demands, fluctuating over time, such as social rewards and cooperation (Carr, Schmidt, Ford, & DeShon, 2003, p. 618), or shared stressors affecting and aligning the group mood, as has been found in a group of nurses (Totterdell, Kellett, Teuchmann, & Briner, 1998, p. 1509). These kinds of resources might be considered forms of dynamic capabilities to a hospital (Rahmandad & Repenning, 2016; Winter, 2003). It is argued that research so far has insufficiently considered time fluctuations of group level 'climates' (Cropanzano & Dasborough, 2015, p. 845; Sonnentag, 2015).

Ilies, Aw and Pluut, in their recent positional paper and commentary paper on the field of employee well-being (Ilies, Aw, et al., 2015, p. 9; Ilies, Pluut, et al., 2015, p. 849), argue for future research to "develop more complex predictions" and for conceptual and empirical work to explicitly address the role of time in the linkages between long term outcomes and the dynamic and endogenous effects of job demands and

resources. They stress the theoretical relevance of research in this field with a long term perspective, such as five to ten years, on organizational and group performances, taking into account the dynamic aspects, next to time delays. This shows that the current state of research on employee well-being is consisting of dynamic theories about a complex system, nevertheless only little simulation modeling research has been conducted in this area (Morrison & Repenning, 2011; Morrison & Rudolph, 2011). System dynamics modeling is a suitable tool for combining and refining existing models and facilitating possible clarification of theories (Edwards, 2010; Vancouver & Weinhardt, 2012, p. 619). It is hoped that these modeling efforts can enhance and inspire current theories, and provide meaningful findings to managers and employees in health care.

1.5. Thesis Structure

The next chapter provides the theoretical foundation of the thesis. It incorporates a literature review and notes from interviews with employees from HNL which serve as the basis for the causal relations of the model. Chapter two also discusses how these causal relations form feedback loops and how it is used in the system dynamics model in this thesis. The literature review leads to the overall dynamic hypothesis, also referred to as 'the model' that will be discussed in the third chapter. The fourth chapter elaborates on the research strategy, empirical methods used for gathering data and the method of simulation. Building on chapters three and four, chapter five provides the results of the data, validation testing of the model, showing model specifications and its limitations, and the model analysis. Chapter six discusses the insights, conclusions and aims for future research.

Chapter 2. Theory

2.1. Health care and System Dynamics

Since the 1970's, various studies have been conducted in the field of System Dynamics regarding the public health sector, ranging from research on patient flows and health care capacity to epidemiological studies (Hirsch & Wils, 1984; J. B. Homer & Hirsch, 2006, p. 453; Luginbuhl, Forsyth, Hirsch, & Goodman, 1981). For example, early research found system dynamics to be useful as a new method for problem analyses, and devising different intervention strategies in health care planning (Luginbuhl et al., 1981). Later, different sorts of epidemiological SD models have been found useful in policy making, from models considering public health to ones more focused on particular issues (e.g. cardiovascular disease in the Netherlands; Hirsch & Immediato, 1999; Hirsch & Wils, 1984). Also, research in 2007 found that the impacts of health care delivered by the means of information and communication technologies, so called telecare, will take a long time before the benefits arise (Bayer, Barlow, & Curry, 2007). The model of this thesis draws on this earlier work for addressing patient flows (see 2.2).

Work by Morrison and Rudolph discusses the fragility of emergency departments, in the context of how receptive they are to disasters (2011). It builds upon the idea that non-novel routine work, and its day-to-day variation, have the possibility to push the stress and accidents to a level of crisis (Rudolph & Repenning, 2002). The works by Morrison, Rudolph and Repenning use system dynamics in explaining how quantity of work and tight schedules can lead to disaster. A similar situation, and the potential disastrous effects, is argued to exist in any organization of which performance depends on its employees coping with daily routine, non-novel demands (Sterman, 2000, p. 563). The model in this thesis incorporates the potentially detrimental effects through the relations between workload, fatigue and the effects on the quality of care and number of patients at the unit (see 2.3 till 2.16).

The last sections of this chapter describe the context of health care in the Netherlands, elaborating on the effects of past policies. In the field of SD, and among thought leaders in health care, it is becoming increasingly more evident that policies designed to enhance the quality and efficiency of health care are currently doing it more harm than good (Porter & Teisberg, 2004; Sterman, 2006). This chapter introduces the literature step-by-step in accordance to the conceptual model in Chapter 3. In each section it briefly touches upon the models conceptualization as a result of the literature and the ethnographic data collected at HNL.

This chapter sets out on providing answers to the first two sub-questions of this thesis: "1) What are the causal effects among work pressure, employee well-being, and patient satisfaction?", and "2) What are the feedback loops resulting from these causal effects?" Next to that it touches upon hypothetical outcomes and results to which these causal effects and feedback loops could lead, and thereby provides a qualitative, systems thinking-approach to answering the third sub-question: "3) What is the dynamic behavior resulting from the feedback loops among work pressure, employee well-being, and patient satisfaction?". Here it should be noted that the majority of the reviewed articles are based on correlational outcomes, and that causality is often not proved but only assumed (see also 4.3). This thesis uses the word causal relations, but only in the context of hypothesized causal relations and its usefulness in making predictions with a simulation model. Without claiming these causal relations to exist in reality.

2.2. Patient Flows

Stocks and flows of patients are the starting point in system dynamics work related to health care capacity (see methods for an example of stocks and flows in system dynamics). In the telecare case each month elderly people enter the system (Bayer et al., 2007). There is a flow called "aging", representing the monthly number of elderly people that become relevant to the telecare model. These flow into a stock called "Healthy", which represents a total number of elderly people for that category. Given this conceptualization, it is assumed that all monthly 'arriving' elders of the "aging" flow will initially be healthy (Bayer et al., 2007, p. 67).

Another example by Royston et al. had the aim to test the effects of policies in different treatment capacities at different stages of a single disease. Their model describes the progression and regression of different states of cervical cancer. It is conceptualized as consisting of five different stocks, starting with 'normal' and ending at 'cancer', with three developmental stages in between (Royston, Dost, Townshend, & Turner, 1999, p. 296). Various other types of conceptualizations have been used in health care capacity, depending on the relevant issues at stake (Royston et al., 1999, pp. 300–306).

In line with earlier work in SD, the dynamic hypothesis of this thesis (see section 3.2) starts with a monthly flow of cardiac patients called "Patients Arrival Rate". These flow into a stock "Cardiac Patients" which is the total number of patients that are being treated at the nursing unit at any given time. This stock is depleted by an outflow called "Patients Treated Rate". To distinguish among the patients at the nursing unit the *Care Intensity* sub-model keeps track of certain characteristics of the patients that are relevant to the workload.

2.3. Intensity of Care

Different patients have different needs for nursing care. The sum of all needs of patients at one unit at a given time contributes to the work pressure at that unit. This is represented in Chapter 3 as the 'Intensity of Care', which is a sub model accounting for the work pressure that originates from the patients. Early in the 1980's researchers recognized that different units, with a similar number of staff per bed, can experience their workload completely different (Levenstam & Engberg, 1993). Since then other factors besides staffing and the number of patients have been developed to refine the measurement of the need for nursing care (Levenstam & Bergbom, 2002). This thesis refers to this sum of needs as the intensity of care, defined as the total need for nursing care at a given moment, for a certain group of patients (Levenstam & Bergbom, 2011).

Currently the amount of staff is often dependent on the diagnosis type of patients only (Knauf, Ballard, Mossman, & Lichtig, 2006; Welton & Dismuke, 2008). For each diagnosis type a certain budget is available, assessed on the average length of stay and costs of care. However, the lengths of stay are highly subjective to changes. Moreover, the average age and severity of illness, also referred to as patients acuity, is changing (Stanton & Rutherford, 2004). Several authors press that patients acuity should be part of accounting for nursing staff since it is a good measure for work pressure (Levenstam & Bergbom, 2011; Welton, Fischer, DeGrace, & Zone-Smith, 2006). The model in this thesis uses the patients age and multiple diagnosis to approach the patient acuity.

Next to these patient characteristics the patient flow is found to be an important aspect in intensity of care (Welton, Unruh, & Halloran, 2006). The arrival and leaving of patients brings an extra burden of physical task and registration tasks. These registration tasks are explicitly addressed by HNL nurses as being a part of the intensity of their work (also as forms of hindrance demands, see 2.6.1, and 5.2.2). The reason for these registration tasks are to assure standards of quality (see 2.18), however it is observed that the current amount of registration tasks at HNL is a burden of unnecessary routines that takes time off to deliver good quality of care, and contributes to the experienced work pressure. The manager of the nursing-cardiology department commented:

"We now have many administrative routines to perform. Each patient has to be asked for their level of pain, asked about their nutrition, checked for decubitus, checked for the chance of falling, checking for delirium to give an indication of their acuity for example. There is the general feeling that these registration procedures have no added value anymore. All values are getting registered, and documented to show in case there is asked for, but nothing is really done with it. And also the differences are very small, it is all generally quite okay. "

The care intensity in the model consists of four aspects: 1) the proportion of patients with diagnosis classified as having a high intensity of care, 2) the proportion of patients with multiple diagnosis, 3) the

proportion of patients aged over 70, and 4) the proportion of registration procedures that have to be fulfilled with every patient (more detailed accounts of these measurements are described in sections 4.6 and 5.2).

2.4. Work Pressure

One of the main interests of HNL's HR department is the work pressure and possible issues for their staff. John Welton's recent guest editorial contribution to the *International Journal of Nursing Studies* succinctly expresses where work pressure comes down to: "it ultimately focuses on 1) *nurse workload*, 2) *characteristics of the nurse* that are associated with 3) *good outcomes*, and the ability of the nurse to do all the 4) *things needed in a shift for the patient* (Aiken et al., 2013; Cho et al., 2015; Schubert et al., 2013; Voepel-Lewis, Pechlavanidis, Burke, & Talsma, 2013; Welton, 2016, p. A1)". The observations of the internal HR Advisor of the nursing-cardiology department expressed concerns:

"I believe the work pressure for the nursing team has been risen in the last couple of years. There are many expressions of concern from different nurses, and I believe the workload has been increased with small steps till the point where it is now, that it is almost critically high. It is like management has been using the cheese slicer method for doing small budget cuts over time, till this moment that there is almost nothing left to slice anymore."

First, the sub-models *Patient Flow* and *Care Intensity*, see A3 for an overview of sub-models, are the 'nurse workload' representing the monthly activities. Second, the 'characteristics of the nurses' are addressed in the sub model *Workforce*. How nurses experience the work pressure is addressed in the sub-models *Job Demands*, *Job Resources* and *Well-being*, which the next sections of this chapter will address. As third, the 'good outcomes' are accounted for in the sub model *Care Quality*, and are reflected on by insurers and medical specialists in *Expectations*. Lastly, the 'things needed in a shift for the patient', can be interpreted as the perception of nurses their effectiveness. Generally nurses see themselves as effective when the patients are satisfied (Newman et al., 2001; Tucker & Edmondson, 2003). This last relation is captured by *Care Quality* and its effect on the nurses *Job Resources*.

In the model, the feedback effects of 'good outcomes' are assumed to determine the future states of workload, nurses' characteristics and outcomes. It should be noted that this thesis approaches these factors on the group level of nurses, not taking into account individual differences.

2.4.1. Yerkes-Dodson Law

There is a long history of studies related to work pressure (Sonnentag & Frese, 2003). Yerkes and Dodson first described a relationship between stimulus strength and habit formation in mice (Yerkes & Dodson, 1908). They found an inverted u-shaped curve, with too little and too much stimuli resulting in a longer time to form a habit, and in the middle an 'optimal' amount of stimuli causing the fastest learning process. This inspired later research to interpret it as a general law, assuming applicability to humans, and reformulating the stimulus strength and habit formation to various concepts related to stress and performance, similar to Figure 2 (Teigen, 1994). However, the relationship is not well-supported among job performance research (Westman & Eden, 1996). Recent authors are even conspicuous of its existence, arguing that it mostly depends on the type of stimuli (Lepine, Podsakoff, & Lepine, 2005, p. 770).

However, Lupien et al. provides evidence for an inverted U-shaped curve for stress, depicted in Figure 1, noting the resemblance to the Yerkes-Dodson's law (Lupien, Maheu, Tu, Fiocco, & Schramek, 2007, p. 215). They state that the relation between glucocorticoids, a stress hormone, and cognitive processing, also referred to as vigilance or 'the optimal state of cognitive efficiency', is equivalent to an inverted U-shape. With too much or too little of the stress hormone resulting in a less than optimal cognitive efficiency (Lupien et al., 2007, p. 215).

In SD literature the effects of the inverted U-shaped curve occurred in conceptualizing the relation between schedule pressure and outcomes (Stermann, 2000, p. 578), explaining disaster as result from normal work interruptions (Rudolph & Repenning, 2002), discussing potential threats to hospitals' emergency departments (Morrison & Rudolph, 2011), and describing how organizations can decrease their capacities while searching for the optimal workload (Rahmandad & Repenning, 2016). In contrast with SD, in agent based modelling the use of the inverted U-shape of stress has led to successful applications for explaining stress and absenteeism (Duggirala, Singh, Hayatnagarkar, Patel, & Balaraman, 2016; Silverman, 2001; Singh, Duggirala, Hayatnagarkar, & Balaraman, 2016).

Figure 1. Hypothesized Yerkes-Dodson Law portraying the association between pressure and performance.

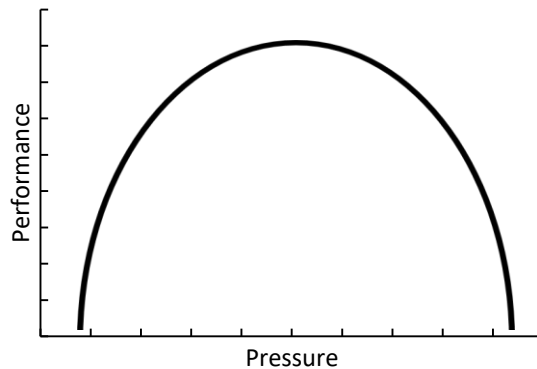
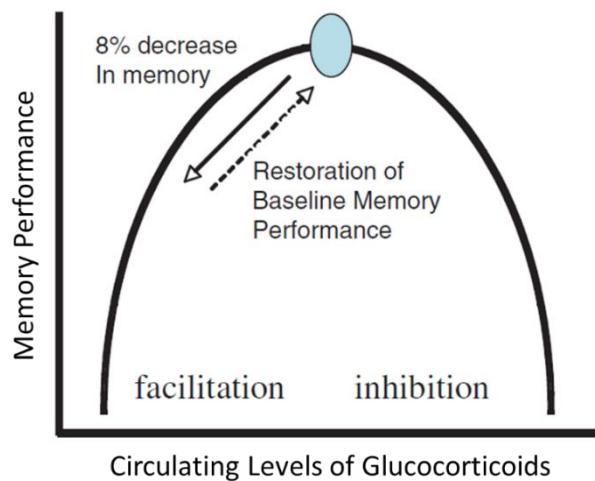


Figure 2. Memory performance as result of levels of circulating stress hormone (graph partially adopted from Lupien et al., 2007, p. 215).



The model in this thesis hypothesizes that the inverted U-shaped curve of stress applies to the context of nurses working at a cardiology unit in a hospital. It is reasoned that when nurses work too often beyond the optimal cognitive efficiency it can erode their working capabilities on the long term. The erosion of these working capabilities might be visible in the quality of care delivered by nurses on the long term; i.e. over a time span of ten years.

2.5. Organizational Capabilities

Organizational capabilities are, in short, defined as high-level routines (or a collection of routines) relevant to continue the operations of an organization (Winter, 2003). In which routines are referred to as “behavior that is learned, highly patterned, repetitious, or quasi-repetitious, founded in part in tacit knowledge, and the specificity of objectives” (Winter, 2003, p. 991). Winter distinguishes among zero-level

capabilities, necessities for the daily operations in an organization, and higher level-capabilities, also termed dynamic capabilities, which are routines able to make change in zero-level capabilities.

Morrison et al. defines separate work interruptions as the quantity of workload: “component mental steps needed to solve interruptions” (Morrison & Rudolph, 2011, p. 1248; Rahmandad & Repenning, 2016). Organizational capabilities are used for coping with the amount of work interruptions (the ‘workload’), and these organizational capabilities are defined as dynamic, due to their representation as stocks which change through flows. This is congruent with Winter stating that zero-level capabilities can also change over time. Winter differentiates between ‘zero-level’ and ‘dynamic’ capabilities, whereas this research uses the word ‘dynamic’ to point out the possibility of non-linear changes over time. Hence, organizational capabilities are all possibly dynamic of which some might be categorized as ‘zero-level’ and other as ‘dynamic’ capabilities. An example is the state of *well-being* of the nurses, serving as a zero-level capability, since it is needed to provide a certain level of *quality of care*, and thus a *time per treatment*. *Job resources* in general might be perceived as a form of dynamic capabilities since these are able to change the level of *well-being*. However, as elaborated on in section 2.8, since *well-being* is also a *job resource* the distinction between zero-level and dynamic capabilities is obscured, and rendered irrelevant.

The model in this research uses the following definition of organizational capabilities: ‘a collection of learned routines subject to change over time’ to justify the use of stock variables for *Need for Recovery*, *Well-being*, and *Patient Satisfaction* (discussed later in sections 2.9, 2.11, and 2.13). *Job resources* are also regarded as an organization capability (see section 2.10). Hence, the vague concepts of *well-being* and *need for recovery* are assumed to be a set of routines, or patterns, in the minds of the employees, consisting of their interpretations of their capacities, environment (work and colleagues), and previous states of being, which can be changed through learning different patterns over time. Furthermore, *patient satisfaction* is also regarded as a learned pattern of patients and potential patients, and serving as an organizational capability since it functions as a *job resource* (elaborated on in sections 2.8 and 2.10). Finally, expectations are equally regarded as learned patterns subject to changes over time and thus modeled as stocks (later addressed in section 2.13).

2.5.1. Stress and Change in Organizational Capabilities

Behavioral coping strategies are an example of routines that function as the *Well-being* of employees. In acquiring behavioral coping strategies -and for new learning in general- stress is found to be useful, and behave according to an inverted U-shaped curve (Lupien et al., 2007, p. 212). The following rationale is applied in this thesis: the effects of stress on brain structures relevant to learning and memory can change the sets of routines -in thought and behavior- which are part of an organization’s capabilities. At the nursing-cardiology department of HNL, similar structures as organizational capabilities are the *Need for Recovery* and *Well-being* (see Figure 3). Both are able to grow and subject to erosion over time, and relevant to the continuation of the operations of the hospital (Rahmandad & Repenning, 2016).

Research found a common relationship between job stress and mental health among health care professionals (LeBlanc, MacDonald, McArthur, King, & Lepine, 2005). It has been shown that paramedics are less accurate in medication dosages under stress (LeBlanc et al., 2005). Research among nurses demonstrated that stress might affect certain lifestyle factors, which contribute to the development of diseases (Lees & Lal, 2016). The same research argues that stress might affect the cognitive capability or performance in nurses (Lees & Lal, 2016, p. 52).

Some research does not find support for the relationship between stress and cognitive performance. One study of nurses hair cortisol levels, which measures the average stress over a 3-month period, did not reveal any effects on cognitive performance (McLennan, Ihle, Steudte-Schmiedgen, Kirschbaum, & Kliegel, 2016). It can be noted that this was only a one-time measurement, leaving out the effects of changes over time.

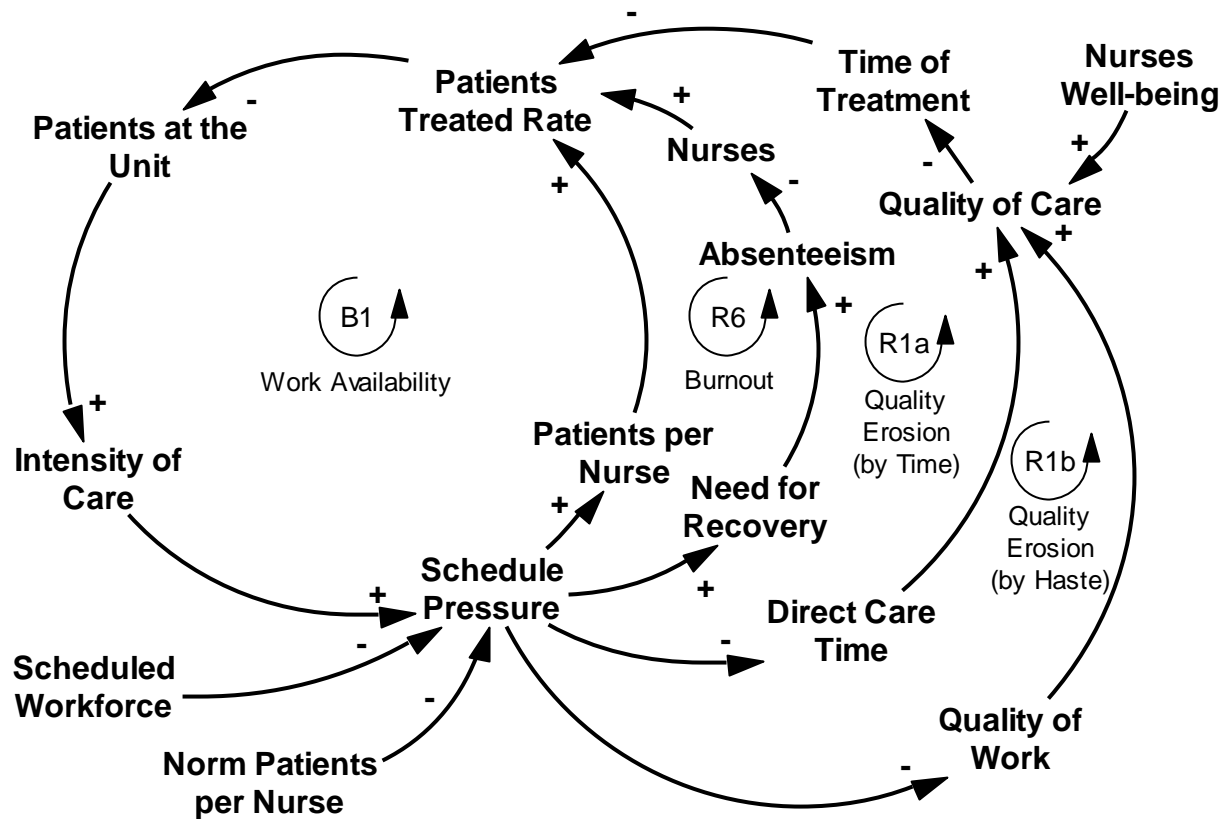
2.6. System Dynamics Modeling on Work Pressure

In an example of a service delivery setting the effect of schedule pressure on productivity represents an inverted U-shaped curve (Sterman, 2000, p. 563). The schedule pressure refers to the balance between on the one hand the number of employees and the normal task time, and on the other hand the number of tasks and the target task times (see Figure 3 and the variable *Schedule Pressure*). The inverted U-shaped curve is due to two effects: first, workload increases the service deliveries (see the “Work Availability” loop (B1) in Figure 3), and second, workload results in fatigue which can decrease the service deliveries (see the “Burnout” loop (R6) in Figure 3). In this thesis, workload that causes fatigue is conceptualized as a schedule pressure that influences a need for recovery (see 2.12.). The service delivery example illustrates effects in systems where the labor is primarily determining the capacity of work. In these types of systems there are only four ways that can affect the workload. Described from the perspective of a health care unit with a predetermined inflow of patients, these four ways are: 1) reducing the arrival of new patients by limiting the number of available beds, 2) add service capacity by having more, or more qualified personnel, 3) increase the number of patients per employee, and 4) reduce the length of stay of the patient at the unit.

At the cardiology-unit of HNL, the first, closing beds, happens only very rarely when the workload is at peak levels. When it happens patients are obliged to move to other units or hospitals. The second, service capacity, is often restricted by the predetermined number of nurses that are scheduled (shown by the variable *Scheduled Workforce* in Figure 3). Occasionally extra personnel are called for when there is an unexpected higher workload or employees call in sick. Next to that, the age, experience, and function play a role in the service capacity, which is further described in section 2.7. Furthermore, the well-being of the employees plays a role in the quality of care (see section 2.12, and the variable *Nurses Well-being* in Figure 3). Thirdly, working overtime generally does not happen. However, the number of patients can increase per employee, providing for a greater workload during the worked hours (see the “Work Availability” loop (B1) in Figure 3). The fourth way, the amount of time the patient stays at the unit, is already seen to decrease over the time-span of 2012 to 2016, and is believed to become even smaller in the future.

How the model in this thesis incorporates the previously discussed aspects is portrayed in Figure 3 which provides a high level overview of a component of the model, referred to as a Causal Loop Diagram (CLD). For an introduction to system dynamics see section 4.10, for explanation on the symbolism see section 3.2). Each of the figures in this chapter, starting from Figure 3 and ending at Figure 6, are representations of components of the complete model. None of these represent the ‘full picture’. The purpose of these figures is to explicitly portray the hypothesized feedback loops relevant to the corresponding sections in this chapter. An aggregated ‘full picture’ stock-and-flow diagram is described in Chapter 3, Figure 7, and the feedback loops of Figure 3 are a more detailed illustration of the “Work Availability” (B1), “Quality Erosion” (R1), and “Burnout” (R6) loops in Figure 7.

Figure 3. Aggregated CLD (Causal loop diagram) depicting a component of the model which illustrates feedback loops related to work pressure.



2.7. Nursing Workforce

Research on the intensity of care starts with observing the patients to nurses ratio (Needleman, Buerhaus, Mattke, Stewart, & Zelevinsky, 2002). This thesis compares the total hours of patients treatment time at the unit, i.e. the sum of all the hours of each patient at the unit in one month, with the total scheduled hours of employees. This is reasoned to give an accurate number of the number of patients per employee. These variables are accounted for in the sub-models *Workforce* and *Patient Flow* (see A2.2 and A2.3. for the lists of equations). Next to the patients to nurses ratio it is also observed that experience and age might play a role in the experience of the workload.

For example it was found that higher staffing of experienced nurses is associated with lower rates of adverse outcomes (Needleman et al., 2002). These effects were not found for increases of helping staff, and unspecialized staff members, suggesting that this holds only for experienced nurses. Research also found that patients at acute care units with more experienced nurses had a smaller time of stay (Yakusheva, Lindrooth, & Weiss, 2014). To the nurses at the cardiology-department of HNL, their own and their colleagues work experience is a major job resource. The sub-model *Job Resources* uses the average experience of the nurses in its effect on their well-being (the variable well-being is not that of being well in the common sense, but refers to the employee well-being which also involves the employees effectiveness with respect to job outcomes, see 2.14, consequently the nurses well-being influences the quality of care which is then assumed to reduce the time of stay of the patient (also see Figure 3).

Research on the role of age among nurses has found counterintuitive results. For example, in the effect of age on fatigue research suggests that younger nurses are more prone to fatigue and score higher on the need for recovery (Bos, Donders, Schouteten, & van der Gulden, 2013; Winwood, Winefield, & Lushington, 2006). For explaining these results it is suggested that older employees have a better fit with their work, and adjust their expectations according to their possibilities (Bos et al., 2013). Another explanation is that younger employees get more nightshifts or otherwise a larger part of the intensity of care, and hence are more affected by fatigue. Research on differences in age also found that older nurses are generally more

satisfied (Bos et al., 2013, p. 999). Bos et al. (2013, p. 999) found that in the 55+ age group the average job dissatisfaction was significantly lower than in the youngest age group, implying that younger workers are less satisfied. The model in this thesis assumes that the average age of the nurses can affect the time they need to recover; i.e. when the average age is lower the fatigue onset time is smaller resulting in a higher level of need for recovery for younger teams (also see 5.3.2.). A higher need for recovery results in a lower nurses well-being, reflecting a greater job dissatisfaction. Also vice versa, when the average age of the nurses is higher it takes longer to build up fatigue, and the levels of need for recovery are lower than with a younger group of nurses. The lower need for recovery causes a higher level of nurses well-being than it would otherwise be, reflecting the lower levels of job dissatisfaction among older nurses.

2.8. Job Demands and Resources Theory

The theory of job demands and job resources (JD-R theory; Bakker & Demerouti, 2014, p. 8), is often used in research on employee well-being and job outcomes. Bakker and Demerouti state: “it is an illusion to think that identifying a few work characteristics in a model on job stress or motivation would be sufficient to describe the complexity of contemporary jobs.”. A strength of the JD-R model is its flexibility of use, due to considering the interaction between all relevant job demands and job resources to predict work outcomes, and based on that identifying important job demands and job resources. The flexibility in the use of the theory results in a broad application over the last decade, such that the model matured into a theory (Bakker & Demerouti, 2014, p. 8).

At the basis of the JD-R model lies the assumption of a dual pathway in which a combination of job demands and job resources each affect motivation (path 1) and strain (path 2), which result in organizational outcomes. According to the authors, the definitions of job demands and job resources are as follows: “Job demands refer to those physical, psychological, social, or organizational aspects of the job that require sustained physical and/or psychological effort and are therefore associated with certain physiological and/or psychological costs (Demerouti et al., 2001). Examples are high work pressure and emotionally demanding interactions with clients or customers. Although job demands are not necessarily negative, they may turn into a form of hindrance demands when meeting those demands requires high effort from which the employee has not adequately recovered (Meijman & Mulder, 1998; see also section 2.9 on the Need for Recovery). Job resources refer to those physical, psychological, social, or organizational aspects of the job that are: (a) functional in achieving work goals; (b) reduce job demands and the associated physiological and psychological costs; or (c) stimulate personal growth, learning, and development” (Bakker, 2011; Bakker & Demerouti, 2007). Examples of job resources are job security, reward, and autonomy.

JD-R theory proposes that employee motivation, health and work characteristics can influence each other over time (Bakker & Demerouti, 2014, p. 22). The theory postulates the idea of loss cycles and gain cycles, similar to the notion of feedback loops in system dynamics. The loss cycle illustrates the causal pathway of daily job demands causing exhaustion, resulting in self-undermining actions, which in turn cause greater job demands (see the “Self Undermining” (R2) feedback loop between *Need for Recovery* and *Hindrance Demands* in Figure 4). The gain cycle represents a virtuous loop in which job resources cause a greater work engagement (see the “Work Engagement” (R4) feedback loop between *Job Resources* and *Well-being* in Figure 4), that result in more job crafting activities, which increases the job resources (Bakker, 2015, p. 841). Additionally these cycles interact with each other. It is proposed that an abundance of job resources can buffer the effect of job demands on exhaustion through the “Striving at Work” (R8) loop, and that with sufficient job resources, job demands can boost work engagement (through the “Challenge Resolvment” loop in Figure 4).

In earlier SD literature the relation between perceived demands and perceived resources are modeled as antecedents to stress (Morris, Ross, & Uliuru, 2010, p. 10), but, thus far, no simulation modeling seems to have been conducted based on JD-R theory. The model in this thesis builds on the propositions of JD-R theory, and an aggregated overview of the feedback loops is portrayed in Figure 4. The two main feedback loops in this domain are a reinforcing feedback loop between job resources and nurses well-being.

Secondly, by the effects that job demands have on the need for recovery, and role that the level of need for recovery plays in hindrance demands. Research in job demands suggests that diagnosing each job demand as a hindrance demand or challenge demand is useful in identifying what influences employee well-being (Lepine et al., 2005, p. 771).

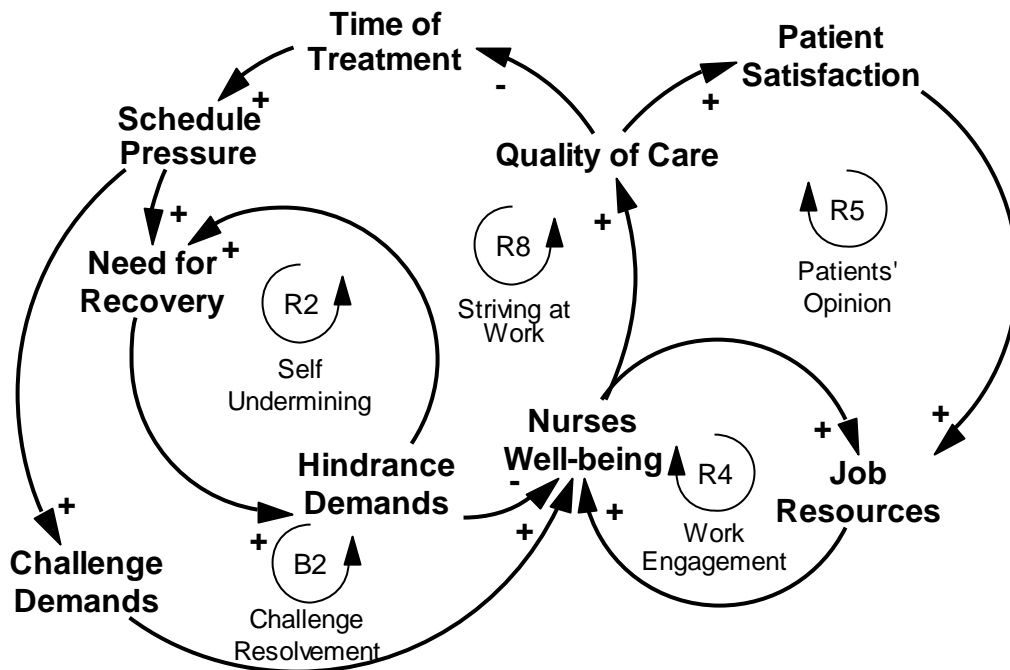
2.8.1. Hindrance and Challenge Demands

Bakker and Sanz-Vergel (2013) build further on the hindrance and challenge demands framework of Lepine and others (2005). In a first study with nurses in home health care they asked how hindering and challenging work pressure and emotional demands were. For the English term “hindrance”, the Dutch word “stressvol” was assumed to have the same connotation. For emotional demands there was asked for how challenging or hindering they thought “dealing with clients”, “demanding clients”, and “emotionally charged situations” were. Based on literature and their own results they conclude that work pressure is perceived as a form of hindrance demand, and emotional demands a form of challenge demands (Bakker & Sanz-Vergel, 2013, pp. 398–400). Furthermore, in a second study with nurses, they found emotional job demands to positively influence the effect of personal resources on personal well-being, and work pressure to undermine that effect (Bakker & Sanz-Vergel, 2013), thus Figure 4 has the variable *Challenge Demands* as a result of *Schedule Pressure*, whereas it actually depends on what type of job demands are part of the schedule pressure. Also the *Hindrance Demands* are mainly due to *Need for Recovery*, however certain job demands are part of *Hindrance Demands*. Figure 4 is drawn to provide a simplified overview of possible feedback loops. Also, Figure 4 shows that *Challenge Demands* and *Hindrance Demands* influence the *Nurses Well-being*. A more detailed discussion of the effects on well-being is provided in section 2.11.

Lepine and others note that the differences of hindrance and challenge demands is in sharp contrast with the inverted U-shaped curve (Lepine et al., 2005, p. 770). Their argument is that the inverted U-shaped curve does not differentiate between types of job-stressors but only accounts for the quantity, such that till some point all types of stress are good (Lepine et al., 2005, p. 770). Nonetheless, the same research argues that challenge demands might be increased, by simultaneously decreasing the strain of those demands, such for buffering the negative effects of demands on long-term health (Lepine et al., 2005, p. 770). This argument, building on the notion that too many demands can have a negative effect on performance after some time, does invoke the notion of an inverted U-shaped curve of job demands.

Hindrance demands in this thesis are defined as those demands that increase perceived work pressure (in Dutch “stressvol”), and which are not directly related to providing care to the patient (“weinig nuttig”), such as various registration procedures (also see section 2.8.1). Challenge demands are defined as emotional demands such as “dealing with clients”, “demanding clients”, and “emotionally charged situations”. Figure 4 provides a comprehensive overview of the hypothesized causal relations based on Job Demands-Resources theory. The feedback loops portrayed in Figure 4 correspond to the loops indicated with the “Challenge Resolution” (B2), “Self Undermining” (R2), “Work Engagement” (R4), “Patients’ Opinion” (R5), and “Striving at Work” (R8) loops of the model in Figure 7 of Chapter 3.

Figure 4. Aggregated overview of a component of the model illustrating the feedback loops corresponding with job demands and resources theory.



2.9. Need for Recovery

Need for recovery is a proven construct for measuring fatigue at work among health care professionals (Sonnentag & Zijlstra, 2006; van der Hulst, Van Veldhoven, & Beckers, 2006; Van Veldhoven & Broersen, 2003). It is reasoned that fatigue from work accumulates when the need to recover from a previous working day is not completely satisfied (Kompier, 1988; van der Hulst et al., 2006, p. 6; Van Dijk, Dormolen, Kompier, & Meijman, 1990; Van Veldhoven & Broersen, 2003, p. 4). In general research finds the most important factors in accumulation of fatigue to be emotional workload, and the pace and amount of work (Van Veldhoven & Broersen, 2003, p. 3). This is consistent with research among home care nurses that found that both emotional demands and work pressure can cause people to feel tired (Bakker & Sanz-Vergel, 2013, p. 398). Need for recovery is found to be a predictor of fatigue-impaired well-being among health care employees (Sonnetttag & Zijlstra, 2006, pp. 333–345).

Earlier, the accumulation of work fatigue is modeled in system dynamics as a result of schedule pressure (Sterman, 2000, pp. 579–582). The model in this thesis incorporates a similar structure. The need for recovery is dependent on the schedule pressure (Sterman, 2000, pp. 579–582), but also on hindrance demands, and challenging demands, since both can cause fatigue (Bakker & Sanz-Vergel, 2013, p. 398). As discussed in 2.11., the time it takes for fatigue to accumulate is reasoned to be dependent on the average age of employees (Bos et al., 2013; Winwood et al., 2006), see also 5.3.2. The hypothesized effects of need for recovery in the model are portrayed in Figure 7, Chapter 3, by feedback loops R2 and R6.

2.10. Job resources

The job resources used in this thesis are based on those generally used in JD-R theory, for example in studying burnout (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001, pp. 503–504). Demerouti and others used the following six factors to conceptualize job resources: 1) feedback, the information received on ones work performance; 2) rewards, the job's salary or benefits; 3) job-control, the autonomy in decision making; 4) participation, the amount of influence on management decision making; 5) job-security, the

threat of losing one's job; and 6) supervisor support, the backing and guidance one receives from their superior.

Next to that, nurses at HNL and literature suggested other factors of which three were included in the knowledge elicitation session and the model: patient satisfaction, well-being, and experience; see also 2.11, 2.13, and 5.2.8. (Newman et al., 2001, p. 65; Sonnentag, 2015, p. 278; Tucker & Edmondson, 2003, p. 60). That patient satisfaction functions as a job resource is reported by previous studies. Research by Newman et al. (2001, p. 63) suggests that patient satisfaction is an important driver for nurses, and that patient dissatisfaction results in nurses dissatisfaction with their work. Similarly, Tucker and Edmondson (2003, p. 60) found that nurses are gratified when they can continue providing patient care after working around a problem that prohibited it. Secondly, well-being is suggested by Bakker to influence job resources (Bakker, 2015, p. 841). More specifically, the gain cycle as described in section 2.8, is incorporated in the model by the feedback loop between well-being and job resources (see Figure 4, and R4 in Figure 7). Third, work experience has a clear fit in the definition of job resources, and nurses and management suggest that this is an important factor in their work. Job resources that are not taken into consideration are the work-home balance, and the interpersonal environment (Sonnentag, 2015, p. 278). The exclusion of these last two factors poses a weakness to the model, since variation in these areas are not measured but suggested to have strong impact on well-being.

2.11. Well-being

Sonnentag, in her review on the dynamics of well-being, describes that employee well-being is not a stable concept; i.e. employee well-being can increase and decrease over longer time periods like months and years (Sonnentag, 2015, p. 262). Building on the previous work in employee well-being, it is suggested that the increases and decreases are due to positive and negative well-being indicators, also dubbed as job stressors and job resources (Sonnentag, 2015, pp. 265–266). Moreover, it is also concluded that the evidence from within- and between-person studies show large similarities (Sonnentag, 2015, p. 281), and are thus useful for testing interchangeably. Furthermore, it was found that employee well-being non-linearly changes with age and within the first few months of organizational entry (Dunford, Shipp, Boss, Angermeier, & Boss, 2012; Kammeyer-mueller, Wanberg, Rubenstein, & Song, 2016; Warr, 1992; Zacher, Jimmieson, & Bordia, 2014). Based on these findings well-being is conceptualized as a stock variable in the model. Differences for age are accounted for in the development of the need for recovery. The newcomer effect, different levels of employee well-being in the first few months, is not taken into consideration in the model.

Sonnentag distinguishes four major positive- and three major negative aspects to employee well-being. The four positive aspects are 1) job resources, 2) positive aspects of the interpersonal environment, 3) personal resources, and 4) positive aspects of the work-home interface. The three negative factors are 1) job stressors, 2) negative aspects of the interpersonal environment, and 3) negative aspects of the work-home interface.

The model in this thesis broadly covers the areas of job resources, personal resources and job stressors as identified by Sonnentag (see the sections 2.9, 2.10, and 2.11.). Effects related to the work-home interface and the interpersonal environment are excluded from the model, assuming in the models behavior that their effects are zero.

In line with the interaction effects found by Bakker and Sanz-Vergel, well-being in this thesis is modeled as an outcome of the effects of job resources, hindrance, and challenge demands, and the need for recovery (Bakker & Sanz-Vergel, 2013, pp. 405–406), see also 5.3.2. They found that the effect of personal resources on work-engagement is strong when there are high challenge demands. In contrast, when there are low challenge demands, virtually no effect was found by personal resources on work-engagement. Next to that they found that there is little effect of personal resources on flourishing when work pressure is high. In contrast, when the work pressure is low, there is a strong effect of personal resources on flourishing.

Flourishing and work engagement are seen as constructs related to well-being but are by definition not the same. Flourishing is considered to be an indication for context-free psychological well-being and optimal human functioning (Bakker & Sanz-Vergel, 2013, p. 402; Diener et al., 2010). Work-engagement is a measure comprising of dedication, vigor and absorption (Schaufeli, Bakker, & Salanova, 2006). It was hypothesized that the interactions among personal resources, and hindrance and challenge demands worked through both flourishing and work-engagement, but to both one of them was not found to be a statistically significant predictor. The authors clearly state that these can be specific findings of that study or due to limited statistical power, and that the explanations of the effects are ad-hoc, that should be tested in future research (Bakker & Sanz-Vergel, 2013, p. 407). Whether it is about flourishing or work engagement, both constructs are closely entangled with employee well-being, and thus with the concept of well-being relevant to this thesis.

Building on these findings, the model in this thesis incorporates the interaction effect among job-resources and hindrance and challenge demands as predictors of well-being. However, this in itself would not fully do justice to well-being, since it is also found to be influenced by the need for recovery (Sonnentag & Zijlstra, 2006). Thus, well-being is conceptualized as depending on the job resources, hindrance and challenge demands, and the need for recovery. This leads to the following definition of well-being for this thesis: the team's mental state, comprised of their job resources, job demands, and fatigue, which is predictive of job performance, and subject to fluctuations over time. This definition is close to descriptions by leading authors in the field on employee well-being (Cropanzano & Dasborough, 2015; Ilies, Aw, et al., 2015; Ilies, Pluut, et al., 2015). Since well-being concerns a team's mental state, it is assumed to correspond with an organizational capability and modeled as a stock variable which changes over time. The construct of well-being as used in this thesis should not be confused with an individual's general psychological well-being.

2.12. Care Quality

Literature strongly suggests a relationship between well-being and job performance (Cropanzano & Wright, 1999; Wright, Bonett, & Sweeney, 1993; Wright & Cropanzano, 2000). Hence, this research assumes that the quality of care is, among others, caused by well-being. Next to well-being, the quality of care is caused by the quality of work, and the direct care time. The well-being measure is a stock-variable accounting for the previous changes in work, whereas the quality of work and direct care time are directly caused by the schedule pressure at any given moment in time. This operationalization of quality of care is not based on literature, but hypothesized to be a good indicator for the quality of care in reality.

In SD literature, an example of a service delivery model describes the effects of available time and quality of work on the work output (the 'midnight oil' and 'cutting corners' loops, Sterman, 2000, p. 563). Similarly, the model in this research assumes that the quality of care can affect the time of treatment.

It is reasoned that the causal effects between nursing care quality and its outcomes cannot be established, since it is only based on observational data, instead of random and controlled lab-experiments (Griffiths, Maben, & Murrells, 2011). However, the lack of statistically sound evidence should not result in concluding that the causal effect is non-existent. It is plausible that the quality of care affects the treatment time, even if it were only through the work-experience of nurses (Yakusheva, Lindrooth, & Weiss, 2014).

In conclusion, the quality of care is hypothesized to be caused by the well-being, quality of work, and direct care time. The *Quality of Care* affects the *Patients Treated Rate* through influencing the *Time per Treatment* (see Figure 3 and Figure 7 in Chapter 3). Next to the *Patients Treated Rate*, the quality of care is also affecting *Patient Satisfaction*, as discussed in the following section.

2.13. Patient Satisfaction and Disconfirmation Paradigm

Patient satisfaction is a long established performance measure of hospitals (Hutchinson, 1993, p. 19; Sitzia & Wood, 1997, p. 1831). Patient satisfaction is found to be strongly affected by demographics and psychosocial variables, but also by expectations (Sitzia & Wood, 1997, p. 1840). Hutchinson also provides evidence that expectations and beliefs play an important role in patient satisfaction, and reasoned that

In this conceptualization of patients' expectations, it is assumed that higher levels of satisfaction, i.e. beyond the expectation, will cause an increase in the expectations. Consequently, when expectations rise and at some point be equal to or greater than the actual perceived quality, patients' satisfaction is limited to average or will even sink to lower than normal values. This will in turn affect the job resources as described in 2.13. Moreover, insurers are increasingly more acting on patient satisfaction and quality of care in competing at the insurers market. Insurers also update their expectations on the quality of care. This results in two balancing feedback loops; an aggregated overview of how this is implemented in the model is shown in Figure 5. These balancing feedback loops are a more detailed illustration of the "Expectations Adjustment" loop (B3) in Figure 7. The following sections elaborate on the role that insurers play in the work pressure of nurses.

2.14. The Dutch health care market

The Dutch health care system has undergone market oriented reforms since the 1980's (van de Ven, 1987; Zuiderent-Jerak, Grit, & van der Grinten, 2011, p. 8). The last 10 years the playing field has become even more market driven by introduction of a single universal health insurance scheme (Bartholomée & Maarse, 2006, p. 10). The intention was to sustain accessibility, quality and fiscal feasibility; while providing more freedom of choice, solidarity and efficiency (Maarse, Jeurissen, & Ruwaard, 2016, p. 161; van de Ven & Schut, 2008).

The changes in the health care system to date had notable effects on hospitals. There was a steep increase in independent treatment centers from approximately 30 in 2000 to 280 in 2010 (these centers mainly provide less complex routine care, and some are (co)-owned by hospitals; KPMG/Plexus, 2014; Maarse et al., 2016, p. 169). Independent treatment centers still cover only 3 to 4 percent of total hospital revenues (Maarse et al., 2016, p. 169; Nza, 2012). Moreover, there has been a decrease of 25% in number of hospitals between 2009 and 2014, and due to financial distress and consolidations a further decline is expected (Maarse et al., 2016, p. 169). In general, it is argued that these changes have made hospitals more efficient, caused some improvements in client service, reduced waiting times in some categories, and increased productivity (Maarse et al., 2016, p. 170).

Nevertheless, there is no definite conclusion on whether the growth on expenditures has slowed down, for retaining fiscal sustainability. Moreover, the changes gave rise to suspicions such as the consolidation of hospitals and health insurance companies, insurers risk selection practices, and hospitals' inappropriate ways of billing (Maarse et al., 2016, p. 175). The current forms of competition and changes are closely resembling what Porter defines as the wrong kinds of competition in health care (Porter & Teisberg, 2004). As summarized currently the locus of competition is on the level of "Who pays", instead of "Who provides the best value" (Porter & Teisberg, 2004, p. 7).

As for making decisions on "Who pays", hospitals are obliged to deliver data on patient satisfaction and patient outcomes, of which the results are publicly available. To assess differences in quality among care providers, insurers need "objective and comparable information", however it still appears to be an open debate on what quality of care substantiates. From the hospitals' perspective, insurers seem to measure quality only in financial terms, without showing interest in better quality for higher costs (Maarse et al., 2016, p. 171; Zuiderent-Jerak et al., 2011). Some insurers had started collecting quality data in the form of performance indicators, and introducing volume norms on their own, making negotiations harder and increasing the pressure for hospital's performance.

2.14.1. Performance Indicators and Registration Procedures

The development of performance indicators (PI's) for the quality of health care is congruent with a more market-driven health care system. PI driven health care management took off in the Netherlands since 2003 (Maarse et al., 2016, p. 171; Pollitt, Harrison, Dowsell, Jerak-Zuiderent, & Bal, 2010). Originally intended to help patients, insurers, and general practitioners to compare care among providers, currently there is suspicion regarding the useful workings of PI's (Pollitt et al., 2010, p. 24). It drives up competition

among health providers for delivering the best PI's, while there is evidence that good PI-composite scores can exist side-by-side with poor service (Jacobs, Goddard, & Smith, 2006). Moreover, the implementation of PI's resulted in managerial target setting, regulatory services (instead of physical inspections), and sanctions at the institutional or individual level; all measures suspected to have no benefits to the quality of care, and only serve as an administrative burden in the work of nurses.

The hypothesized effect of this administrative burden is portrayed in Figure 6 with the "Earning Autonomy" feedback loop (R7) in which registration procedures increase the workload, visualized as a link to the intensity of care. In turn, an increased intensity of care causes a lower quality of care since there is a slightly greater schedule pressure. Because the quality of care is lower, the difference to the expectations of the market is greater, which is an incentive to policy makers to create more performance indicators, eventually resulting in more registration procedures. Next to that, the "Patients' Opinion" loop (R5), plays a role in this process, where a lower quality of care causes a lower patient satisfaction, which negatively affects the job satisfaction of nurses, shown by the causal links between job resources, well-being and patient satisfaction. Furthermore, the "Hindrane Drenching" loop (R3) is at work. The registration procedures are perceived by nurses as unnecessary administrative work, not adding to the quality of care. Thus an increase in these registration procedures function as additional hindering demands, further reducing the possible effect that job resources could have on well-being.

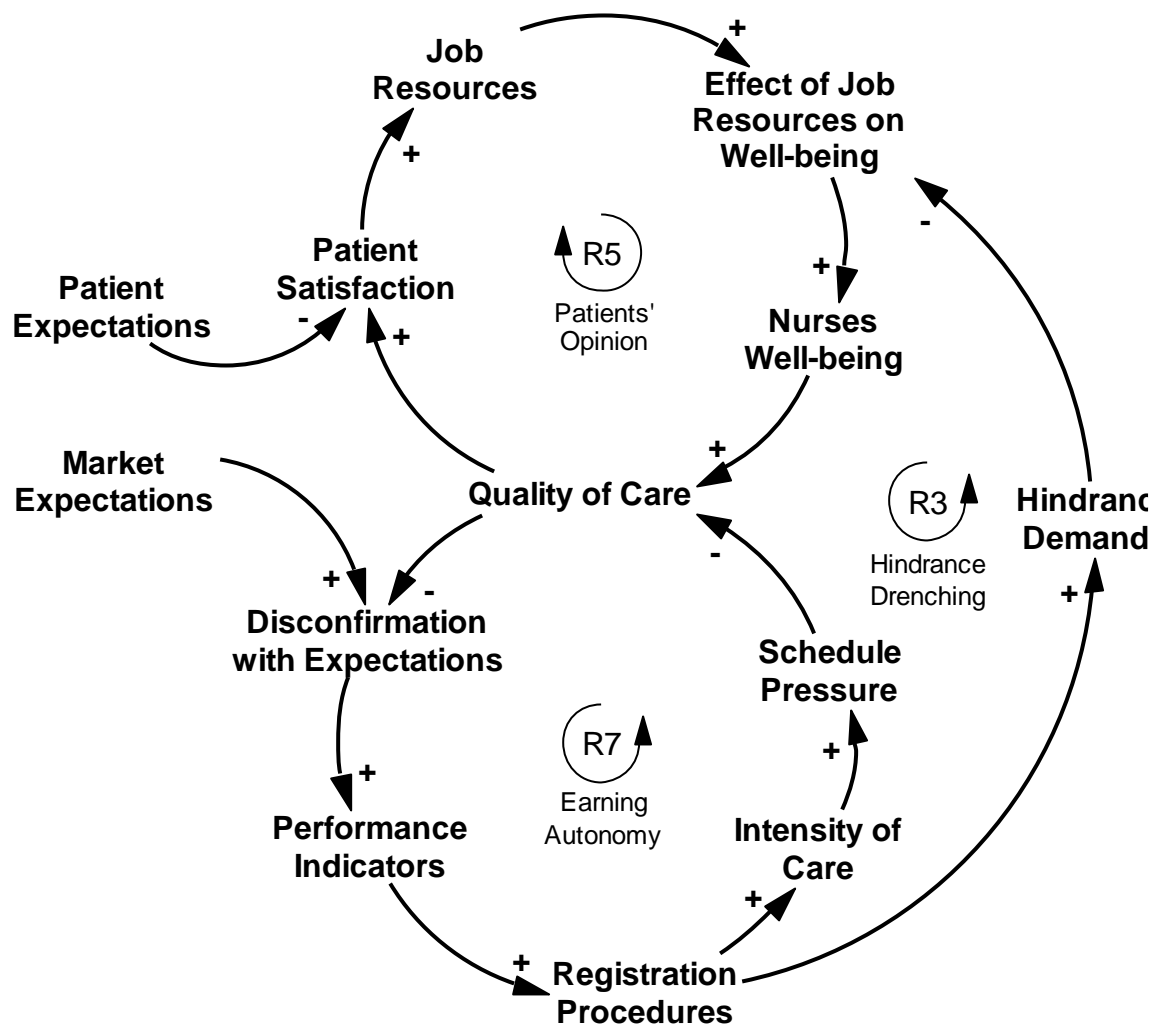
Pollitt and others (2010, p. 9) describe a *logic of escalation*, reasoning that PI's, and the interaction among various stakeholders, cause an increase in the number and complexity of PI's, substantiating the existence of the "Earning Autonomy" loop in Figure 6.

It is observed that the development of quality indicators, the PI's, is mostly dependent on the self-initiative of stakeholders such as insurers, but also on medical communities of physicians who started to develop their own quality indicators as a countermove to those of insurers (Maarse et al., 2016, p. 168; Maarse, Ruwaard, & Spreeuwenberg, 2013). Moreover, as a result of these PI's, currently at the nursing-cardiology unit of HNL, various registrations regarding pain, decubitus, nutrition and patient risks have to be conducted multiple times a day for each patient, contributing to the overall workload of nurses.

Next to its contribution to the workload these registration procedures limit the professional judgment of nurses, such that PI's cause regular surveys to substitute nurses' professional autonomy. Similar development has been seen in SD work in the emergence of a compliance culture among social workers in child protection (Lane, Munro, & Husemann, 2016). Here it was found that more prescriptive, rules based work led to less use of professional judgement, which increased the number of errors and simultaneously decreased the ability of acknowledging errors since one acted according to the rules (Lane et al., 2016, p. 616). The rules based work and registration procedures are regarded as hindrance demands by the nurses at the cardiology-department of HNL. These hindrance demands then impair the effect of job resources of well-being, in a similar fashion as rules impairing professional judgement. In the model of this research the nurses well-being –a mental state predictive of job performance- is then lower than it could otherwise be, resulting in a lower quality of care.

The feedback loops as discussed in this section form the theoretical foundation for the "Hindrane Drenching" loop (R3), "Patients' Opinion" loop (R5), and "Earning Autonomy" loop (R7) of the model shown in Figure 7. Figure 6 is a more elaborate description of the rationale of these loops in the actual model.

Figure 6. Aggregated overview of a component of the model illustrating the effects of performance indicators and expectations on the quality of care.



The diagrams presented in Figure 3 till Figure 6 together comprise the dynamic hypothesis of this thesis. A full diagram and loop description which brings all the variables of the theory together is provided in Figure 7 in the following chapter. Still, the figures 3 to 6, together with figure 7, do not portray all relations specified in the model. For all specifications see the supplementary material and appendix 2.

3.1. Loop Descriptions

The literature review and data collection provide a basis for the dynamic hypothesis, also referred to as 'the model' of this thesis. Figure 7 -a 'stock and flow model' in the system dynamics tradition- provides an aggregated overview of the non-linear causal relations that are hypothesized. Table 1 provides a short explanation on the symbols, and section 4.10 an illustration of system dynamics as a simulation method. Figure 7 portrays an aggregated overview of the model; i.e. not all variables are shown, but only those relevant to communicate the essence of the feedback loops. Table 2 provides a list of endogenous, exogenous, and excluded variables, and table 3 lists the details which are omitted from Figure 7. The figure contains 'feedback loop symbols', R1 to R7 and B1 to B3, together with names of the loops. The symbols and names of the loops indicate the non-linear dynamics of the system.

The *Intensity of Care* variable comprises of four stocks listed in table 3, which keep track of different characteristics of the *Cardiac Patients*. These total intensity of care results in the *Schedule Pressure*, and the relative amounts of *Challenge Demands* and *Hindrance Demands* nurses experience. The schedule pressure, together with the actual number of *Employees* and the *Quality of Care* result in a *Patients Treated Rate*.

In Figure 7, the "Work Availability" loop (B1) shows the non-linear relation between the *Schedule Pressure*, the *Patients per Employee*, and its effects on *Patients Treated Rate*. The *Patients Treated Rate*, and the *Patients Arrival Rate* determine the change in the number of *Cardiac Patients* over time, which is responsible for the *Schedule Pressure* for the next month, resulting in a causal loop. For example, a higher *Schedule Pressure*, results in more *Patients per Employee* which increases the *Patients Treated Rate*. A higher *Patients Treated Rate*, results in less *Cardiac Patients* than would otherwise be at the unit, such that the *Schedule Pressure* will also be smaller than would have been the case otherwise.

A greater *Schedule Pressure* is also found to reduce the *Quality of Care*. A lower *Quality of Care* in general causes patients to stay at the unit longer than necessary, shown by its effect on *Time of Treatment*. If more patients stay at the unit, this results in a greater *Schedule Pressure* than would otherwise be the case, resulting in an even lower *Quality of Care*. This describes a vicious or virtues feedback loop named "Quality Erosion" (R1).

The "Challenge Resolution" loop (B2) indicates that *Challenge Demands* positively influence the well-being of nurses. This results in a greater *Quality of Care*, causing a lower number of patients than would otherwise be the case. If there are less patients, there are also less *Challenge Demands*. Thus, the "Challenge Resolution" loop is a limiting or counteracting effect on the amount of challenging tasks.

The "Self Undermining" loop (R2) is a vicious loop portraying the effect of *Need for Recovery* on *Hindrance Demands*. Fatigue results in self-undermining actions that are hindering at work, and eventually result in a greater *Need for Recovery*.

Parts of the effects of the previously described "Challenge Resolution" and "Self Undermining" loops, (B2 and R2), are combined in the "Hindrance Drenching" loop (R3) in which *Hindrance Demands* negatively affect nurses well-being, that in turn affect the *Time of Treatment*. For example, when the amount of *Hindrance Demands* decreases, the nurses well-being rises and positively affects the workflow, resulting in less *Hindrance Demands* than would otherwise exist.

The "Work Engagement" loop (R4) portrays a reinforcing effect between *Job Resources* and *Well-being*. Well-being functions as a job resource at the same time, which reflects the 'job crafting' activities that working teams can show, as discussed in section 2.8.

Next to well-being, also *Patient Satisfaction* serves as a *Job Resource* as discussed in section 2.13. The dynamic effect is shown by the "Patients' Opinion" loop (R5). For example, with more job resources, a higher *Quality of Care* results in a greater *Patient Satisfaction*, which in turn, enhances the *Job Resources* of the nurses some time later. Equally, less satisfied patients can cause a downward spiral, in that the negative effect on nurses well-being can decrease the *Quality of Care* at a later stage.

The “Burnout” loop (R6) shows the effect that *Need for Recovery* has on *Absenteeism*. Absenteeism can, over a long time, result in less work done than would otherwise be the case. This creates a greater *Schedule Pressure*, and thus an even higher *Need for Recovery* in the next days or months.

The “Expectations Adjustment” loop (B3) comprises of the *Quality Expectations* stock. The *Quality Expectations* stock is a simplified representation of four stock and flow structures, of which the stocks represent: 1) the expectations of insurers and of medical specialists with respect to the quality of care, 2) the perceived quality of care of insurers and medical specialists, 3) the expectations of patients regarding the quality of care, and 4) the expectations of potential patients. These together form two balancing feedback loops since these limit and counteract on the effects of *Disconfirmation*, as shown in Figure 5 in section 2.13. For example, a long endured high *Patient Satisfaction* results in increased expectations of patients. Given that the *Quality of Care* does not change, but the expectations are higher, the *Patient Satisfaction* drops. With a lower *Patient Satisfaction* the enthusiasm of the nurses will be lower after a while; i.e. the lower *Patient Satisfaction* lowers the *Job Resources*, which in turn decreases the employee well-being of the nurses. The decreased employee well-being eventually leads to a somewhat lower *Quality of Care*, and this makes the *Patient Satisfaction* go down further, and simultaneously decreases the expectations. This gives rise to a counteracting effect of the role of expectations of patients.

The “Earning Autonomy” loop (R7) portrays a feedback loop in which the expectations of insurers and medical specialists can change the amount of registration procedures: the extend of rule-based working and autonomy of the nurses. The registration procedures are a form of *Hindrance Demands*. A greater number of *Registration Procedures* means more *Hindrance Demands* which decreases the effect of *Job Resources* on *Well-being*. This results in a lower *Quality of Care*, which is opposed to what was aimed for by imposing registrations and protocols. When this is not recognized, which is currently often the case, even more registration procedures and rule-based working gets implemented, resulting in a vicious causal effect. Lastly the “Striving at Work” loop (R8) describes a reinforcing feedback loop through the well-being of nurses. When there are higher levels of well-being this results in a better quality of work, causing a slight overall decrease in the necessary time for treatment. This decreases the schedule pressure, which reduces the negative effect on well-being. This description is of the virtuous effect this loop might have, but it works as a vicious causal circle in case the well-being goes down.

3.1.1. Operationalization

Many parts of the model rely on improvisation while attempting to stay as close as possible to the existing literature. Major aspects of improvisation that should be noted are: 1) the quality of care, 2) the expectations of patients, 3) the graphical functions, and 4) the time delays.

First, the quality of care is operationalized by multiplying the effect of well-being with the standard quality of care, resulting in the variable *Potential Quality of Care* (see formula 1). The deviation that the level of well-being has from its normal value, becomes the deviation that the *Potential Quality of Care* has from the standard. Furthermore, this *Potential Quality of Care* is evenly affected by the current *Quality of Work* and *Direct Care Time* (see the first part of formula 2), as represented in Figure 3, to create the variable *Actual Quality of Care*. That the *Quality of Work* and *Direct Care Time* evenly affect the *Actual Quality of Care* is provided by the multiplication with $\frac{1}{2}$.

Potential Quality of Care due to Wellbeing

$$= \text{Effect of Wellbeing on Quality of Care} * \text{Standard Quality of Care}$$

Unit: *QualityofCare*

(1)

Actual Quality of Care

$$= \frac{1}{2} * \text{Potential Quality of Care due to Wellbeing}$$

$$* \text{Effect of Quality of Work on Care Quality} + \frac{1}{2}$$

$$* \text{Potential Quality of Care due to Wellbeing}$$

$$* \text{Effect of Direct Care Time on Care Quality}$$

Unit: *QualityofCare*

(2)

Secondly, the operationalization of patient expectations is roughly improvised, based on the literature discussed in section 2.13. Formula 3 shows the monthly ‘flow of expectation’ that is brought in by each patient. It has a similar structure as *Quality of Care*, in the sense that the expectations of the insurers and the potential patients are assumed to contribute equal parts in the expectations of patients (both multiplied by ½).

Total Patients Expected Quality Arrival Rate

$$= 1/2 * Patients Arrival Rate * Insurers Expectations + 1/2 * Patients Arrival Rate * Potential Patients Quality Expectations$$

*Unit: QualityofCare * Patients/Months*

(3)

The three formulas above are examples of a simple ‘default’ approach to variables that are not defined in literature to be suitable for an SD model. The multiplication by ½ is such a ‘default’ setting, which, in reality, could be different, or even change over time.

Third, the graphical functions are numerous in the model. For example, graphical functions exist in formulas 1 and 2 in the variables starting with ‘*Effect of...*’. The graphical functions are further discussed in Chapter 5, as part of the model validation in section 5.3.2. Lastly, the model incorporates various time delays which are either guessed or calibrated by visual inspection during the behavior reproduction tests. This is further touched upon in the parameter assessment in section 5.3.3.

3.2. Model

Figure 7. Dynamic hypothesis (aggregated overview).

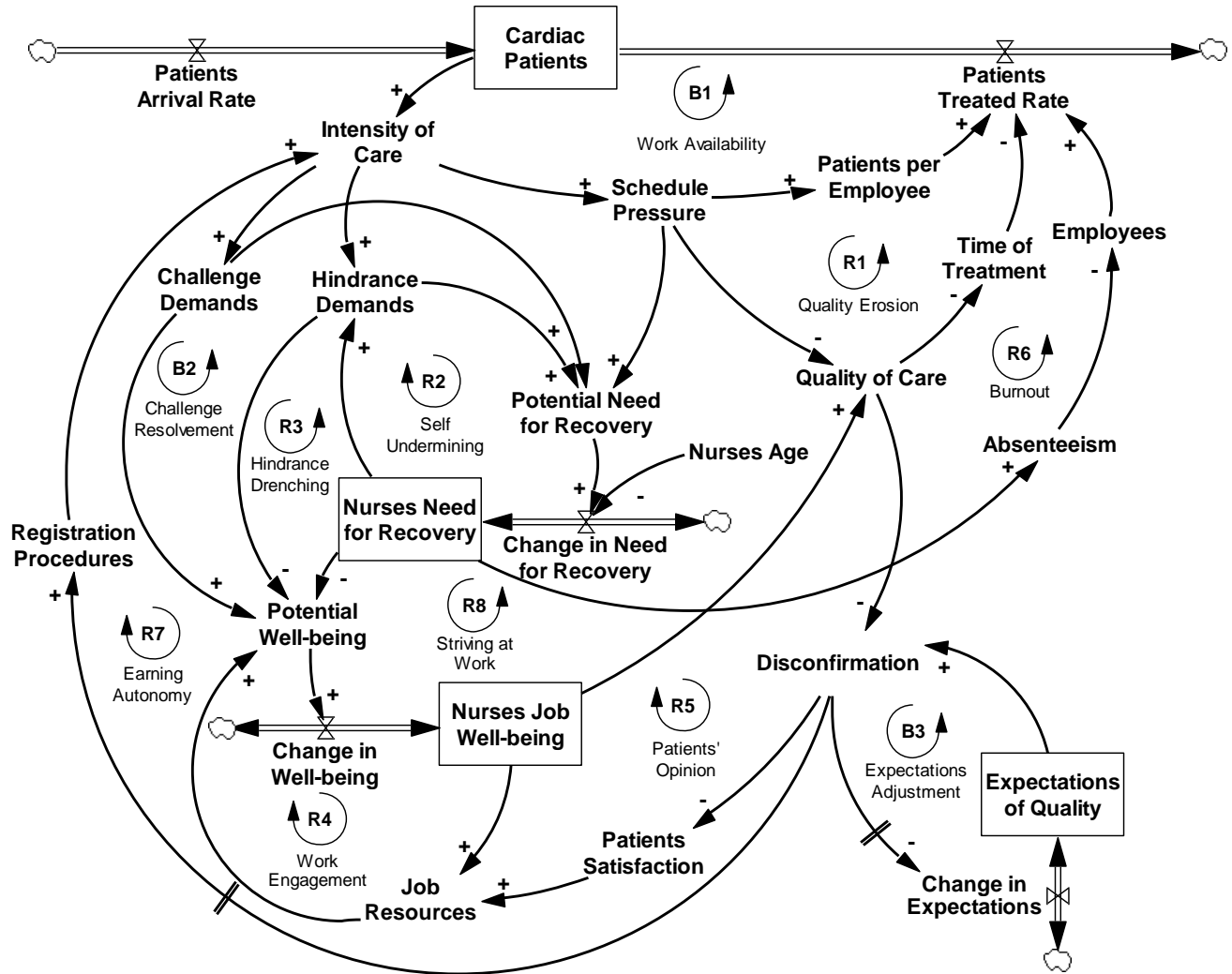


Table 1. Components of stock and flow diagrams in system dynamics.*

	Positive causal link; variables move in same direction		Stock; variable possible to accumulate over time, only changed through flows		Reinforcing loop; symbol of vicious or virtuous causal circle
	Negative causal link; variables move in opposite direction		Flow; rate-of-change variable, responsible for changing stocks		Balancing loop; symbol of counteracting or limiting causal circle

*arrows marked with double stripe icons represent significantly longer delays (which is the case for the change in expectations and the implementation of registration procedures)

Table 2. Model Boundary Chart.

Endogenous Stock variables	Exogenous variables	Excluded
Patients at the Unit	Patients Arrival Rate	Nurses level of education
Need for Recovery	Average Time of Treatment	Other Job Resources [‡]
Well-being	Workforce Characteristics [†]	- Autonomy
Patient Satisfaction*	Intensity of Care Factors [†]	- Participation
Patient Expectations	Time Delays**	- Supervisor support
Insurers Expectations		- Feedback
		- Rewards
		- Job security
Endogenous variables		Personality characteristics
Job Resources [†]		
Job Demands [†]		
Quality of Care		

* regarding nursing personnel only (see also section 4.8)

† see table 3

‡ see section 2.10

**see section 5.3.3

Table 3. Model Coflows & Levels of detail.

Level of detail per sub-model			
<i>Intensity of Care</i>	<i>Workforce</i>	<i>Well-being</i>	
		<i>Job Demands</i>	<i>Job Resources</i>
Diagnosis types	Age (in years)	Challenge Demands	Patient Satisfaction
- High Intensity	Experience (in months)	- Multiple Diagnoses	Nurses Well-being
- Low Intensity	Function	- High Intensity Diagnoses	Experience
Age	- Telemetric	Hindrance Demands	- Experience (in months)
- Fraction ≥ 70 years	- Non-telemetric	- Registration Procedures	- Fraction Telemetricians
Multiple Diagnoses		- Patients ≥ 70	Other
- Fraction ≥ 2 diagnoses		- Need for Recovery	
Registration Procedures			

Chapter 4. Methods

4.1. Research strategy

This research aims to build a quantitative SD model on patient satisfaction and nurses work pressure. It is argued that this area of research covers many already known causal relationships but shows a lack of dynamic implications and effects over time (Ilies, Pluut, & Aw (2015: 849). Hence, this research applies the logic of discovery research, searching for implications of causal relations that had not yet been considered, such as dynamic behavior over a period of 10 years (De Gooyert, 2016, p. 6). To underpin the causal relationships as identified by the literature review ethnographic data is collected at HNL by the means of semi-structured interviews, unstructured interviews (e.g. corridor talks), notes of field observations, and hospitals documentation and data (Partington, 2002, p. 110). The quantitative SD model is calibrated and validated based on this ethnographic data of HNL. By the use of this research strategy -discovery through literature review and modeling, complemented by ethnographic data- this research aspires to a sufficient level of triangulation (Jick, 1979, p. 610).

4.2. Level of analysis

Schneider and Reichers (1983) argue that people on the same team, but with different individual work settings, tend to agree instead of disagree. This work assumes that there is a useful average of all the variables taken into consideration, such as Well-being and the Need for Recovery. For example, earlier research with the Job-Demands and Resources theory aggregated group scores on burnout, although it is evident that there is a large discrepancy among individuals' experiences of burnout levels (Demerouti et al., 2001, pp. 502–503). Next to that, not all research on well-being used as sources for this thesis are analysis on the group level. However, Sonnentag argues that the effects of well-being on work performance are found to support the homology perspective, that within-person studies find similar results as between-person studies (Sonnentag, 2015, p. 281).

4.3. Simulation Modeling and Causality

A simulation model in itself is a theory of how different variables influence each other over time (Lomi & Larsen, 2001). This might as well be 'hidden' variables, such as felt or perceived values generally not measured at all, or variables that are measured less often. Based on the assumptions of the model -which can be seen as the theory itself- these variables provide quantitative output that can be compared to existing data. Simulation modelling can be seen as what Karl Weick named 'disciplined imagination', in which the method of construction of the model provides the discipline (Weick, 1989).

For constructing simulation models one is forced to make fictional assumptions of causality, which directly poses the scientific issue of whether causality can be known or not. I would like to argue that the equations of the model in this thesis are no claims of causality (Barlas & Carpenter, 1990, p. 162). The purpose of the formulated equations are an attempt to provide for useful predications. The work in this thesis is largely based on correlational models, in which there is only a hypothetical claim for causality. Hence, the focus is on the accuracy of the predictions (Barlas, 1996, p. 185). Next to that, by anchoring in consolidated literature and earlier modeling work it is attempted to retain the validity of individual relationships.

By applying these notions, this thesis works in the relativist/holistic philosophy of science, and recognizes that knowledge is "relative to a given society, epoch, and scientific world-view" (Barlas & Carpenter, 1990). The system dynamics method can be seen as a socially justified belief among practitioners, and a 'shared language' (Barlas & Carpenter, 1990, p. 155). However, this poses challenges to justify the scientific rigor; and it has to be stated that the model in this thesis could have been much more rigorous if a more rules-based approach to literature reviewing and model building was taken.

4.4. Literature research

Google Scholar was used to find relevant articles by searching for keywords related to each topic (e.g. “nurses well-being”, “Dutch health care”). Articles with the most citations relative to the other search results were preferred, and the choice was limited to those with at least one citation. Next to Google Scholar, articles and books are included on advice by supervisors and students from my Master Thesis peer group.

For analyzing the well-being aspect of nurses at HNL, there is mostly drawn from Dutch work-and-organizational psychologists (WOP) like Bakker and Schaufeli. This I deem to see fit with the relativity of knowledge to a given society (see 4.1.1.), as such that WOP might be perceived differently in other cultures. I reasoned that WOP scientists working and living in the same culture as the one under study might have the best models for that culture. This in contrast with for example articles on the biological effects of stress, in which I preferred meta-analysis of the field. On quantitative modeling I have attempted to comply to the consolidated methods of the field (Stermann, 2000).

4.5. Data Collection

The aim of the ethnographic data collection for the system dynamic model was to elicit primary qualitative and quantitative data on possible structure and behavior of soft variables (Luna-Reyes & Andersen, 2003: 276, 280). I conducted all interviews, such that a clear link of context was assured from interview to interview (Turner, Kim, & Andersen, 2013: 253, 261). HNL provided quantitative secondary data on patient characteristics, nursing personnel characteristics, absenteeism, and patient satisfaction over the period from January 2012 till December 2016. The external consultancy and advisory organization SKB (2016), provided quantitative research on employee perceptions of well-being and workload from March 2012, March 2014, and October 2016.

Much of the numerical data cannot be found in literature. A quote of Homer applies to much of the numerical data in this thesis as well: “the numbers were drawn primarily in an impressionistic fashion” (J. Homer, 1985, p. 46). Next to interviews, the quantitative data collection, and the Knowledge Elicitation sessions there has been no further attempts on measuring parameter values.

4.6. Knowledge Elicitation Session

A knowledge elicitation session was conducted to provide the model with better-than-guessing estimations on several variables, and construct graphical functions. The session consisted of eight discussion points namely: 1) perceived intensity of care, 2) challenge and hindrance demands, 3) patients with multiple diagnoses, 4) older patients, 5) registration procedures, 6) differences among diagnoses types, 7) working under pressure, and 8) job resources. The procedures closely resembled those of the methods Direct Rating (Goodwin & Wright, 2004, p. 36), Expert Knowledge Elicitation (Ford & Sterman, 1998, pp. 6–9), the Hopes and Fears script, and the Graphs over Time script (Hovmand et al., 2011; Luna-Reyes et al., 2006).

The Graphs over Time script was used for discussion points 1 and 5. The participants were asked to draw a line that indicated their perception of the intensity of care from January 2012 till now (and similar for the number of registration procedures). The sheets of paper contained pre-drawn axes. The horizontal axis contained labels from January 2012 till December 2021. The vertical axis did not contain labels. An example of previous use of the Graphs over Time script was shown about a justice chain, with graphs on the development of prosecutions and prisoners. The participants were asked to draw a dot in the middle of the vertical graph area at April 2017. They were asked to draw a line back to January 2012 from this dot.

The participants were then asked to draw three lines from the dot at April 2017 to the future, of what they thought that the ‘realistic’ development would be, and what they ‘hoped’, and ‘feared’ that the development would be. Here also first an example was shown of the earlier use of these graphs in the justice chain example that portrayed lines with which the participants themselves wrote ‘realistic’, ‘hoped’, and ‘feared’.

The Direct Rating method was used for discussion points 2, 3, 4, 5, 6, and 8 (Goodwin & Wright, 2004, p. 35). For example in discussion point 2 on challenge and hindrance demands, each of the participants was given a sheet of paper with a number line from 100 to 0, see A4.2. There was one box drawn at the 0 of the number line in which was written “no patient/empty bed”, and two boxes of which one at 100 and one at the right, in which was written “hindrance/challenge demands with an average patient”. First, the participants were asked to decide for themselves which of the two was most common in their work, hindrance demands or challenge demands, and was asked to cross out the other at the 100 level at the number line, and cross out the most common at the remaining box right of the line (see A4.2). Further, the participants were asked to draw a line from the less common demand to the number line, relative to the most common demand at 100, and “no patient/empty bed” at 0. It was explained that if they thought there was no hindrance/challenge at all, they could position this one at 0, and if they thought it was even with the most common at 100, they could position it at 100 too.

A variant of this procedure was used for discussion points 6 and 8, in which multiple options were asked to be ranked. This was not done individually but as a group. The facilitator placed the options at the number line after consensus was reached. Initially the plan was to make use of the nominal group technique. Time constraints made the facilitator decide to only do the tasks individually or as a group.

Direct Rating is used for comparing the interval of two variables with the intervals of other combinations in the same rating, since the zero value is often arbitrarily determined (Goodwin & Wright, 2004, p. 35). In the ratings performed in this session a zero value was allocated by “no patient/empty bed”. Hence, in the use of the numbers, a ratio scale is constructed in contrast with an interval scale, such that a 100 is interpreted twice as high as a 50. During the rating sessions it was often checked whether the ratio scale was approved by the participants by asking for example “do you perceive Well-being as weighting twice as heavy as a job resource than Feedback?” (which is the case in Appendix 3.8).

Parts of the Expert Knowledge Elicitation method was used in discussion points 7 (Ford & Sterman, 1998, pp. 6–9). In the positioning phase the facilitator elaborated on the purpose of the relation, and how it affects other variables in the system. After that, the facilitator verbally described how the graph had to be constructed. As a result the participants started with verbal descriptions, in which each participant contributed their point of view. The verbal descriptions brought consensus on what the normal values where, in this case the usual number of patients the nurses cared for individually. The facilitator started with asking for the amount of minutes of direct care (in the second part of the discussion point for the quality of work as a grade) for the usual number of patients. After this the same question was asked for more and less patients. This resulted in the construction of graphs for how the direct number of minutes and the quality of work changed depending on the number of patients per nurse. The results of the discussion points are elaborated on in section 5.2.

4.7. Employee Well-being Questionnaires

In March 2012, March 2014, and October 2016 employee well-being questionnaires were conducted in HNL by the external research and consultancy firm SKB (SKB, 2016). This questionnaire is based on the ‘Questionnaire for Experience and Evaluation of Work’ (QEEW, Dutch abbreviation VBBA; van Veldhoven & Meijman, 1994). All employees were invited to take the questionnaire. Around two out of each three employees took part each year, a response rate of around 66% ($N_{2012}=33$, $N_{2014}=33$, $N_{2016}=28$). Part of the well-being questionnaires consisted of the recovery after work-scale (*herstel na het werk*), consisting of six multiple-choice questions. Example questions are “I find it hard to relax at the end of a work day” and “When I come home I have to be left alone for a while”. The patients had four answering options: never, occasionally, often, and always. These answering options were coded in values of 1 to 4, with never corresponding with 4, and always with 1. The scores on the six questions were summed to create a scale for recovery after work. The average values of the complete samples were used, and recoded on a scale of 0 to 1. Furthermore, these average values were subtracted from 1 to make a greater score on the recovery after work-scale correspond with needing more recovery (higher is worse). From these values the average over the three years was compared to 1 - the initial value and assumed average in the simulation

model- and each of the three values was added with the difference, such that the average of the three years of the data was equal to 1, making it similar to the initial and assumed average value of 'need for recovery' in the simulation. This resulted in the three values 0.987, 0.989, and 1.023.

The questionnaire has lower and upper possible values. However, the need for recovery value in the simulation model is dependent on the schedule pressure, which does not have an upper value since it is determined by patients and employees. The lack of an upper value in schedule pressure postulates a flaw while comparing it with data from the questionnaire. However, to still make an attempt to compare the two I used the average of 1.

Next to that the aggregated scores per participant were also categorized under positive, neutral, and negative. This is common practice within SKB, to provide more in-depth results beyond the average, since the average values of the scales are very close together. The percentage of participants indicating a high need for recovery are 30, 33, and 50 percent for March, 2012, March 2014, and October 2016 respectively. In the behavior reproduction tests in section 5.3.6 these values have been normalized, and compared to the normalized simulation run.

4.8. Patient Satisfaction Questionnaires

Internal questionnaires among patients at HNL result in bi-annual reports on patient satisfaction. This thesis is concerned with the patient satisfaction that arises from the care that the nursing personnel provides. Only three questions from the questionnaire had the sole focus on care delivered by nurses. An example of these questions is "Did the nurses have enough time for you?". The patients had four answering options: never, occasionally, often, and always. These answering options were coded in values of 1 to 4, with never corresponding with 1, and always with 4. The scores on the three questions were summed to create a scale for nurses-related patient satisfaction. This scale had a Cronbach's alpha of 0.81, which is regarded as sufficiently reliable. No deletion of any of the three items could increase its Ca.

The variable 'recent patient satisfaction' in the model has an initial and normal value of 0.5 and can deviate between 0.1375 and 0.8625 (see 5.3.2). The average scores of patient satisfaction are able to deviate between 3 and 12. Thus, to compare the patient satisfaction scores with the 'recent patient satisfaction' variable in the model the scores were recoded by subtracting with 3, dividing with $9/0.725$, which is the division of the range of the data ($12-3=9$) with the range of the simulation variable ($0.8625-0.1375=0.725$), and adding 0.1375, such that 3 and 12 correspond to 0.1375 and 0.8625.

4.9. Data Analysis

The data is analyzed by a System Dynamics model built in Stella Architect version 1.1.2 (a system dynamics software built by iSee Systems). The unit of time is months. The time step, or DT, is set to 1/30. The integration type is Runge-Kutta 4. In historic data mode the model runs for 60 months, from time 1 to 60, representing the time from January 2012 till December 2016. In equilibrium mode the simulation time is from 1 till 120, representing a time horizon of 10 years.

Statistical tests were used to determine if there was a significant difference in changes between telemetrically trained nurses, and non-telemetrically trained nurses (see 5.1.3). This was done for deciding if the distinction should be in the model or not. The validity of the model is discussed through various validation tests in section 5.3.

The accuracy of the simulations are statistically tested with Theil's U, his later forecast accuracy coefficient (Bliemel, 1973; Theil, 1966). Theil's U is a value of 0 or higher. Theil's U of 0 means that the simulation is equal to the data, i.e. the simulation is perfect. A Theil's U of 1 indicates that the prediction is not better than 'naïve no-change extrapolation' (Bliemel, 1973, p. 445). A value of greater than 1 results in rejection of the model since it is worse than extrapolation.

The error in the simulations are analyzed by Theil's Inequality Statistics (Stermann, 2000: 876; Theil, 1966). The Theil inequality statistics decompose the root mean square percentage error (RMSPE) among three composite scores of which the sum equals 1. The three composite scores are: (U^M), the error due to bias; (U^S), unequal variation between the simulation and data; and (U^C), unequal covariation.

4.10. Illustration of System Dynamics as a Modeling Tool

System Dynamics is a computer simulation based modeling tool that can address endogenous dynamic aspects (feedback effects), and explicitly incorporates the role of time (Forrester, 1961, 1971; Sterman, 2000). An example of a single feedback effect from research in employee morale is portrayed in Figure 8 (Kristekova et al., 2012, p. 467).

Figure 8 shows a causal loop diagram (CLD) with the causal assumptions made between employee morale and customer satisfaction. It is found that higher employee morale leads to greater customer satisfaction (portrayed with the arrow and the + sign), and that, in turn, greater customer satisfaction leads to higher employee morale. It is an example of a feedback loop with a reinforcing nature, of which its effect is described as “tends to amplify whatever is happening in the system” (Sterman, 2000, p. 12).

Figure 8. A single feedback loop in Causal Loop Diagram (CLD) representation (adapted from: Kristekova et al., 2012, p. 467)

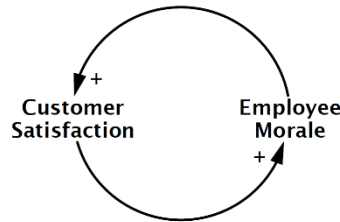
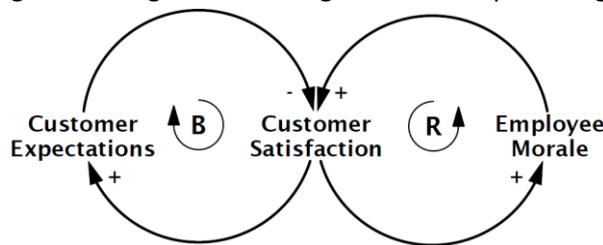


Figure 9 portrays another feedback loop as hypothesized in customer satisfaction and expectations literature (King & Geursen, 2005, p. 9), assuming that greater customer satisfaction will increase the expectations. Consequently, when expectations rise and are greater than the actual perceived quality, customer's satisfaction will decrease or eventually be limited in its growth. Customer satisfaction is reasoned to be a result of expectations and actual quality (Oliver, 1977, 1980). Given that the actual quality stays the same an increase in expectations can lead to a decrease in satisfaction. Moreover, when the satisfaction is rather low for some time, the expectations might be adjusted downwards (and vice versa).

The positive and negative relations amongst variables are shown by the + (and -) sign which prescribes that variables –in this case the customer expectations as result of the customer satisfaction- move in the same direction (instead of a - sign, in which variables move in opposite directions). This is an example of a feedback loop with a balancing nature, of which the effects are described as “counteracts reinforcing developments and opposes changes” (Sterman, 2000, p. 12). The CLD in Figure 9 explicitly shows the reinforcing and balancing feedback loops with B and R symbols.

Figure 9. CLD portraying reinforcing and balancing feedback loops among customer satisfaction.

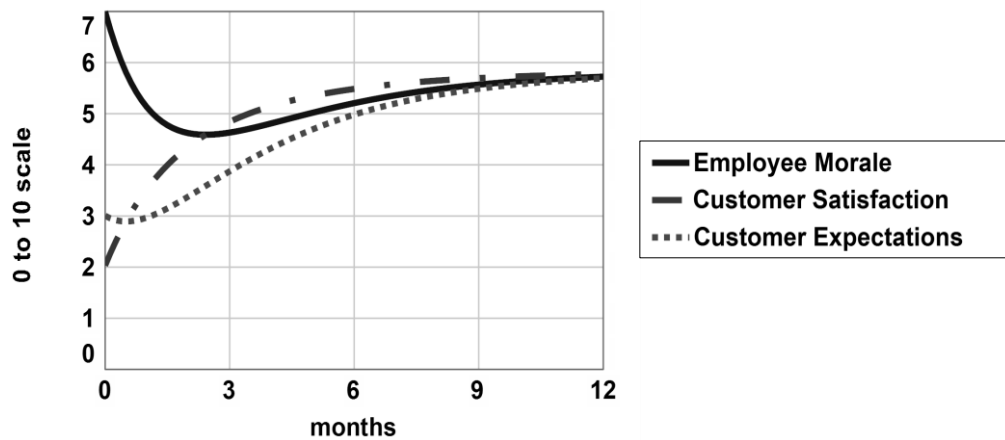


Limiting the description of customer satisfaction to this example of feedback loops would be absurd. Customer satisfaction is affected by many more variables than expectations and employee morale only, hence a broader, more realistic perspective needs to be taken into account. Nonetheless, this operationalization causes so called dynamic behavior over time. Customer satisfaction might increase due to a rise in employee morale, and employee morale can be strengthened thanks to more satisfied customers. However, this does not amplify forever due to the fact that greater customer satisfaction will not endlessly increase morale. Moreover, when the expectations of customers are fully met, and there is

no reason for being unsatisfied, the dynamic behavior over time can show development towards a stable equilibrium (see Figure 10, and Appendix 1).

Figure 10 is an example of dynamic behavior over time, which starts with growing customer satisfaction, thanks to an initial relatively high employee morale. At the same time customer expectations and employee morale decline, due to the low customer satisfaction. Customer expectations reach their lowest point when they are equal to customer satisfaction, and start climbing when customer satisfaction becomes greater than customer expectations. Meanwhile employee morale is still dragged down by the low customer satisfaction, and reaches its greatest depth of this simulation once it becomes equal to the customer satisfaction. After that, thanks to an increasing customer satisfaction, employee morale starts to grow too. After a hypothesized time of one year all reach a stable equilibrium. Although employee morale has been growing most of the time, it ends being at a lower point than it started out with.

Figure 10. Example of dynamic behavior over time in a hypothetical scenario.



Chapter 5. Data Results, Validation, and Analysis

This chapter elaborates on the process of analyzing the numerical data in section 5.1. It continues with discussing the results of the knowledge elicitation session, and how the results were used in the model in section 5.2. Furthermore, section 5.3 provides results of various tests and simulation runs to provide a basis for judging the validity of the model. Last, 5.4 provides analysis of the model with the purpose of answering the research question, and providing more insight in the workings of the system. For the sake of brevity, not all possible results have been reported, but those deemed to be important and interesting for reporting.

5.1. Data Handling

Data on patients and nurses was retrieved from the accounting department. To distinguish amongst different types of treatments for patients there is focused on so called 'diagnoses-treatment combination categories' (*diagnose-behandel combinatie codes*). These categories were used to group different patients amongst those with high intensity diagnoses, who needed more care, and low intensity diagnoses, providing a lower workload. Specifications of handling the data are provided in the next sections.

5.1.1. Patient Flows

The data set included only patients that had arrived in the corresponding month. Hence, for time 1 (January 2012), values of the patients that were already at the unit were missing. The values for time 1 were corrected to correspond with the average of times 2 to 4, which are the first 3 months with full data. The missing values were for the patients at the unit, and the values for the patients arriving rate needed for various initial stock levels).

5.1.2. Intensity of Care

There were 17143 unique patient intakes. From these intakes 1446 patients, 8.4% of the total, were recorded with two or more diagnoses-treatment-combinations. Nurses stated that patients with multiple diagnosis needed more care. Based on that, this group is treated as a separate factor in the sub-model Intensity of Care as discussed in Chapter 3. Section 5.2 elaborates further on the results from the Knowledge Elicitation Session and 5.3.2 provides description on the model specifications. The Knowledge Elicitation Session revealed that patients with multiple diagnosis are a challenge demand to nurses, hence the proportion of patients with multiple diagnosis contributes to the challenge demands in the model.

Next to that 42 patients were more than one month on the unit. For establishing the variables related to the patients per employee, the total hours of patients presence on the unit are compared with the total number of nurses worked hours for that month. The total number of hours of each of those 42 patients is allocated to the month that they arrived, providing for a flaw in the data. However the number of 42, less than .3% of the total number of patients, is reasoned to be small enough for not significantly affecting the data.

5.1.3. Telemetric and Non-telemetric nurses

Before doing statistical analysis on the number of nurses and their working hours the data has been cleaned and checked for outliers. The financial data for worked hours occasionally contained several corrections for one employee in one month. After cleaning the data each employee had only one entry with worked hours per month, the data was clear on which number of hours and in what function type for each month. No outliers were found.

A chi-square test found significant differences between 2012 and 2016 on the fraction of telemetric nurses working at the unit per month ($\chi^2(4, n = 2732) = 10.89, p < .05$). The numbers in the table are not all unique nurses. From month to month different nurses are working at the unit due to flexible working.

Hence, the number of nurses each month are treated as unique, resulting in the cumulative year numbers in the table.

A t-test showed significant differences between the monthly hours worked by telemetric and non-telemetric nurses over the total last 60 months, with telemetric nurses having on average more working hours ($M_{\text{Telemetric}} = 119.86$, $SD_{\text{Telemetric}} = 33.35$; $M_{\text{Non-telemetric}} = 115.10$, $SD_{\text{Non-telemetric}} = 34.88$, $t(2785) = -3.62$, $p < .001$).

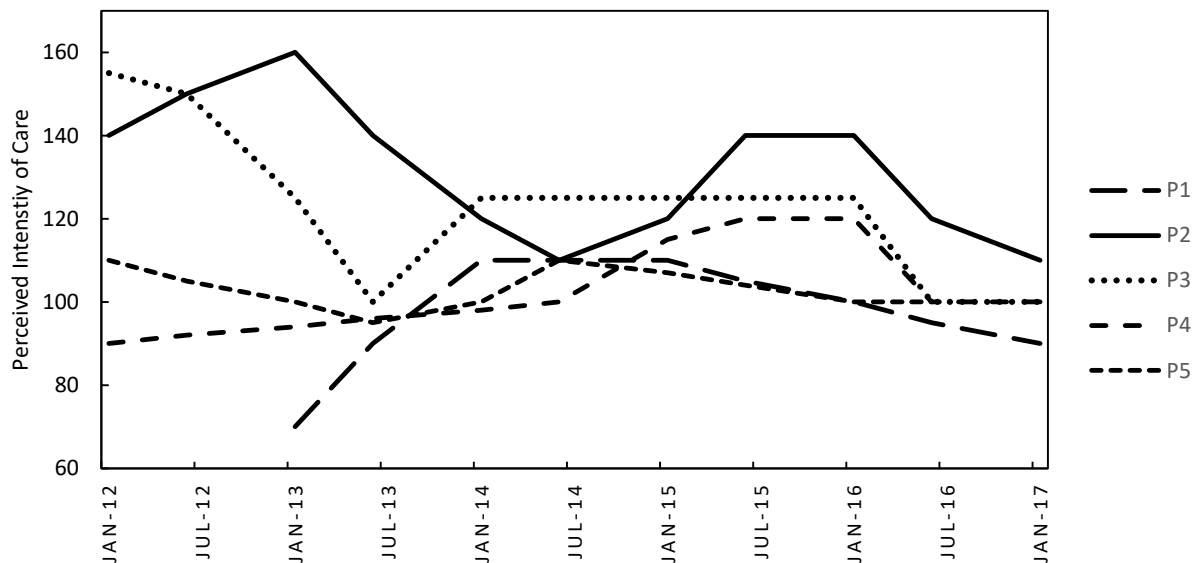
5.2. Results Knowledge Elicitation Session

A knowledge elicitation session was conducted to provide the model with better-than-guessing estimations on several variables, to conclude on the categorization amongst hindrance and challenge demands, and for constructing graphical functions. The session consisted of eight discussion points namely: 1) perceived intensity of care, 2) challenge and hindrance demands, 3) patients with multiple diagnoses, 4) older patients, 5) registration procedures, 6) differences among diagnoses types, 7) working under pressure, and 8) job resources. The procedures closely resembled those of the methods Direct Rating (Goodwin & Wright, 2004, p. 36), Expert Knowledge Elicitation (Ford & Sterman, 1998, pp. 6–9), the Hopes and Fears script, and the Graphs over Time script (Hovmand et al., 2011; Luna-Reyes et al., 2006), which are discussed in detail under 4.2.1. The workshop led to various results which are described in the sections 5.2.1 till 5.2.5, and the use of these results to the model are discussed in the structure assessment part of the validation in section 5.3.2.

5.2.1. Perceived Intensity of Care

In discussion point one the participants were asked to indicate their perceived intensity of care over the last five years. The experienced intensity of care drawn by each of the five participants is shown in Figure 11.

Figure 11. Experienced Intensity of Care from start 2012 till end 2016/start 2017 (P1..P5 = participants).



5.2.2. Challenge and Hindrance Demands

During the session definitions for challenge demands and hindrance demands were introduced. Challenge demands can be those tasks on the job that are perceived as directly useful (in Dutch “nuttig”) and challenging (in Dutch “uitdagent”). To nurses the challenge demands can be similar to ‘emotional

demands' like 'dealing with clients', 'demanding clients', and 'emotionally charged situations' (Bakker & Sanz-Vergel, 2013, p. 399). Hindrance demands are those procedures on the job that are perceived as 'less useful', and resulting in stress (in Dutch "stressvol"). An example of hindrance demands are registration procedures.

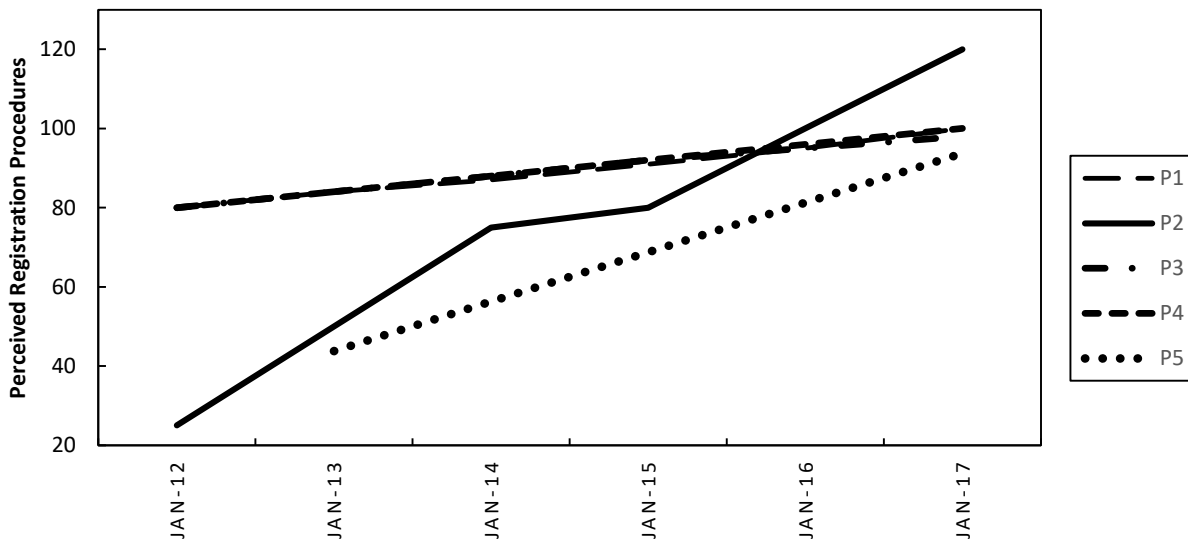
The participating nurses confirmed that these were part of their challenging and hindering demands. They added that acute situations in the care for their patients is also part of their challenging demands (later this was reflected in different diagnoses, see also 5.2.6). Next to that it was added that what they see as 'challenging' in general, is to find enough time with the patient. For hindrance demands the nurses added that some of the requirements of patients are excessive (this was later reflected in the hindrance demands of older patients). Next to that the expectations of patients and stakeholders were perceived as hindering. Stakeholders in this case are medical specialists, medical specialists in training, and family from patients. A4.2 provides the material and calculated results of this discussion point. It was found that on average, nurses perceive their work as slightly more challenging, although there was no consensus on this among the participants.

The results of the previous discussion point 2 were combined with the discussion points 3, 4, 5, and 6 to establish conclusive results in categorizing on hindrance and challenge demands. The raw and calculated scores can be found in appendices A4.3 till A4.6, and the application of the values in the model can be found in section 5.3.2.

5.2.3. Registration Procedures

The experienced change in the number of registration procedures is shown in Figure 12. The two most conservative projections were taken as input to the model.

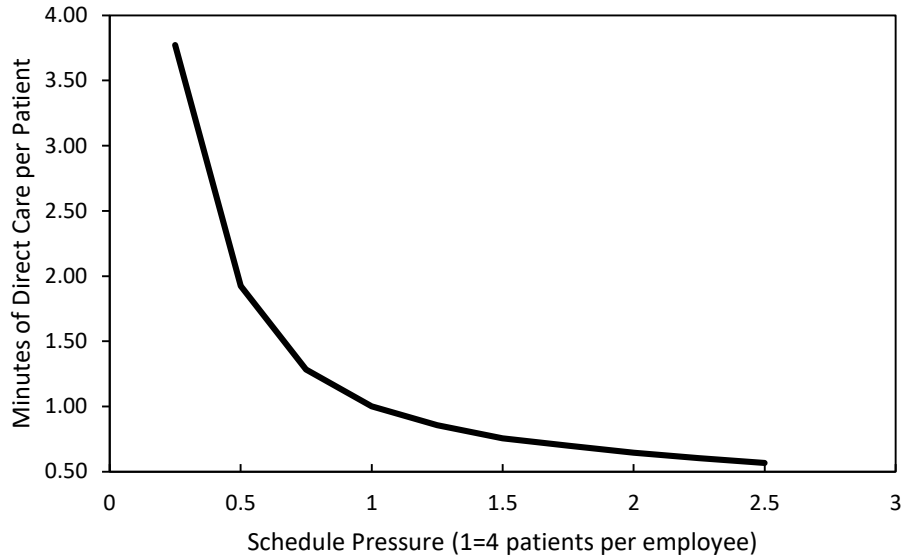
Figure 12. Experienced Number of Registration Procedures.



5.2.4. Working under Pressure

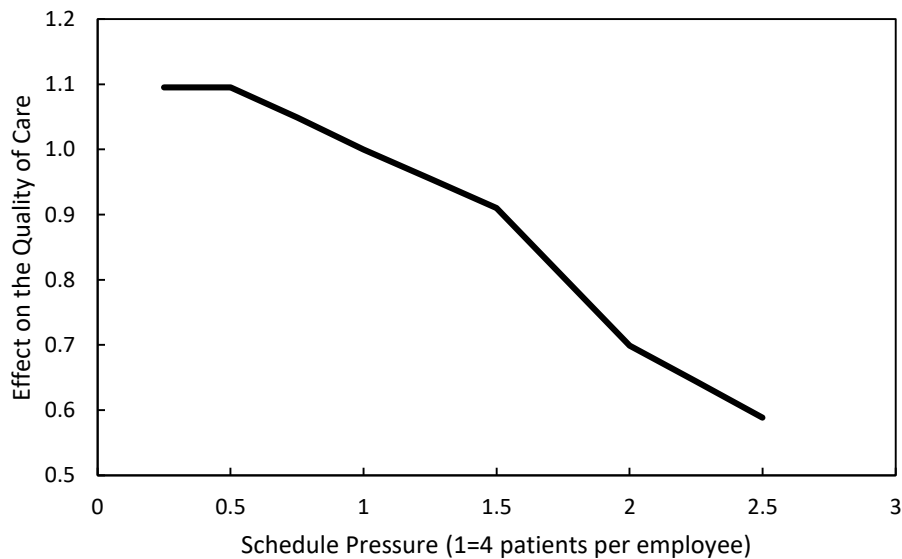
During discussion point 7 two graphical functions were created. One of the effect of the number of patients per employee on the direct care time, and the other on the quality of care. There was no consensus on how the direct care time would be influenced, but the average provided for a smooth line, see Figure 13.

Figure 13. Effect of Schedule Pressure on the Minutes of Direct Care per Patient.



There was consensus on how the quality of care would be affected, of which the average is shown in Figure 14. Appendix 3.7. provides the full data on this discussion point.

Figure 14. Effect of Schedule Pressure on the Quality of Care.



5.2.5. Job Resources

A total of nine job resources, as described in section 2.10, were ranked to establish their relative importance: 1) well-being, 2) autonomy, also referred to as job-control in section 2.10, 3) participation, 4) work experience, 5) patient satisfaction, 6) supervisor support, 7) feedback, 8) rewards, and 9) job security. The results of this ranking can be found in appendix A3.8. Section 5.3.2 elaborates further on the implementation in the model.

5.3. Validation

A model can never be confirmed as truth (Oreskes, Shrader-Frechette, Belitz, & others, 1994; Sterman, 2002). Physics philosopher Nancy Cartwright states that models are a work of fiction, of which, in short, some elements do genuinely represent reality, and other elements are “merely properties of convenience”. Especially this model, many conceptions are highly simplified and currently lack a genuine quantitative counterpart in reality, such as well-being which is only a theoretical construct. Hence, in Cartwright’s words, many variables are “properties of convenience [...] to bring them into the range of mathematical theory” (Cartwright, 1984, p. 153). A system dynamics model is an “imperfect theory about reality that is valid if it proves to be a useful tool in making decisions” (Barlas & Carpenter, 1990, p. 162; Forrester, 1973). For consolidating to some extent the validity of this model, and mostly for articulating its limitations, various validation tests recommended for SD models are discussed in the following sections (Barlas, 1996; Sterman, 2000, pp. 859–890).

5.3.1. Boundary Adequacy Test

Table 2 and Table 3 provide boundary charts indicating endogenous, exogenous and excluded variables. A2 shows a list of equations and descriptions. The literature review of chapter 2 is an attempt to substantiate the structure and equations. Statistical tests were conducted for variables of which significant changes were doubted. Significant differences was decisive for use in the model, see 5.1.3. The main variables of the research question of this thesis: “how are changes in 1) patient satisfaction related to 2) employee well-being and 3) work pressure over a time period of ten years?”, are each present as endogenous variables.

The boundaries of the model imposed limitations to other factors. First, financial incentives are present at various levels that affect the system, e.g. the unit’s management, negotiations between hospitals and insurers, and nurses reasons for working. These financial incentives affect staffing schedules, and availability of budget for informal gatherings. The exclusion of financial incentives poses a weakness to the model. Second, as identified in Chapter 2, the model excludes important factors for employees well-being like the work-home interface and the interpersonal environment. A third factor is the decision rules regarding staffing, and possible burnout. Currently the model assumes in the equilibrium tests that the number of employees stays equal, this means that there are no extra employees hired when the workload is higher. Neither does a fraction of the employees burnout when the workload has been high for too long. Only the effect of *Need for Recovery* on *Number of FTE* (the variable accounting for the average number of nurses present at the unit) reflects the possibility that part of the nurses stop working, are absent, or contribute less when the need for recovery is higher.

A first boundary adequacy test explores the effect that insurers might have in negotiating the number of patients. It currently does not happen regularly that insurers negotiate for different numbers of patients with a hospital. Although, there has been a case described in 2010 in which an insurer decided to no longer contract certain hospitals because they did not meet the insurers quality standards (Maarse et al., 2016, p. 168). The models boundary could be extended by having the *Insurers Expectations* influence the *Patients Arrival Rate*, dependent on the level of *Disconfirmation*. This would imply the existence of a fourth balancing feedback loop, which could be named “Insurers Market Control”. In Figure 7 this feedback loop would be present by a connecting arrow from *Disconfirmation* to *Patients Arrival Rate*. Figure 15 provides this hypothetical scenario: if insurers expectations regarding the quality of care are not met, the patients

arrival rate is lowered and if the quality of care is greater more patients are send to the unit. Figure 23 and section 5.3.2 provide explanation on how this effect could be implemented, by specifying the decision rule on which more or less patients are assigned dependent on the level of *Insurers* Disconfirmation. This could result in a more severely oscillating number of patients at the unit, depending on the decisions of the insurer, as is shown in Figure 15. The current behavior that the model produces shows only very small differences, in which the negotiations result in roughly one patient less halve of the time. However, this is merely an indication of what possible effects could be, suggesting that in reality the impact could be more severe. The oscillating pattern shows the effect of the adjustments that the insurers make to the contract with the hospital. If the market forces work more directly on the number of patients this could cause greater changes in the workload of nurses, asking for more flexibility and complexity in scheduling. Moreover, in this experiment, receiving initially more patients results in even more changes in workload due to the reactions of insurers. This illustrates that regulations, intended to safeguard the quality of care, could cause greater and prolonged fluctuations in the same quality of care, as shown in Figure 16. Hence, this fourth balancing loop “Insurers Market Control”, could increase the amount and intensity of fluctuations in workload, due to the delayed effects it has on the quality of care.

Figure 15. Effect of Insurers Negotiations on Patients Arrival Rate with a step increase of 10 patients at time 13.

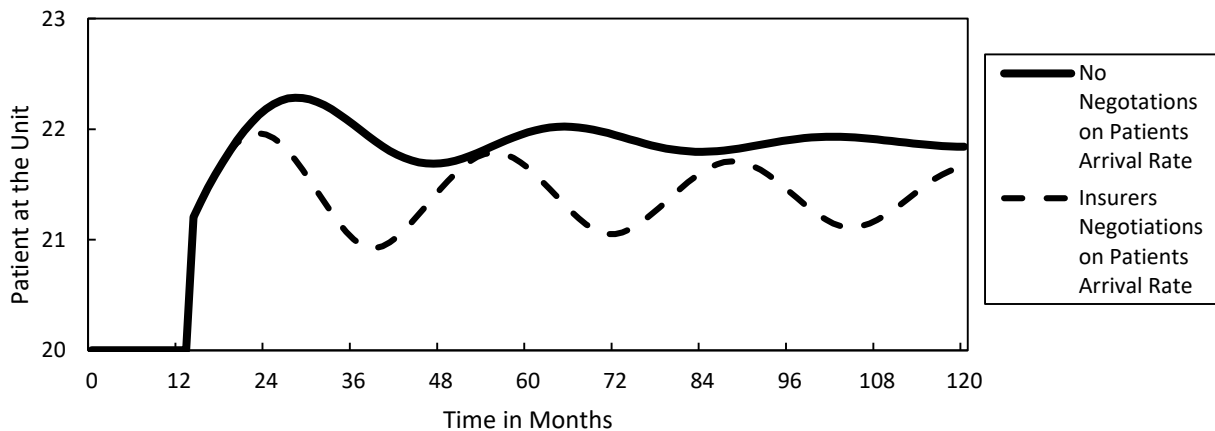
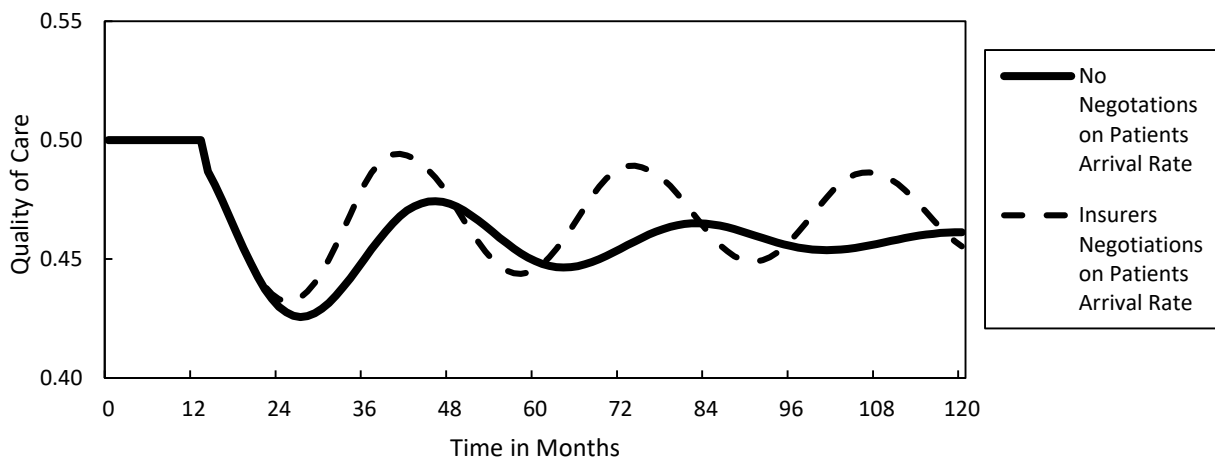


Figure 16. Effect of Insurers Negotiations on Quality of Care with a step increase of 10 patients at time 13.

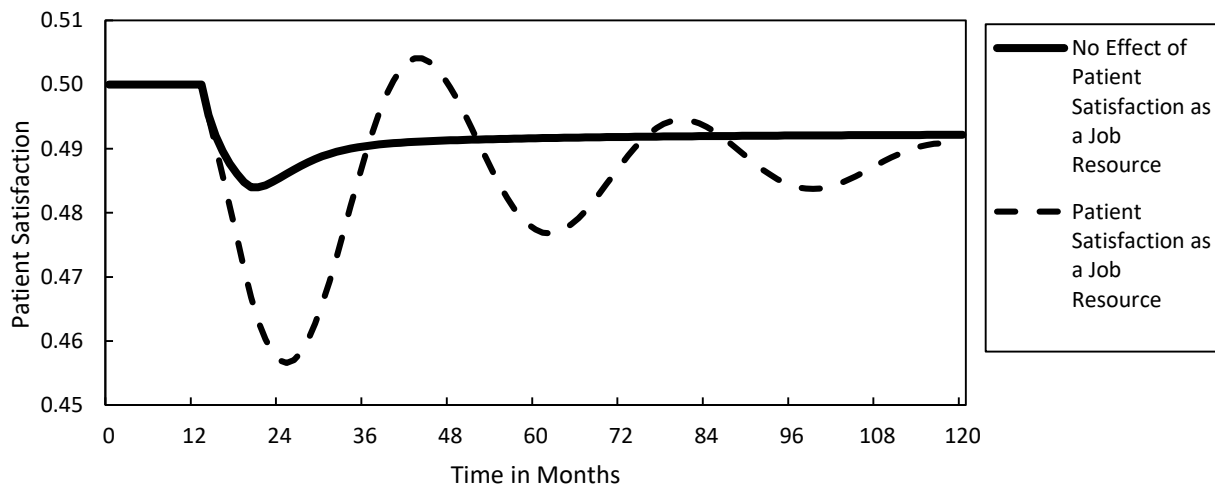


A second boundary test explores the effect that patient satisfaction has as a job resource to nurses. Both the literature as discussed in section 2.10, and results from the knowledge elicitation session at HNL, see section 5.2.5, suggests that patients’ satisfaction can be regarded as a job resource. The default settings of the model are that patient satisfaction is part of the job resources to nurses. As an illustration

of testing this boundary of the model the effect of an increase of 10 in monthly arriving patients is shown in Figure 17.

The solid line, without the effect of patient satisfaction as a job resource, shows that the patient satisfaction will initially fall, which is due to a lower quality of care that resulted from the increase in patients. After the initial fall it will slightly rise again, since patients adjust their expectations, and stabilize on a lower level than it started with, since the workload is continuously higher. Comparing this with the dashed line, which shows the behavior in the default settings, the fall in patient satisfaction is much higher. This is due to the effect that the patient satisfaction has on the job resources, which reduces the nurses well-being on the job. Due to a lower well-being, the quality of care falls even lower, resulting in the extended fall in the dashed line. Over time, patients adjust their expectations, such that it levels up with the actual quality of care. Next to that the marginal effect of the fall in patient satisfaction on well-being through the job resources becomes smaller. These are responsible for the turning point of patient satisfaction from a decrease, to its lowest point, and towards an increase again. The patient satisfaction then rises till it grows somewhat beyond the expectations (around time 42, above 0.5 in the graph). This is due to the nurses well-being, which, with a small delay, increases together with the patient satisfaction. This interaction -between the adjustment of expectations, and the well-being of nurses which is a delayed result from the patients satisfaction- result in an oscillating pattern of behavior.

Figure 17. Effect of patient satisfaction as a job resource, with a step increase in *Patients Arrival Rate* of 10 patients at time 13.



5.3.2. Structure Assessment

The model is dimensionally consistent and all units are reported in the equation list in A2. The smallest delay time in the system is 0.1 months. Sensitivity testing on the time-step (DT) resulted in a default setting of 1/30. The integration type is set to Runge-Kutta 4.

Patient Flows

The sub-model *Patient Flows* represents the *Patients Treated Rate* as a function of the *Time per Treatment*, *Patients per Employee*, and *Number of FTE*. This would mean that the number of patients that is cured, or goes elsewhere, is partially dependent on the number of nurses and the patients per nurse. For treating a patient it is necessary that there are nurses. However, a patient moves out of the unit will mainly depend on the progression of the patient's health, and thus is not directly related to the number of nurses.

The *Patients per Employee* is dependent on the *Patient at the Unit* and the *Employees*, which is the number of employees that is scheduled. In conclusion, when the model runs on the real data the number

of patients that leave the unit is mostly dependent on the number of patients that arrived at the unit, and is almost not influenced by any of the other factors. Thus, the changes in the number of patients that leaves the unit is close to not influenced by the changes in *Time per Treatment* or *Number of FTE* when the model runs on real data. This shows that in the historical data and behavior reproduction mode, the amount of patients that is treated is mainly dependent on the progression of the patient's health (the average stay per diagnoses) which is close to common sense in normal circumstances, and not on the number of nurses or the time per treatment.

Graphical Functions

The model is rich in graphical functions which are not based on literature or data. The graphical functions explained in section 5.2.4, providing the effects of schedule pressure on quality of care, are the sole ones based on empirical findings. The model incorporates graphical functions as shown in Figure 19 in between the effects of *Challenge Demands*, *Hindrance Demands*, *Job Resources*, *Care Quality*, and the *Nurses Age*. These graphical functions are based on a linear development around the normal levels, which is smoothed out in the extremes. I chose to use this curve since it reduces the strength of the effect in the extreme circumstances and to make the effects approach the lower and upper limits. When graphical functions are not defined by prior research or expert knowledge this is a typical way of defining the relationship between two variables. The lower and upper limits in the graphical functions are 0 and 2 since the graphical function multiplies with the standard or norm values of stocks of 0.5, such that the graphical function prescribes that the stock can move on the domain of 0 to 1 (Sterman, 2000, p. 552). For the effect of *Nurses Age* on the *Change in Need for Recovery*, and for the additional effects that *Challenge Demands* and *Hindrance Demands* have on the *Need for Recovery*, lower and upper limits of 0.9 and 1.1 in the graphical functions are specified. These are used arbitrarily, and based on sensitivity tests at earlier stages of the model. Eventually these small lower and upper limits are chosen to reduce the effects on the *Need for Recovery* since wider limits resulted in less realistic behavior.

The effect of *Need for Recovery* on the *Number of FTE* is a graphical function based on a textbook example (Sterman, 2000, p. 581). The numerical values of the textbook example are transformed to having a similar fit to the effects of schedule pressure in the model, see Figure 18. The positive effects, beyond 1, would in the current model imply that more people are working on the job than are actually present, hence the function is corrected to stop at 1. Next to that, the 0 value is changed to 0.001, since a value of 0 would mean that the *Patients Treated Rate* drops to 0. In extreme scenarios some patients might remove themselves from the unit.

Figure 19. Graphical function based on a linear development in the middle and smoothed out in the extremes.

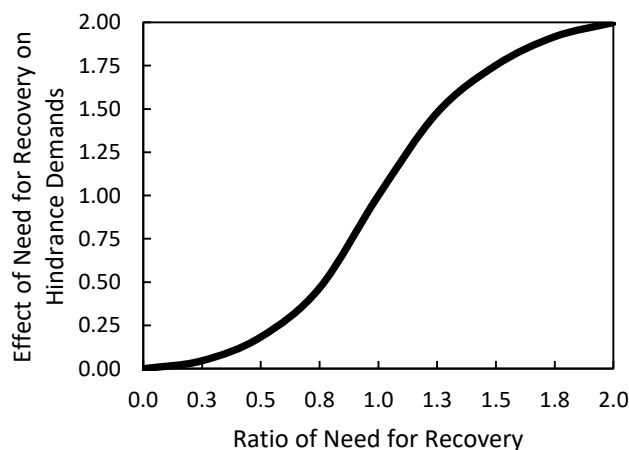
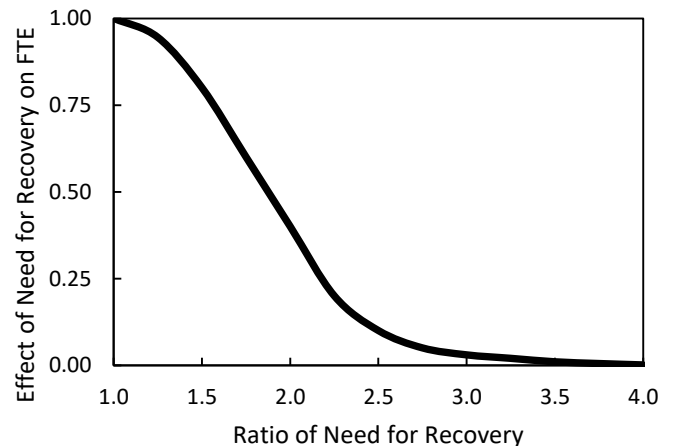


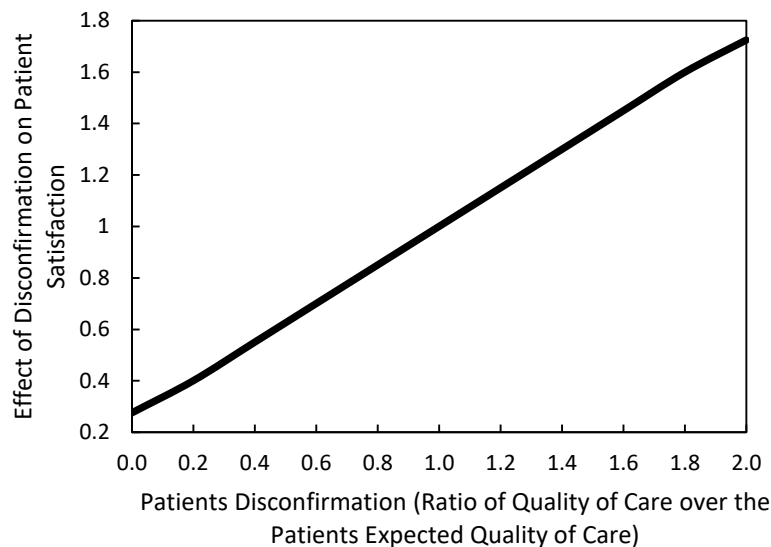
Figure 18. Graphical function specifying the effect of the need for recovery on the number of FTE.



The graph in Figure 20 portrays the relation between the patients disconfirmation and their satisfaction. This line is found by performing sensitivity analysis, and depended on the effect that patient satisfaction eventually had on the patients treated rate (by affecting the patient satisfaction, caused by the quality of care, which in turn is affected by the well-being, which is a partial result of the job resources).

Depending on the slope of this line the oscillations, such as in Figure 17, are either intensifying or fading out over time; i.e. the oscillations are governed by the steepness of this relationship, in which small changes in the steepness result in large differences in amplitude and prolongation of the cycles. As a result of the sensitivity analysis of this relation the upper and lower values of the effect on patient satisfaction are 0.275, and 1.725, which, since it is multiplied by the 'norm recent patient satisfaction', that is 0.5, results in a range of patient satisfaction between 0.1375 and 0.8625.

Figure 20. Graphical function specifying the effect of patients disconfirmation on patient satisfaction.



The graphs in Figure 21 and Figure 22 show the effects of hindrance demands and challenge demands on potential well-being. These effects are drawn to resemble the interaction effects of *Job-Resources* on *Well-being*, according to the results of Bakker and Sanz-Vergel (2013, pp. 405, 406), also see the next subsection providing simulation runs based on these graphical functions.

Figure 21. Graphical function specifying the effect of challenge demands on well-being.

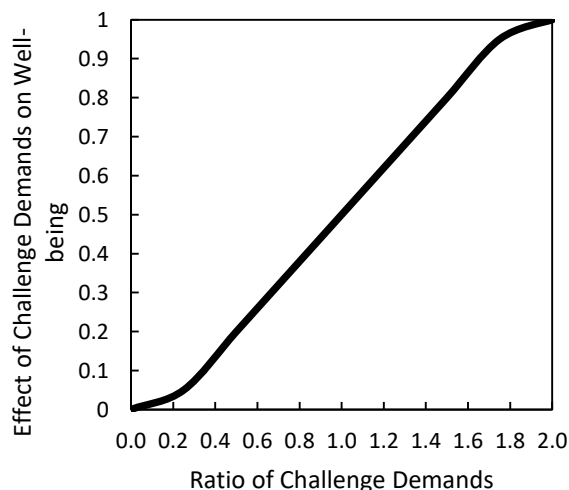


Figure 22. Graphical function specifying the effect of hindrance demands on well-being.

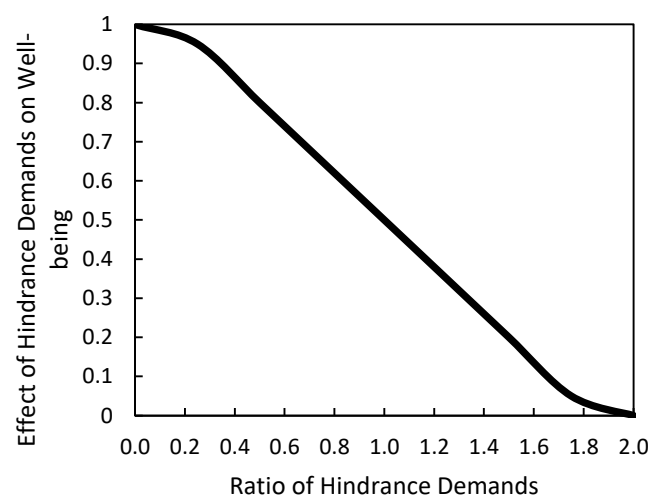
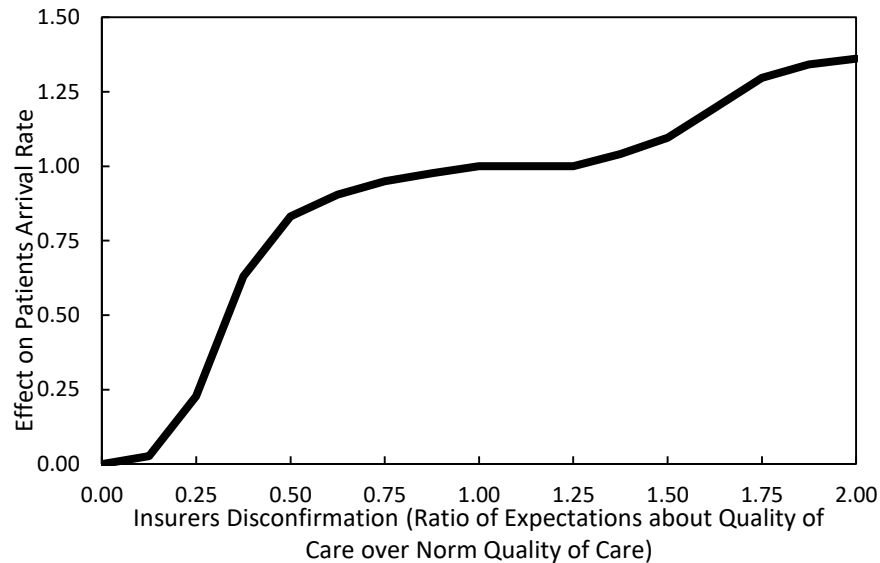


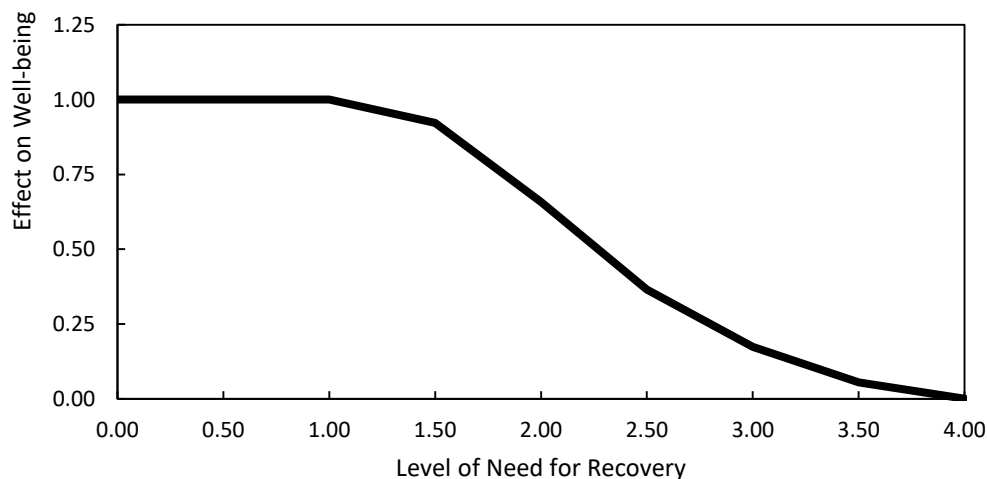
Figure 23 shows the graphical function governing the effect of insurers expectations on the patients arrival rate. This effect is only active in the first boundary adequacy test in section 5.3.1. The numbers are improvised. The rationale is that, once expectations about the quality of care are below average, the negotiations will focus on less patient admissions to the hospital. In addition, when insurers expect a quality of care greater than 25% from the norm (1.25), the insurers are willing to send more patients to the hospital.

Figure 23. Graphical function specifying the effect of Insurers Expectations on Patients Arrival Rate.



Lastly, Figure 24 shows the effect of need for recovery on well-being. The levels of hindrance and challenge demands, as discussed earlier, control the balance between the job resources and the need for recovery, in how much they affect the potential well-being. For example, with the highest level of hindrance demands, the job resources have no influence, and the need for recovery solely has influence on the potential well-being due to hindrance demands. In contrast, when there is an average amount of hindrance demands the potential well-being from hindrance demands consists for $\frac{1}{2}$ out of the level of job resources, and for $\frac{1}{2}$ out of the level of need for recovery, specified by the relationship in Figure 24.

Figure 24. Graphical function specifying the effect of Need for Recovery on Well-being.



Well-being

Graphical functions as provided in the previous paragraph are used to incorporate the interaction effects of *Job-Resources*, *Challenge Demands*, and *Hindrance Demands* on *Well-being*, according to previous research (Bakker & Sanz-Vergel, 2013). The graphs in Figure 25 and Figure 26 portray the interaction effects as result of the model, and show similarity with the results of Bakker and Sanz-Vergel (2013, pp. 405, 406).

Figure 25. Interaction effect of Job Resources and Challenge Demands on the Potential Well-being.

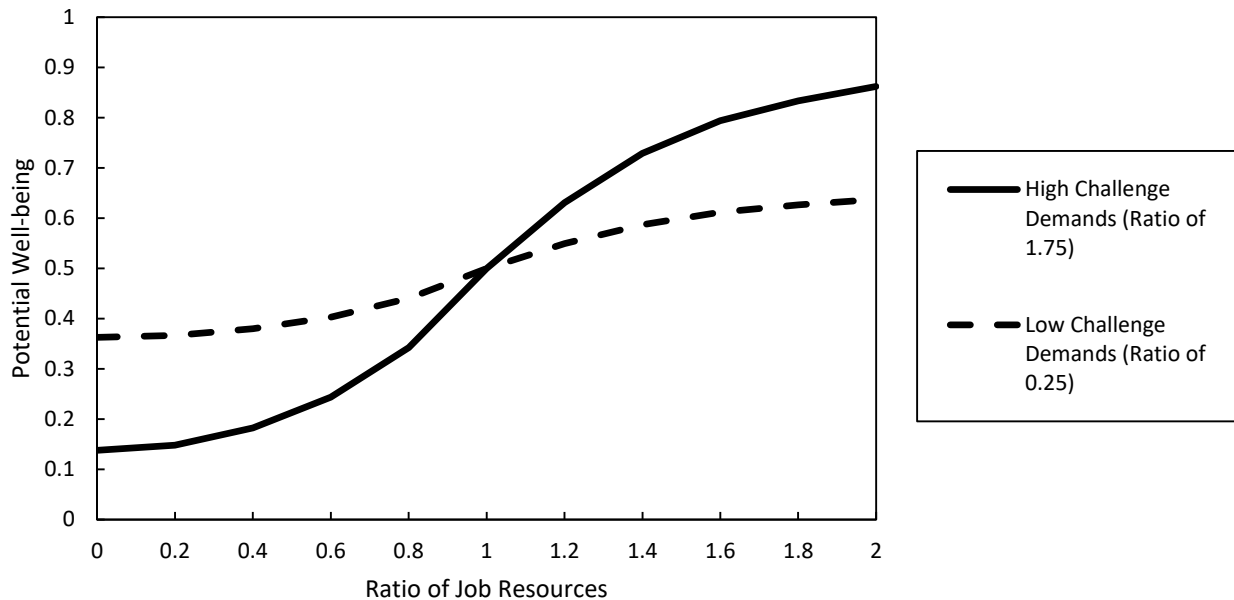
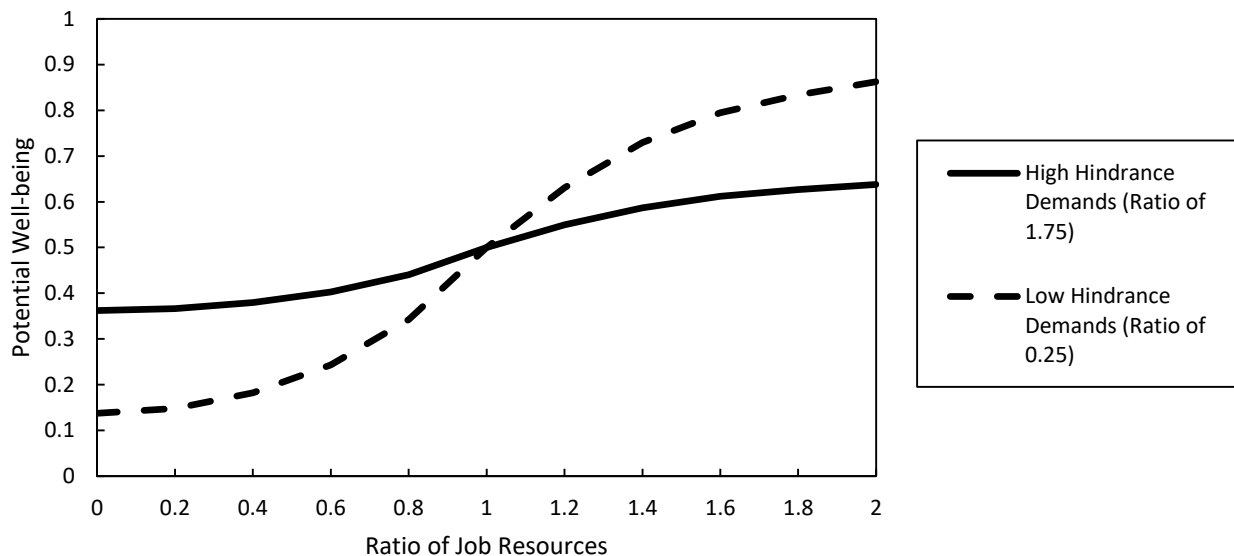


Figure 26. Interaction effect of Job Resources and Hindrance Demands on the Potential Well-being.



Number of Registration Procedures

From discussion point 5 of the Knowledge Elicitation Session (see appendix 3.5) it was derived that currently half of all the hindrance demands consist of registration procedures. Based on these results the

amount of registration demands and the number of older patients are equally weighted in their contribution to the total hindrance demands (together with the need for recovery each accounts for 1/3).

Next to that, discussion point 2 (appendix 3.2) provided that the proportion of hindrance demands are 0.5 (rounded from 0.47 for convenience). This is a basis for equally weighting the contribution of hindrance and challenge demands to the need for recovery.

Discussion point 5 from the Knowledge Elicitation Session also provided hindsight graphs drawn by the participants of how the number of registration procedures developed (see also appendix A2.1). To incorporate these in the model the most conservative numbers are chosen from participants 3 and 4 and rounded.

Multiple Diagnoses

Appendices A4.2 and A4.3 shows that patients with multiple diagnoses provide slightly more challenge demands than average patients do. First, the intensity of care of patients with multiple diagnosis is assessed to be 1.3 times greater than that of an average patient. Next to that, the swing from hindrance demands to challenge demands for an average patient is 0.06, and for a patient with multiple diagnosis 0.10. These numbers indicate that patients with multiple diagnosis can emphasize the total challenge demands. In the model the actual challenge demands is adjusted for the change in fraction of patients with multiple diagnoses.

Older Patients

Appendices A4.2 and A4.4 provides evidence that older patients are more hindering than average patients. Older patients are perceived to be more hindering than challenging with a swing of 0.1, whereas for the average patient there is a swing from hindering to challenging from 0.06. Moreover, an older patient is felt as being 1.25 times more intense in care. This indicates that older patients can emphasize the total hindrance demands. In the model the actual hindrance demands is adjusted for the change in fraction of older patients.

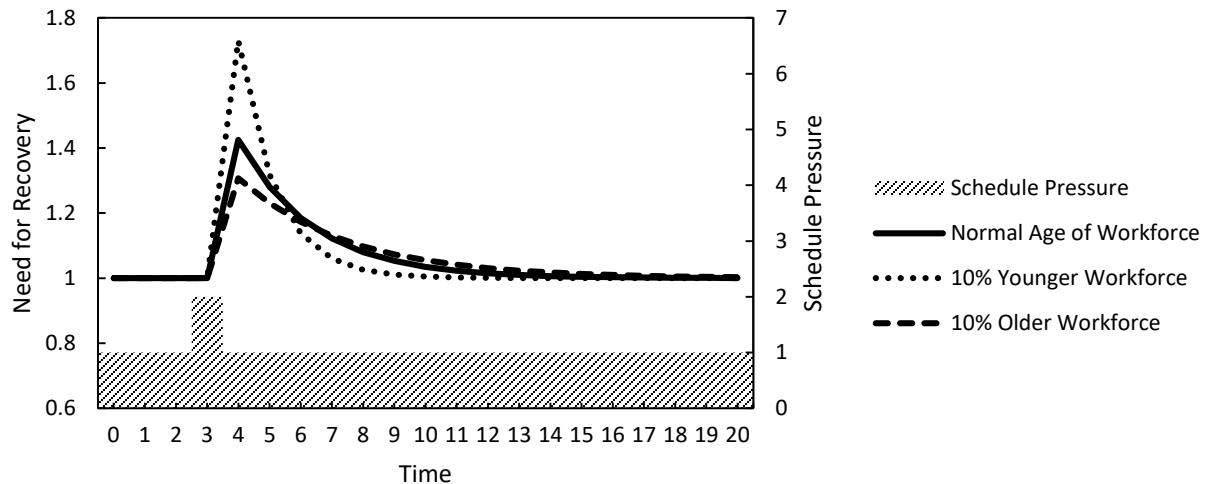
Diagnosis Intensity

Appendix A3.6 shows the differences in hindrance and challenge demands among groups of diagnoses. The diagnoses are grouped according to intensity of care, with half of the highest in the high intensity group, and the lower half in the low intensity group. The swing of challenge demands from low intensity to the high intensity group is 0.3, whereas the swing of hindrance demands from the low intensity to the high intensity group is 0.26. According to these results it can be reasoned that the high intensity group is slightly more challenging than hindering in comparison with the low intensity group. In the model the actual challenge demands is therefore adjusted for the change in fraction of high intensity patients.

Nurses Age and Fatigue Onset Time

The fatigue onset time is reasoned to be affected by the age of the nurse. Research suggests that younger employees are more prone to fatigue and have a greater need for recovery (Bos et al., 2013; Winwood et al., 2006). The graph in Figure 27 demonstrates the model's ability to account for and test the effects of employees' age on the need for recovery. The current default setting is that younger employees are more prone to fatigue, in line with previous research, of which the results are shown in Figure 27, portraying the results of a partial model test with schedule pressure as an exogenous variable.

Figure 27. Hypothesized Effect of Average Age of the Workforce on the Need for Recovery in case of a one month doubling of arriving patients at time = 3.



Job Resources

The variable *Resources* is composed of the variables used in the direct rating process in discussion point 8 (previously introduced in sections 2.10 and 5.2.5). The proportion of telemetrically trained nurses, and the average experience are based on historical values, the patient satisfaction, and well-being are endogenously represented. Appendix A3.8. shows that the weighted scores of well-being, patient satisfaction, and experience are 0.16, 0.13 and 0.13 respectively. Hence, these are assumed to explain together 42 percent of the variation in *Resources* ($0.16 + 0.13 + 0.13 = 0.42$). The other variables relevant to *Resources*, which are not represented in the model, are assumed to account for the other 58 percent, and are by default set to 1 during the full simulation time.

5.3.3. Parameter Assessment

The default settings of the physical stocks, i.e. the stocks with the unit Patients, are based on historical data. These are validated numbers and correspond to the patients at the unit, number of older patients, patients with high intensity diagnoses and patients with low intensity diagnoses.

The default settings of all non-physical entities, all stock variables with the units Quality of Care, Satisfaction, Well-being, and Dimensionless, as well as the norm and standard values associated with them, have initial (starting) values of 0.5. Moreover, the model is calibrated as such that at the starting time in January 2012, the schedule pressure, as well as the need for recovery, is 'normal' and has the numerical value 1. Next to that, the starting values, as well as the norm values, for well-being, the expectations of the quality of care, and patient satisfaction are set to the 'normal' or average numerical value of 0.5. However, it is likely that the experienced schedule pressure, need for recovery, and the expectations, well-being and patient satisfaction have not been at their 'normal', average value in January 2012. The model regards January 2012 as embodying the initial starting values, at which there was no pressure for the model to change. Only through the change in number of patients, patients characteristics, and number of employees and employees characteristics, do the numerical values change.

The variables named *Time to Change...*, that update information stocks, are mostly guessed values ranging between 1 month and 48 months. Calibration is used to find a suitable value for the *Time to Change Recent Patients per Employee*, this variable governs how fast nurses get used to a certain number of patients per employee. This variable is set to 4 months, based on visual inspection of the behavior reproduction of the *Need for Recovery* and *Patient Satisfaction*. For the same purpose, the *Time to Change Well-being* is set to 1 month. The *Time to Change Potential Patients Quality Expectations* is set to 48 months, since it is guessed that a reputation of a hospital takes a long time before it changes among

potential patients. The *Time to Adjust Insurers Perceived Quality* is set to 3 months, since the insurers depend on quality assessments and accreditation, which usually do not take place more often. The variable *Fixed Time Delay in Adjustment of Insurers Expected Quality* is set to 6 months and indicates a fixed time delay in decision making of insurers for what they negotiate for. It is reasoned that negotiations for contracts between hospitals and insurers are not made based on the most recent data, but on those of 6 months earlier, based on the information and reporting delay from quality assessments and accreditations.

5.3.4. Extreme Conditions

High Expectations

Insurers might decide that the quality norms should change. In this extreme condition test, the *Norm Insurers Expected Quality* raises with 50% at time 13, this shows the effect of the policy that insurers expectations cause registration procedures (loop R7 in Figure 7). This causes the insurers to exercise pressure on the hospital to impose quality norms. The quality norms result in an increase of registration procedures to the nurses, as discussed in section 2.14.1. Since nurses have to oblige to more rules, and have less room for their own professional judgement this serves as a *Hindrance Demand*, causing less job satisfaction which is reflected in a decrease of *Well-being*. This in turn affects the *Quality of Care*.

However, the *Norm Registration Procedures*, the value that indicates what nurses see as a normal amount of registration procedures, might catch up with the actual amount of registration procedures (this is due to a variable *Time to Change Norm of Registration Procedures* set to 24 months). In this extreme conditions test two scenarios are shown: the first with *Time to Change Norm of Registration Procedures* set to 24, the second set to infinite (9999). It is reasoned to imply that, in the first scenario, what nurses perceive as a normal amount will rather soon catch up with the actual amount, such that they do not perceive it as extra *Hindrance Demands* anymore after some time as shown in Figure 28. This will cause the *Quality of Care* to approach the normal value of 0.5 as shown in Figure 29. In the second scenario, the increase in registration procedures keeps being perceived as a burden of increased hindrance demands, which results in a lower quality of care.

Figure 28. Hindrance Demands with a *Norm Expectations* increasing with 50% at time 13

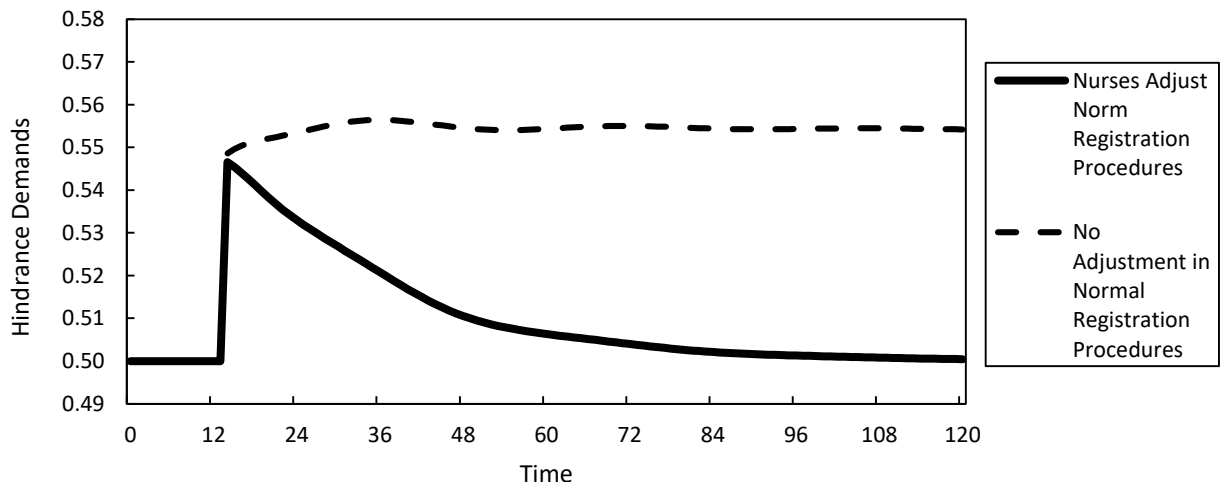
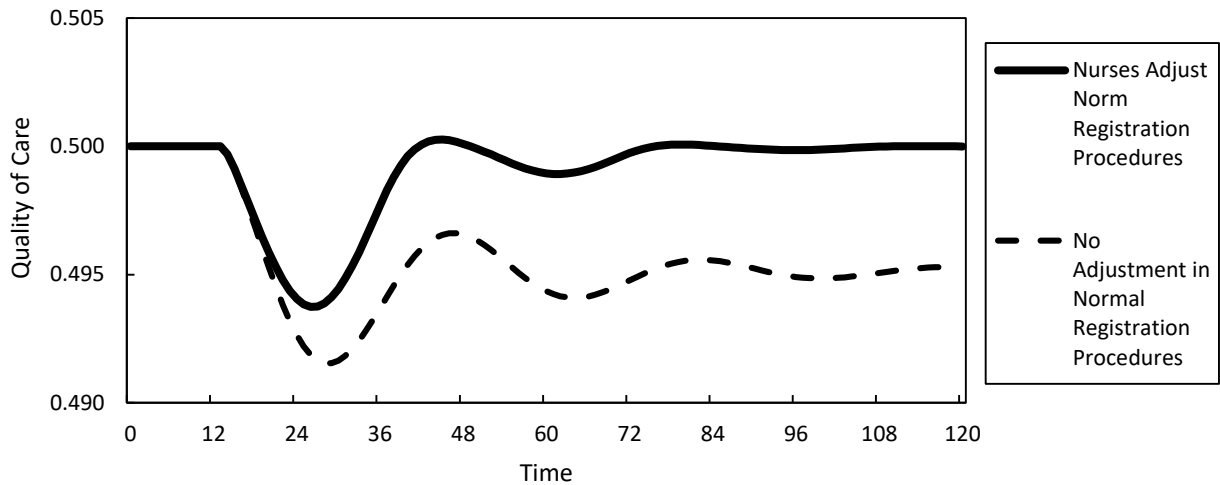


Figure 29. Quality of Care with a *Norm Expectations* increasing with 50% at time 13



This extreme condition test shows the hypothetical effects that the quality norms of the market might have on the workload of nurses, and eventually how it could affect the quality of care. Some nursing units might be reluctant to registration procedures, and keep perceiving it as a hindrance demand that undermines their work (corresponding with the dashed line in Figure 28 and Figure 29). Other nursing teams might get used to it more quickly, and the negative effects of more registration procedures might be gone after some time. The results of this extreme conditions test also show that the model only incorporates a negative effect of registration procedures. During interviews nurses reported that the majority of the registration procedures are perceived as hindering, and that there is no positive effect on the quality of care mentioned. Nevertheless, these registration procedures are often intended to ensure the quality of care, such as using questionnaires for asking patients the amount of pain they have or how they have eaten. A positive effect of these registration procedures is currently not accounted for in the model and future research could address the question of what the effects of registration procedures are on the quality of care.

Registration-Free Working

For this extreme condition test two scenarios are shown with a step increase in *Patients Arrival Rate* of 10 at time 13: the first scenario shows the base case with the step increase in patients (solid line in Figure 30 and Figure 31); the second scenario additionally includes that all registration procedures are waved at time 13 (portrayed with the dashed line). This causes a lower than normal amount of hindrance demands. When the hindrance demands are lower the effect that job resources have on well-being are greater, as discussed under section 5.3.2. Due to the increase in patients, the quality of care goes down and so does the patient satisfaction. Since patient satisfaction has a greater effect on well-being through job resources in a low-hindrance demands scenario, the well-being will go further down, and this also results in a lower quality of care. However, when the patients adjust their expectations, and the patient satisfaction returns to an average number there is also an enhanced effect of patient satisfaction due to low hindrance demands. Besides, lower hindrance demands cause less fatigue, and thus also cause lower levels of need for recovery. This results in higher peaks of well-being in the scenario with low-hindrance demands.

The results of this test suggest that, contrary to intuition, instantly waiving all the registration demands at a moment that more patients come in might result initially in lower levels of well-being and thus lower levels of quality of care. This is happening because with less hindrance demands, the job resources have a stronger effect on well-being, of which patient satisfaction is a part.

In later stages the quality of care might rise higher due to less fatigue. Although the average quality of care over time is greater in the scenario with low-hindrance demands; i.e. all registration procedures are

waived ones more patients arrive, the changes (oscillations) are more severe than in the case of sticking with the registration procedures, since patient satisfaction more strongly affects the well-being.

Figure 30. Hindrance Demands with a step increase of 10 more patients arriving each month at time 13

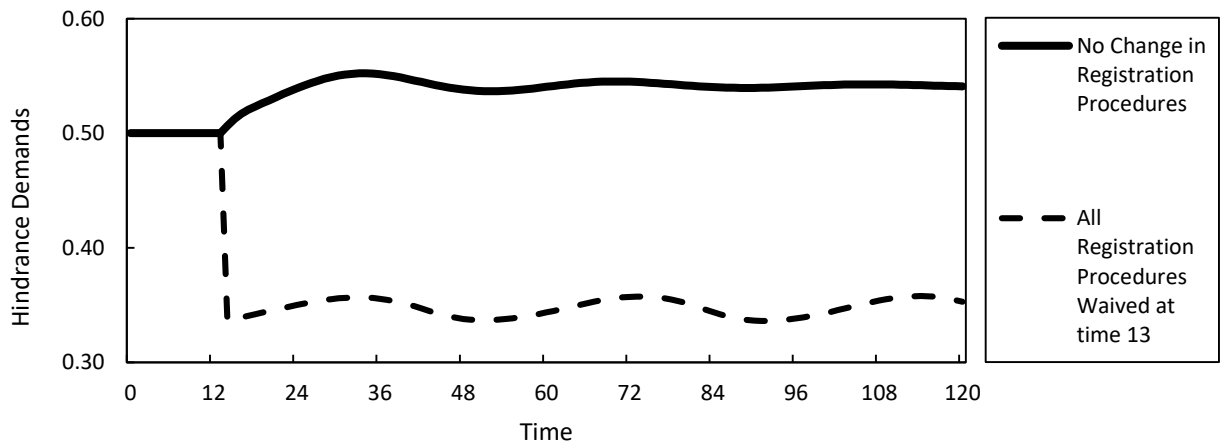
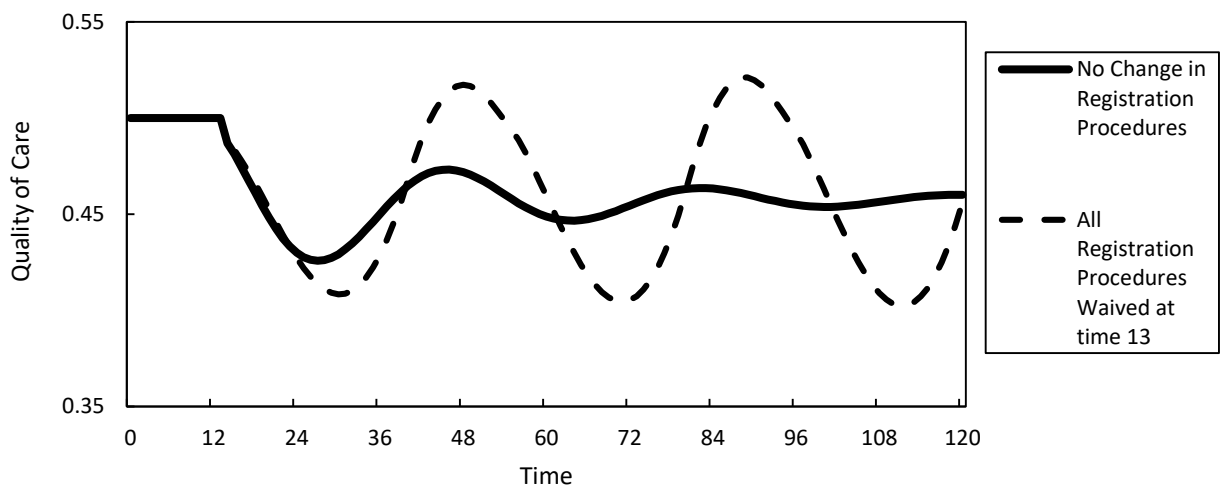


Figure 31. Quality of Care with a step increase of 10 more patients arriving each month at time 13



5.3.5. Loop Knockout Analysis

A loop knockout analysis is performed to see the effects of the different feedback loops. The variable of observation is the *Patients at the Unit* and the analysis is performed starting in equilibrium with a step increase in the *Patients Arrival Rate* of 23 patients at time 13. With all loops active this results in an escalation of workload around month 50, and with an hypothetical number of 100 patients at the unit at month 54. The naming of the different loops in the following paragraphs corresponds to those explained in Chapter 3 and portrayed in Figure 7. For each test one loop is individually turned off. The hypothetical number of 100 patients is used to provide a point of comparing amongst the effects of different feedback loops.

In case nurses will not respond to increasing levels of workload by only provide care to the same number of patients per hour as they always did the “Work Availability” loop (B1) has no effect on the system. Still, the overall quality of care will drop, since the extra number of patients are not completely ignored. This means that an increased number of arriving patients, together with working at the same pace, will rapidly develop in escalation, reaching a number of 100 patients at the unit already before the

start of month 15. This happens because at the equilibrium level each month 200 patients arrive, and 200 patients are treated and leave the unit. However, during month 13 the increase of 23 more arriving patients (so 223 in total), will negatively affect the overall quality of care, increasing the time of treatment for all patients, and thus the total patients treated rate will fall down.

If unmet expectations of insurers and medical specialists does not result in more registration procedures, knocking out the “Earning Autonomy” loop (R7), escalation starts later around month 55, and with a number of 100 patients reached only after month 65. This demonstrates that the implementation of more registration procedures can accelerate adverse developments in the model. In this case with five months earlier.

When need for recovery has no effect on absenteeism, disabling the “Burnout” loop (R6), the number of patients slides into a stable, limited oscillating, amount of 23 patients. This shows that the variable *Absenteeism* is an important factor to escalation in the model.

In case the patient satisfaction does not affect the job resources, eliminating the “Patients’ Opinion” loop (R5), the number of patients also develops towards a stable, very little oscillating, amount somewhat above 24 patients. A similar behavior is the result when suggesting that there is no virtuous or vicious causal circle between well-being and job resources, by eliminating the effect of the “Work Engagement” loop R4. This shows the significance of *Patient Satisfaction* to the development of well-being of nurses.

Contradicting intuition, if hindrance demands are not affecting the potential well-being, eliminating the “Hindrance Drenching” loop (R3), the escalation already starts around month 36, with reaching the hypothetical number of 100 patients already at month 45. Intuitively, when hindrance demands would not affect well-being, one would assume that the escalation occurs later or not at all. An explanation of the earlier escalation could be that high levels of hindrance demands reduce the effect that job resources, and thus patient satisfaction, have on well-being. Hence, when hindrance demands are in place, the possible negative effect of patient satisfaction on well-being is less strong, causing a buffering effect in case the system is on course to escalation. In conclusion, high levels of hindrance demands might cause nurses to take less notice of the opinion of patients. This might seem reasonable imagining a lot of stressful but not challenging work.

The feedback loops “Quality Erosion” (R1), “Self Undermining” (R2), and “Expectation Adjustment” B3, are also partially responsible for the escalation, since eliminating these results in a similar development as earlier discussed for the “Burnout” (R6), “Patients’ Opinion” (R5) and “Work Engagement” (R4) loops.

In the case that the need for recovery is not affecting the level of hindrance demands, suggesting that the feedback loop of “Self Undermining” R2 does not exist, the simulation develops to a stable, limited oscillating, number of patients at the unit, of around 25 patients. In case “Quality Erosion” is eliminated, and the quality of care does not affect the time per treatment, the number of patients keeps around 24 patients. Furthermore, in case patients are not changing their expectations, taking out the role of the “Expectation Adjustment” loop, escalation also does not occur, stabilizing around 24 patients as well.

The “Challenge Resolvment” feedback loop (B2), suggesting that higher levels of challenge demands can enhance the effect of job resources on well-being, has no effect on the simulation since the proportion of patients with multiple or high intensity diagnoses stays the same, only the numbers of patients grow larger, which does not make the work relatively more challenging.

A fourth balancing feedback loop named “Insurers Market Control”, suggests that insurers can influence the number of patients that arrives by negotiating different terms of contracts with the hospital. In all previous loop knock-out tests and when not explicitly mentioned this balancing loop is switched of. When this loop is active it amplifies the oscillations in the number of patients at the unit. The first boundary adequacy test in section 5.3.2 provides a more detailed description of the effect of the “Insurers Market Control” loop.

5.3.6. Behavior Reproduction

The following sections provides graphs and the results of statistical tests showing the ability to reproduce the behavior of the system. The behavior reproduction graphs are shown for four variables: 1)

the patients treated rate, 2) need for recovery, 3) patient satisfaction, and 4) absenteeism. The statistical tests are only provided for the patients treated rate, the patient satisfaction, and absenteeism. The discussion of the need for recovery provides no statistical tests since there are only 3 data points, too little for useful values.

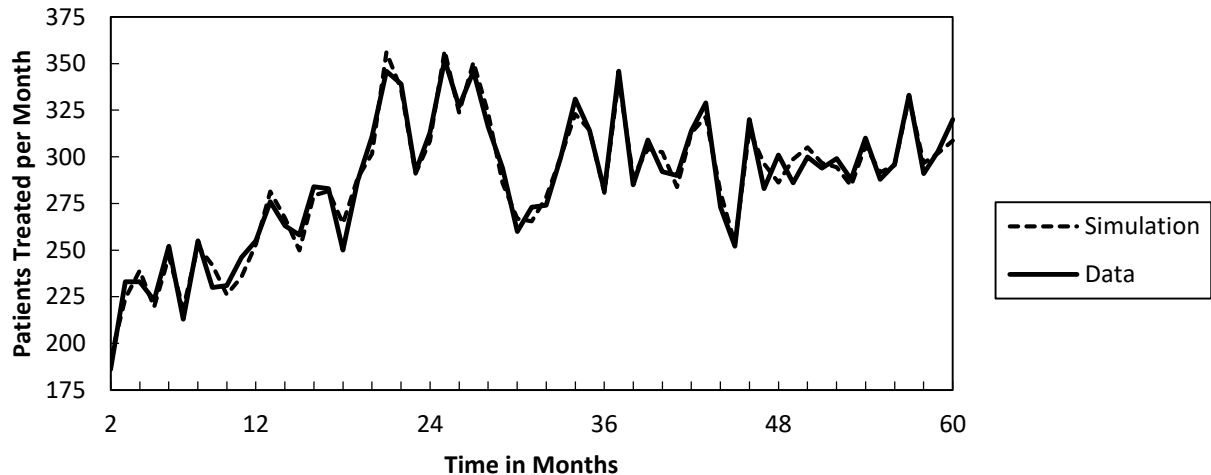
Patients Treated Rate

The data was assumed to provide accurate information on the actual patients treated rates from February 2012 till December 2016. The dataset included only patients that had arrived in the corresponding month. Patients leaving the unit in January, but who had arrived in December 2011 were not in the dataset, thus January 2012 was left out of the test and the Theil statistics are reported for the time period of 2 till 60. Figure 32 shows the simulated and actual patients treated rates. Since the average stay of the patient's is around three days, and the patients arrival rate is exogenously driven by historical data, a highly accurate capture of the trend was expected. This is confirmed by Theil's U, in table 4, which is near 0, showing that the simulation is almost equal to the data. Theil's Inequality statistics show that almost all error is concentrated in unequal covariation. These type of errors are assumed to be generated by noise, i.e. factors not accounted for in the model, and points out that the simulation is accurate for its purpose regarding the patients treated rate.

Table 4. Theil Statistics for Patients Treated Rate

Theil's U	Theil's Inequality Statistics				
	RMSPE	$U^{(M)}$	$U^{(S)}$	$U^{(C)}$	R2
0.02	0.02	< 0.01	< 0.01	> 0.99	0.97

Figure 32. Simulation and actual data of patients treated rate.

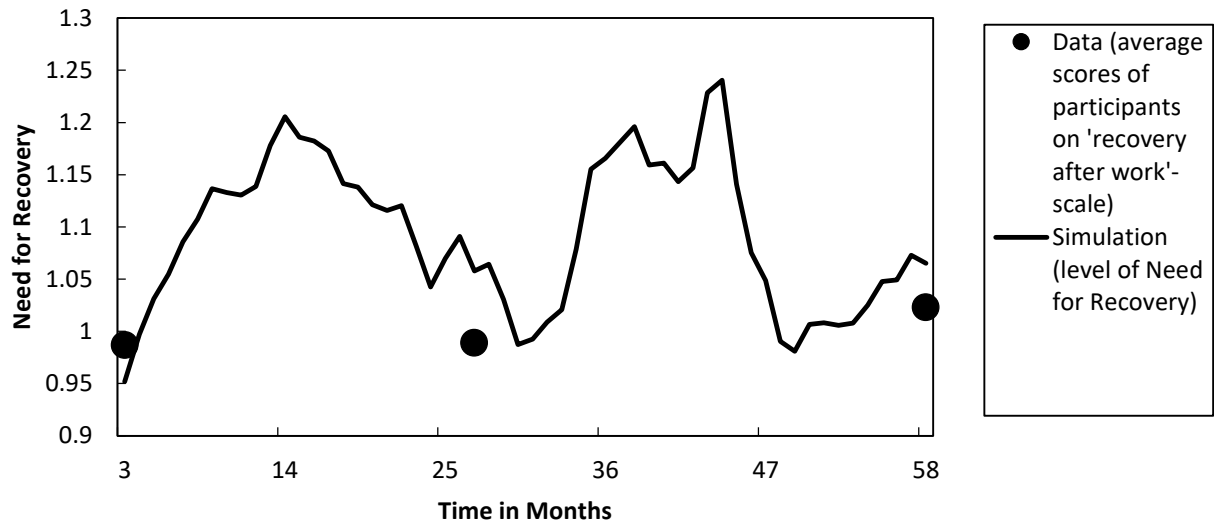


Need for Recovery

The level of need for recovery is majorly influenced by the recent schedule pressure, and to some extent by levels of hindrance demands and challenge demands, and the age of employees (section 2.9). Its initial and equilibrium value is 1, similar to that of schedule pressure, which resembles normal circumstances. When the schedule pressure is twice as low as normal, it adopts the value 0.5, whereas twice as high corresponds with a value of 2. The simulation reports the average level of need for recovery among the team of nurses.

Employee well-being questionnaires provided data from the ‘recovery after work’-scale, see section 4.7 (SKB, 2016). The data from this scale is chosen as a proxy for visually comparing with the simulated values of the model. The questionnaires were conducted in March 2012, March 2014, and October 2016, which are respectively the time-steps 3, 27 and 58. A comparison of the average values, as discussed in section 4.7, is shown in Figure 33. The data show very little variation, and the simulation is too low at the first data point, and too high at the second and third.

Figure 33. Simulation of need for recovery and adjusted averages of the ‘recovery after work’-scale



A second visual comparison of the simulation and the data is done with the percentage of participants scoring high on the need for recovery, since this might provide a better proxy to the need for recovery. I chose to normalize under the assumptions that the average and standard deviation are similar for these values, providing only a visual representation of the change in the variables. Figure 34 portrays the normalized simulation run and the three normalized values of the percentage of participants scoring high on the questionnaire. If the simulation should represent the normalized data, the simulation is too low for the first and third data points.

A third visual comparison is done with the average experienced intensity of care as reported during the knowledge elicitation session (see section 5.2.1, and Figure 11). A hindsight bias is present, and it is the average of only five participants who are not randomly selected but recruited by the senior nurse. Nevertheless, the experienced intensity of care might provide a reasonable proxy to the need for recovery of the simulation.

Figure 35 shows the similarity between the simulated need for recovery and the experienced intensity of care as reported by the nurses, starting with a value of 1 at December 2016, and drawn backwards (original value was 100, as in Figure 11, the average is divided by 100).

The first two visual comparison tests for the need for recovery provide no basis for concluding any similarities. Three data points are too little to draw any conclusions anyway. The last visual comparison, with the experienced intensity of care, shows a somewhat similar pattern of highs and lows but with different phasing, and large bias in the starting point at time 2. This error might be due to hindsight bias, the incongruence between need for recovery and experiences intensity of care, or the scope of the model. Based on visual comparison the need for recovery might be a possible indicator to the actually experienced intensity of care. This is confirmed by the Theil Statistics, Table 5, which shows a Theil’s U close to 0, which means that the simulation is much better than simple extrapolation. The $U^{(M)}$ shows that some part of the error is due to systemic bias, which might be based in the way the values of experienced intensity of care were adjusted, i.e., these do not go below 1, whereas the simulation does.

In conclusion, the employee well-being questionnaires should be conducted more often to provide for enough data points to do statistical testing. Also the experienced intensity of care can be regularly asked for, such that hindsight bias can be excluded. Moreover, the model does not incorporate important effects that has been spoken of among the nurses such as work pressure from doctors and change in supervision style, these might be responsible for the differences between data and simulation.

Figure 34. Normalized simulation and fraction of high scoring participants on the 'recovery after work'-scale.

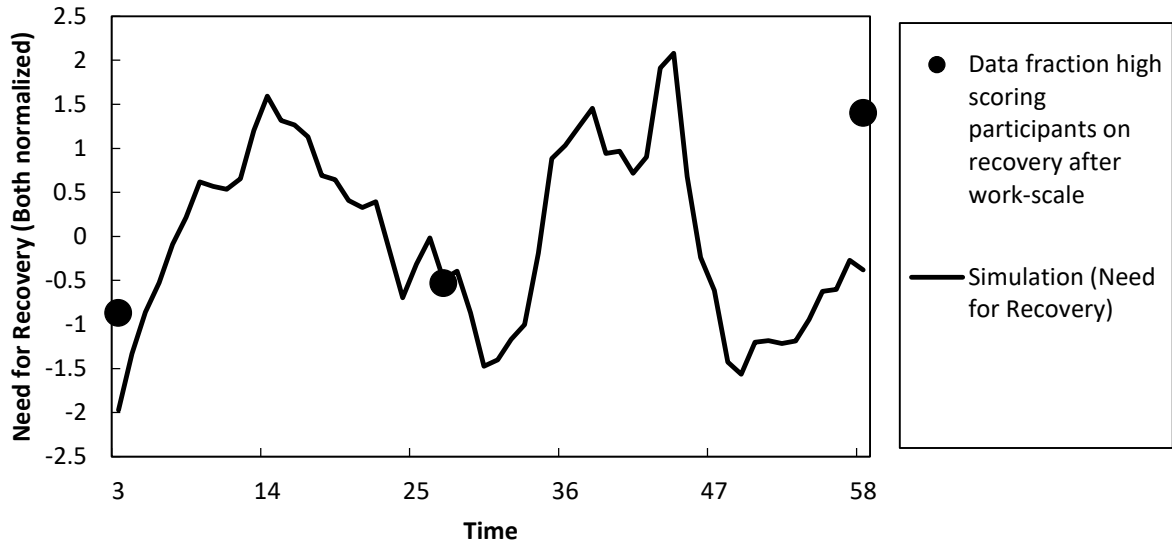


Figure 35. Simulation of Need for Recovery and data of Experienced Intensity of Care

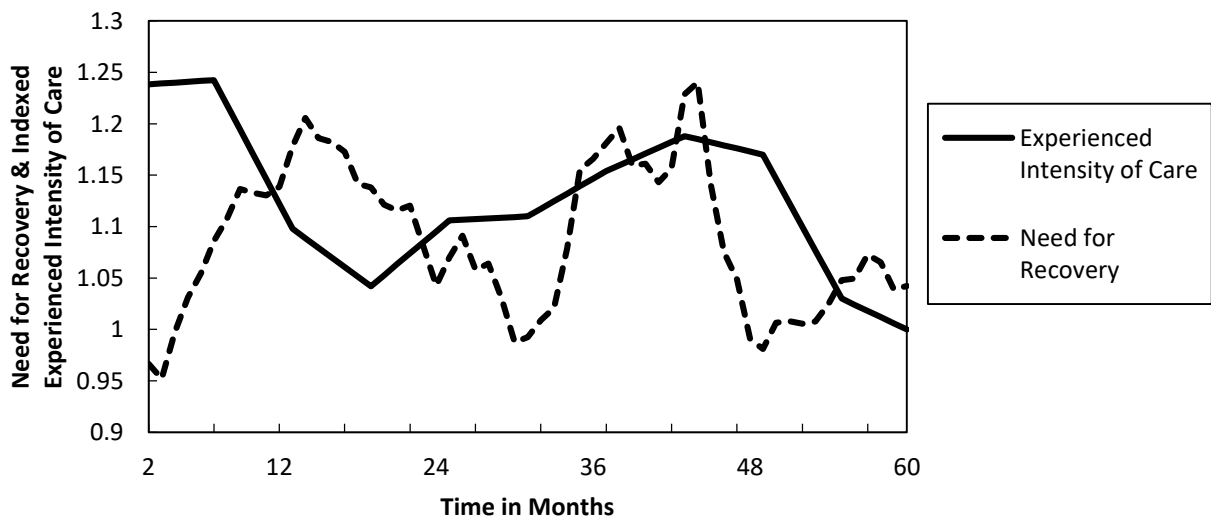


Table 5. Theil Statistics for Need for Recovery and Experienced Intensity of Care

Theil's U	Theil's Inequality Statistics				
	RMSPE	$U^{(M)}$	$U^{(S)}$	$U^{(C)}$	R2
0.09	0.09	0.13	< 0.01	0.86	< 0.01

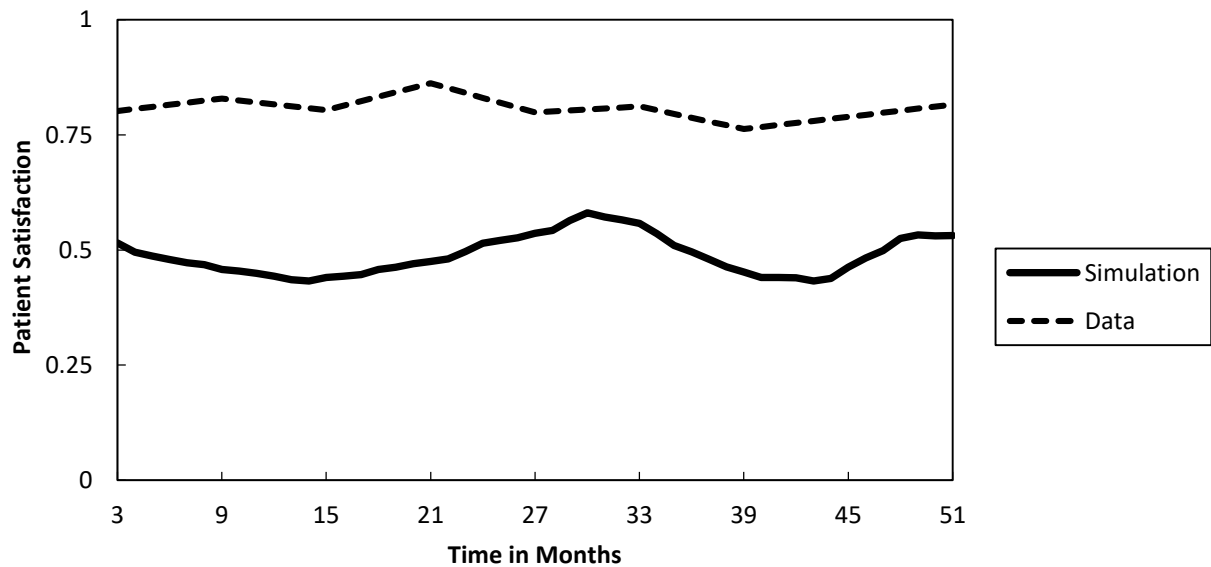
Patient Satisfaction

The third behavior reproduction test is conducted with patient satisfaction. The recent patient satisfaction is a result of the difference between the expectation and the actual quality of care, smoothed out over the last month. The recent patient satisfaction of the simulation is compared with the bi-annual reports of HNL as shown in Figure 36 (section 4.8 provides background on comparing the variables). The available reports are from the first quarter of 2012 till the first quarter of 2016, corresponding with time-steps 3 till 51 of the simulation. Table 6 shows the Theil Statistics, of which Theil's U shows that the model does better than extrapolation, but has room for improvement regarding accurately predicting reality, which is also reflected in the RMSPE of 0.19. Theil's Inequality Statistics reveal that there is a systemic bias, which is clearly visible in the difference in height in both graphs. This is due to the fact that the simulation regards 0.5 as the 'normal' value, but that the 'normal' value on the questionnaires might be higher. I conducted the statistical tests without correcting for this since there is no way better than guessing or calculating what the mean would be, and I regarded this as obfuscating the tests more. The largest part of the error is concentrated in variation. This might reveal errors in the assumptions of the model, which is a probable explanation due to its boundaries. A way of solving this might be to include more important variables as discussed earlier.

Table 6. Theil Statistics for Patient Satisfaction

Theil's U	Theil's Inequality Statistics				
	RMSPE	$U^{(M)}$	$U^{(S)}$	$U^{(C)}$	R2
0.32	0.19	0.32	0.63	0.05	0.99

Figure 36. Simulation and data of patient satisfaction.



Absenteeism

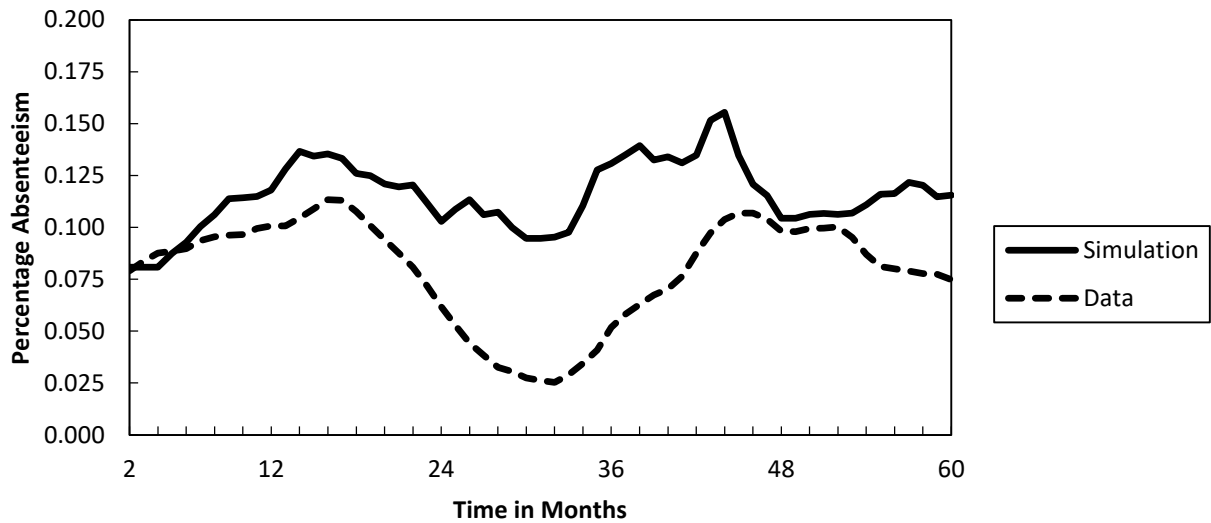
Figure 37 provides graphs of the simulated and actual absenteeism. The Theil statistics (Table 7) show that the majority of the error is due to a systematic bias. This is visible in the graphs in that the simulation is always higher than its starting point. This might be due to the assumption that January 2012 are normal values in the model. Further research could address whether the values in January 2012 can be considered

normal values. Furthermore, the remainder of the error is mostly in unequal covariation which points to noise and variables not taken into account in the model, such as effects related to the work-home interface and the interpersonal environment (as discussed in section 2.11). The Theil's U suggest that the simulation is better than extrapolation and visual inspection also suggests that the simulated absenteeism might be partially explanatory for the actual absenteeism.

Table 7. Theil Statistics for Absenteeism

Theil's U	Theil's Inequality Statistics				
	RMSPE	$U^{(M)}$	$U^{(S)}$	$U^{(C)}$	R2
0.53	1.04	0.65	0.04	0.32	0.09

Figure 37. Simulated and actual percentage of absenteeism



5.3.7. Sensitivity Analysis

Sensitivity tests are conducted to see what the limitations and robustness of the system are. The first test here described searches for the values of monthly arriving patients at which the system will escalate. The graph in Figure 38 shows the model's behavior for the monthly average *Patients at the Unit*, which is the number of internal patients that are occupying beds and require care. The system starts in equilibrium, in which each month 200 patients arrive, and an equal amount of 200 patients is treated. At time 13, the number of monthly arriving patients, *Patients Arrival Rate*, will be higher, after which it stays equal at that amount for the rest of the simulation. Also, the variable "*MAX Norm Patients per Employee*" is set to 2.67 (8/3), such that the simulation in equilibrium starts out at the maximum amount of patients that is considered normal (in the non-equilibrium tests this maximum value is 4 which was discussed during the knowledge elicitation session, see section 5.2.4).

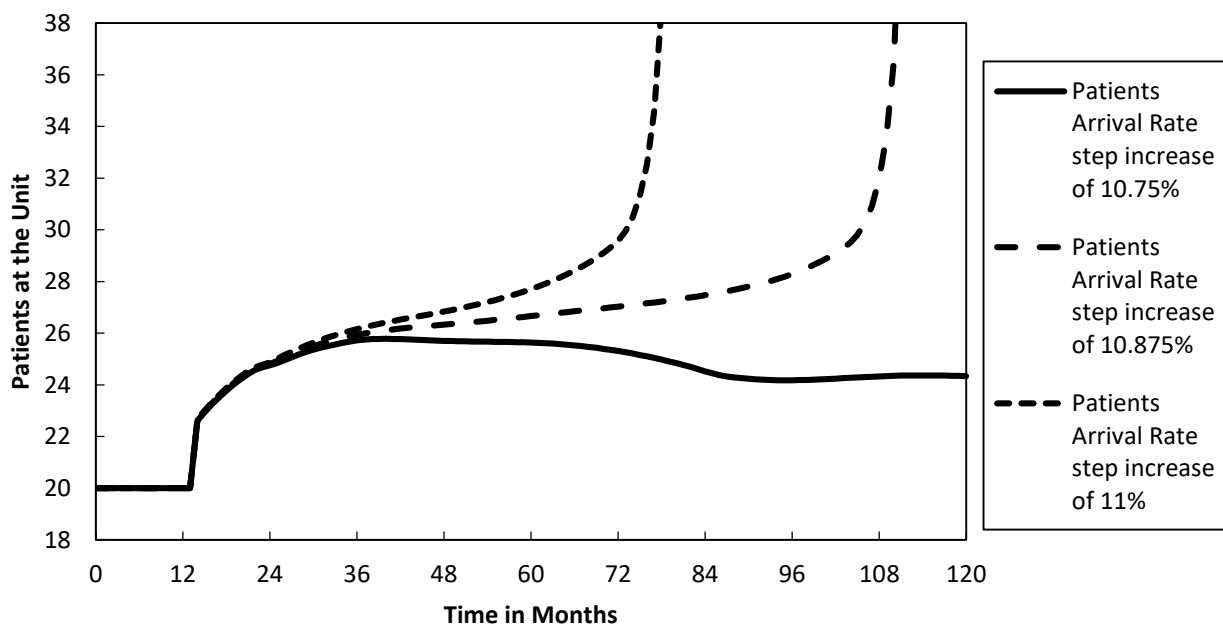
Figure 38 portrays three possible scenarios: 1) the *Patients Arrival Rate* increases from 200, to 221.5, an increase of 10.75%; 2) the number of arriving patients increases from 200, to 221.75, an increase of 10.85%; and 3) the number of arriving patients rises to 222, which is 11%. The sensitivity tests show that a step increase of 10.75% can hypothetically be handled each consecutive month, with a number of *Patients at the Unit* stabilizing at 24 patients after some time of having more patients. In contrast, with an

increase in arriving patients of 10.85%, or 11% the number of patients at the unit seems to stabilize after month 36, however the number of patients keeps rising very slowly for a while and eventually accelerates in exponential growth. The rise with 11% gets into an accelerated pace after around time 60, roughly 4 years after the systemic rise in *Patients Arrival Rate*. In comparison, when the *Patients Arrival Rate* increases with 10.85%, this results in an exponentially increasing workload only after 90 months, roughly 7 years after the initial step increase in arriving patients.

This shows that the model is very sensitive to the number of patients that is arriving, and that very small increases can result in escalation at very different times. Also, in each of the three scenarios the system seems to stabilize after month 36, and the small increases in workload that happen afterwards are hardly recognizable, till it results in escalation.

This behavior is caused by the interplay between patient satisfaction, patients' expectations, and need for recovery of the nurses. In the first scenario of 10.75% increase, the increased amount of patients results in fatigue (need for recovery). Also, the decreased quality of care results in lower rates of patient satisfaction which also influences the nurses well-being. However, at the same time, potential patients are adjusting their expectations over the years, which is why the escalating curve in the second scenario, 10.85%, is different from the escalating curve in the third scenario; i.e. the turning point is quicker in the second scenario, since expectations had already been scaled downwards. Moreover, the fact that patients adjust their expectations, i.e. are satisfied with less since they expect less, is the explanation for the downward curve in the first scenario.

Figure 38. Sensitivity Tests with *Patients Arrival Rate* step-wise increasing at time 13



The second sensitivity test shows the relation between schedule pressure and performance. The performance is shown by the amount of patients that are treated each month. The start settings of these simulation runs are equal to those of the equilibrium values in the previous test (with the variable "*MAX Norm Patients per Employee*" set to 8/3, instead of 4).

The schedule pressure is the ratio of the desired treatment rate (based on number of patients and past average treatment times), and the normal treatment rate (based on the number of employees, normal patients per employee ratio, and past average treatment times). The patients treated rate is taken as performance measure to see how many patients are able to be treated at different schedule pressures. Next to that the level of job resources is used as a sensitivity parameter to show the possible model behavior with normal and enhanced levels of resources. The variable *Other Resources* refers to the levels of the exogenous six factors to conceptualize job resources: 1) feedback, the information received on ones

work performance; 2) rewards, the job's salary or benefits; 3) job-control, the autonomy in decision making; 4) participation, the amount of influence on management decision making; 5) job-security, the threat of losing one's job; and 6) supervisor support.

The graph in Figure 39 shows a scatterplot with connected dots between levels of schedule pressure and the patients treated rate of the same moment in time of 100 simulations. The 100 simulations are performed over two sensitivity parameters. The variable *Other Resources* is divided in two scenarios: with its normal setting of 1, maximum of 2. The second sensitivity parameter is the *Patients Arrival Rate*, with 50 incremental steps from 0 to 300, together making up for 100 simulations.

The result shows that schedule pressures below 1 and around greater than 3 can yield smaller patient treated rates than normal. With the simulation settings used, the schedule pressure between 1 and 3 will cause more patients to be treated than usual. These results show that the landscape of possible model behavior has similarity to an inverted U-shaped curve, with too little and too much pressure resulting in a lower than optimal performance. This shows that an effect similar to the Yerkes-Dodson law (see 2.4.1) is present.

What substantiates an optimal performance in the previous paragraph is based on the number of treated patients, regardless of the quality of care. However, an optimal performance might also consist of a satisfactory quality of care. The graph in Figure 40 shows how the quality of care is affected by different levels of schedule pressure in three scenarios. The graph in Figure 40 are not definite numbers governing each possible scenarios, but only appeared in the three scenario runs conducted for creating the graph. These three scenario runs suggest a relation between schedule pressure and quality of care similar to exponential decay. Next to that, it shows an exceptionally large fall in the quality of care around a schedule pressure of 1.25, a workload of 25% above normal. This is due to the graphical functions that were specified by the nurses which govern the quality of care and direct care time (see section 5.2.4).

Figure 39. Structure graph between schedule pressure and patients treated.

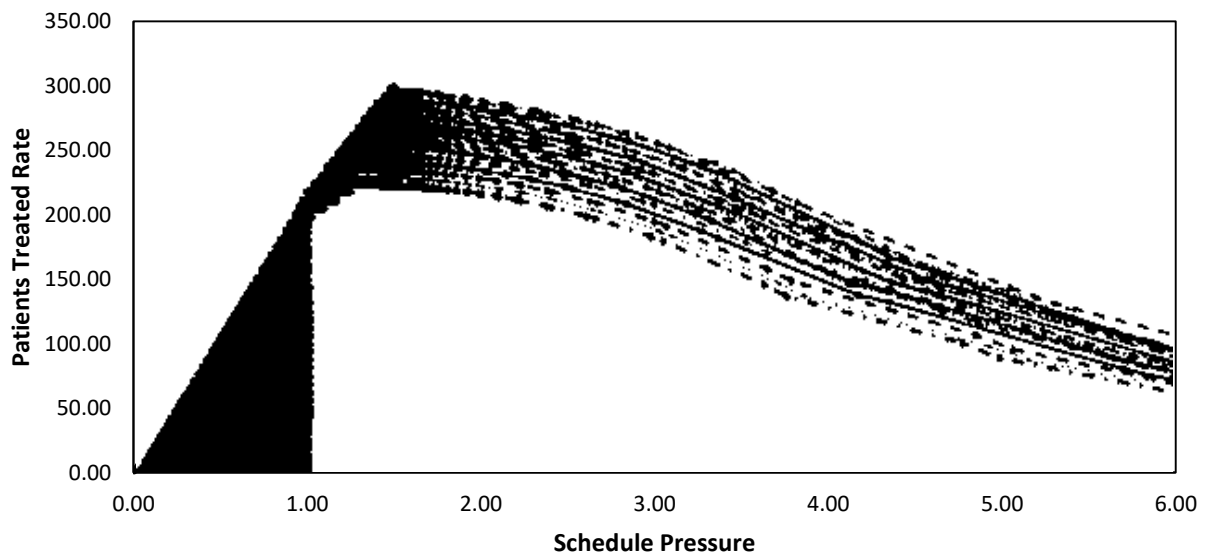
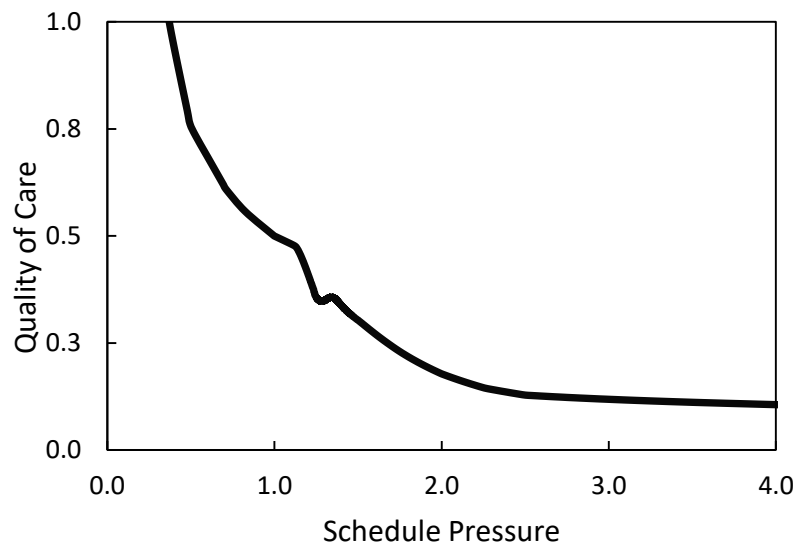


Figure 40. Structure graph between levels of schedule pressure and associated quality of care in three scenarios: *Patients Arrival Rates* of 0, 80, and 222.5.



5.3.8. Validity Results

The results of the previous sections point out that the model is based on many assumptions, best guesses, and improvisation. The causal connections reflect the literature and statements from HNL personnel, but it is hard to provide for detailed support on the numerical implementation. The behavior is explainable and plausible in reality.

During the tests in equilibrium, the model does not incorporate logical decision rules in cases of greater number of patients such as scheduling for extra personnel, or a stop on incoming patients. Instead it assumes that the characteristics of employees stay equal. Therefore it can portray the effects of escalation, in which the same amount of employees has to cope with an increasing workload, but this makes it less realistic.

Furthermore, the Theil statistics from the behavior reproduction tests in section 5.3.6 show that the simulated behavior is in many occasions not matching the data of reality. Nevertheless, the Theil's U coefficients show that the model is better than naïve extrapolation and thus provides a better than guessing estimation for the future development of those variables. In conclusion, based on the Theil's U coefficients the model seems valid enough to use for careful predictions, and at least better than extrapolation would do.

Extending the boundaries of the model might improve the statistical fit of the simulation with reality. The model could be substantially improved by extensions incorporating the effects of the work-home interface and the interpersonal environment (discussed in section 2.11), the job resources currently not accounted for (see section 2.10, and table 2 in Chapter 3), the scheduling of personnel based on the workload, and the maximum number of patients. The general limitations of this research are further discussed in section 6.2.

5.3.9. Policy Recommendations

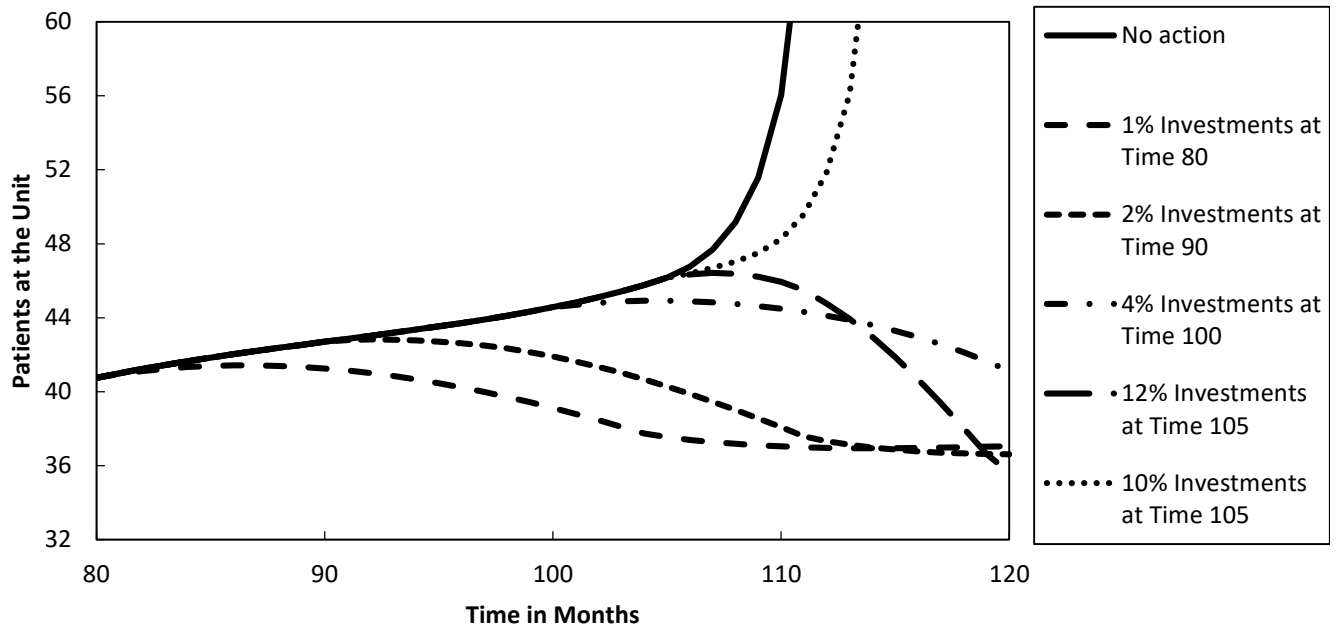
Although the model has limitations to its predictive power it can provide insights to management of the unit. In this section 'what-if' analyses are performed to show the effects of different policies. It is assumed that, after the time period of January 2012 till December 2016, the number of arriving patients

stabilizes at 330 per month. Levels of arriving patients of this amount has been seen in the past such as September 2013 (360), January 2015 (349), and September 2016 (335). The simulation runs till December 2021 (time 120). Six scenarios are shown in which investments are done in other job resources. The variable *Other Resources* refers to the levels of the exogenous six factors of job resources: 1) feedback, the information received on ones work performance; 2) rewards, the job's salary or benefits; 3) job-control, the autonomy in decision making; 4) participation, the amount of influence on management decision making; 5) job-security, the threat of losing one's job; and 6) supervisor support. Thus, examples of investments in other job resources are more working hours assigned to supportive supervision, more working hours spend on participation in decision making, or increases in job benefits that are supportive to employee well-being.

The six scenarios shown in Figure 41 are different investments in resources at different times:

- 1) No investments,
- 2) 1% in time 80 (August 2018),
- 3) 2% in time 90 (June 2019),
- 4) 4% in time 100 (April 2020),
- 5) 12% at time 105 (September 2020), and
- 6) 10% at time 105.

The investments for scenarios 1 till 5 are the least full percentage points to steer away from escalation. Scenario 6 is an example of investing a relatively significant amount -10% is much more than the necessary 4% of 5 months earlier- but not enough to steer away from escalation. The systems 'state' variables such as the need for recovery, patient satisfaction, and nurses well-being, are at such levels in time 105 that 10% investments are not enough to prevent escalation. At time 105 the work pressure does not seem much higher than at time 100, however the 'state' variables, which are not directly observable, are responsible for the course towards escalation and the high costs of turning back to sustainable working conditions. Table 8 provides an overview of the values of the state variables, external variables, and necessary investments corresponding with those values to prevent escalation. The values in the table for need for recovery, patient satisfaction, and well-being show the percentage change from the normal value. For example a need for recovery of +50% indicates that the level of fatigue is on average, 1.5 times higher than normal. In the model the normal level of need for recovery is indicated with 1, so in the model this would correspond to 1.5. In the case of patient satisfaction, the normal level of the model is 0.5, so -10% means a level of patient satisfaction of 0.45. In case the values of the state variables could be accurately monitored, and assuming a stable amount of monthly arriving patients, Table 8 provides for a decision rule to when and what amount of investments to make in job resources.

Figure 41. Policy Options of Investing in Job Resources at Different Times

The levels of the state variables, and the amounts of investments are not as perfectly accurate in reality as they are in a model. There is a large uncertainty around the effects of these percentages. One has only vague information on the state variables and the work pressure of the actual system, and a certain level of confidence about the effectiveness of investments. Moreover, the number of arriving patients is never stable. Regardless of this uncertainty, the model shows that investing earlier is much cheaper than investing later. The costs of doing an effective intervention at a later moment exponentially increases. Thus, in the long run it is more cost-effective to do small investments at an earlier stage, making sure to stay well below critical levels. Unfortunately, in practice there are more and more budget restrictions which push a system close to, or beyond its limitations, resulting in the need for more costly interventions at later stages. Investments of 1% in supervision might for example be an extra half an hour a week of performance evaluation conversations or preparation. Or 1% in autonomy on decision making could be half an hour a week of extra time for a team meeting (based on 1% of a 40 hour workweek = 24 minutes).

Table 8. Values of State- and External Variables, and necessary Investments in Job Resources

State Variables				External Variables		Investments in Job Resources
Need for Recovery	Patient Satisfaction	Well-being	Patients at Unit	Stable Patients Arrival Rate	Average FTE present	
+7%	-4%	Norm	33	308	7.7	Non needed
+33%	-14%	-8%	41	330	7.1	1%
+40%	-10%	-8%	43	330	6.7	2%
+45%	-12%	-8%	45	330	6.5	4%
+50%	-15%	-10%	46	330	6.3	12%

5.4. Analysis

5.4.1. Qualitative Analysis Results

The first two sub-questions of this research ask for identifying causal effects and feedback loops among work pressure, employee well-being and patient satisfaction. This research assumes that there are various causal relations in play when considering employee well-being and patient satisfaction. However, the literature that is used in this thesis mostly reports on correlational research and observations. Only controlled lab-experiments are able to point out causality, and even then have limitations to generalizability to outside the lab. Thus, no definite answer can be given to what the causal effects are since it is not possible to know. However, the experts, the authors of the reviewed literature, argue and are mostly in agreement on the existence of causality in their variables under study. This research reviewed a body of knowledge ranging from patient satisfaction and employee satisfaction, to nursing studies and employee well-being studies, and by using the system dynamics method, constructs new hypothesized chains of causal effects based on the literature. The Figures 3, 4, 5, 6, and 7 provide these causal chains that constitute feedback loops responsible for the dynamic, non-linear behavior that is perceived in reality. To answer the first two sub-questions of this thesis several feedback loops are suggested: the reinforcing feedback loops called “Quality Erosion”, “Burnout”, “Self Undermining”, “Hindrane Drenching”, “Patients’ Opinion”, “Work Engagement”, “Earning Autonomy”, and “Striving at Work”, and the balancing feedback loops called, “Work Availability” “Challenge Resolution”, “Expectations Adjustment”, and the hypothesized future feedback loop “Insurers Market Control” (for detailed descriptions and the associated theory see Chapter 2, for short descriptions see sections 3.1 or 6.1).

During answering the first research questions, it was found that the theory that is used for the model includes contradicting views with regard to work stressors. Current research in work-and organizational psychology studies job-performance and stressors by differentiating job demands into challenging and hindering demands (Bakker & Sanz-Vergel, 2013; Lepine et al., 2005). The research in quantity induced organizational mistakes and disasters argue that an inverted U-shaped curve is present (Morrison & Rudolph, 2011; Rudolph & Repenning, 2002). The relation between the quantity and performance at work would be governed by an inverted U-shaped curve, with too much and too little work resulting in a less than optimal performance. Having too much work for too long could eventually result in disaster. Lepine and others argue that the differences of hindrance and challenge demands is in sharp contrast with the inverted U-shaped curve, arguing that till some point all types of stress are good (Lepine et al., 2005, p. 770). However, Lepine argues in the same research that challenge demands might be increased, by simultaneously decreasing the strain of those demands, such that the negative effects of demands on long-term health can be buffered (Lepine et al., 2005, p. 770). I believe this perspective is reconcilable with the inverted U-shaped curve. For example, assume that most employees are working close to their most productive level with the current ‘mix’ of challenge and hindering demands. More of the same mix is suggested to result in long-term health issues by Lepine. This means that employees are at an optimal point on the curve, and increasing the workload results in a sub-optimal outcome, hence the theory of the inverted U-shaped curve applies to this statement of Lepine. This thesis postulates that the inverted U-shaped curve plays a role together with challenging and hindering job demands, and that they should not be considered separately. Considering the challenge-hindering framework while omitting the stress-curve opens the way for theorizing that the amount of demands is not relevant, but only the type. Whereas considering only the stress-curve leaves out the strain imposing effects of hindering demands, and the motivating effects of challenging demands.

5.4.2. Quantitative Analysis Results

Modes of Dynamic Behavior

This section provides the analysis of the third sub-question of this research: What is the dynamic behavior resulting from the feedback loops among work pressure, employee well-being, and patient satisfaction? Many management practices are aimed at stable, *linear* developments in factors such as absenteeism or quality of care. Section 5.3 shows the results of various validity tests including simulation runs. These show various types of, *non-linear*, dynamic behavior such as goal-seeking, exponential decay, exponential growth, overshoot-and-collapse, and oscillations. To answer the third sub-question, a selection of these are discussed in the following paragraphs.

The solid line in Figure 30 shows the amount of hindrance demands in case of a 5% increase in number of arriving patients (from 200 monthly arriving patients to 210 from time 13 onward). Initially the number of hindrance demands increases fast, but after a while this smooths out to a somewhat stable level. This is a form of goal-seeking behavior, in which the number of patients at the unit responsible for the number of hindrance demands grows towards a new stable level.

The solid line in Figure 31 represents the quality of care in the same scenario. A clearly oscillating pattern in the quality of care emerges, due to the feedback effects of patient satisfaction on nurses well-being, and thus on the quality of care. Whereas at the same time, the insurers and patients are changing their expectations of the care quality. Next to that, the line around which the oscillations appear is decreasing fast in the beginning, but smooths out after a while, this might be the result of an exponential decay or small overshoot-and-collapse pattern in the underlying behavior.

The dashed line in Figure 31 shows the scenario in which all registration procedures are waived simultaneously with the increase in patients. This causes for greater fluctuations in the oscillating pattern of the quality of care, since patient satisfaction has a greater influence on well-being (explained in 5.3.4). In contrast, the registration procedures were invoked to ensure the quality of care in the first place. The positive effect of registration procedures is not considered in the model in this thesis. Hence, the model illustrates only plausible hypothetical results in case the registration procedures do not add to the quality of care.

An example in which exponential decay plays a role is shown in Figure 25. It provides the hypothesized effect of the average age of the team on the level of need for recovery. At time 3 in the simulation, the number of arriving patients is doubled once, after which it returns to normal values. The level of need for recovery increases fast, due to the instantaneous increase in workload. However, after the workload returns to normal it takes some time for the fatigue to reduce again to normal levels. After the peak in need for recovery it falls down rather quickly, but a heightened level of need for recovery is present while it takes time to smooth out to normal values, an example of exponential decay.

Furthermore, Figure 17 portrays the effects on patient satisfaction. It shows that, with a 5% increase in monthly arriving patients, the patient satisfaction drops down fast, but after its lowest point increases again after which it smooths at to a stable line, lower than its starting value. This is an example of overshoot-and-collapse behavior, caused by the balancing effect that the expectations have on satisfaction. It is hypothesized that potential patients and insurers adjust their expectations based on assessments and accreditations. When the quality of care starts to decrease, the satisfaction will decrease with it, but after a while the expectations of patients and insurers will get adjusted downwards, resulting in a smaller difference between expectation and reality. This updating of the expectations results in the small increase in satisfaction compared to its lowest point.

Figure 38 provides the results of greater increases of the monthly patients. The scenarios with 10.875%, and 11% increases in arriving patients show the hypothetical result of exponential growth of the number of patients at the unit. Between 10.75% and 10.875% lies the point at which the nurses are not able to provide the needed care for all patients anymore. This initially causes small increases in patients at the unit for some years. However, at some point, the workload becomes so high, that the small increases of patients at the unit become rapidly bigger, resulting in escalation within only a few months.

These are merely examples of the dynamic behavior that occur in the system, and of which some might be observable in reality. Various other tests might be conducted which could reveal different developments. The system represents only a limited part of reality, but it underpins the notion that developments do *not follow linear* paths, but are more probable to evolve *non-linearly*. The complexity of the system creates hardships to understanding outcomes of possible interventions, such as changing the amount of registration procedures or allowing for more patients at the unit. Some results of an intervention might take longer to appear, like the 4 to 7 years in the escalating scenarios, or are not even considered to be a result of an earlier intervention, such as the counter intuitive effect that waiving all registration procedures causes heavier fluctuations, might hint at. Due to this complexity policies can have counterintuitive, and long delayed effects, worsening problems in health care they were designed for to solve (Sterman, 2006).

Dynamic Behavior at the nursing-cardiology department of HNL

The following section discusses the sub-questions four to six, which focus on the dynamics on the cardiology department of HNL, and possible future threats and opportunities. The method that is conducted in this thesis did not lead to satisfactory outcomes with respect to reproducing behavior of reality. Chapter 5 concludes that no inferences should be drawn about the nursing-cardiology unit of HNL based on the results of the model. Thus, the last three sub-questions of this research will be left unanswered. However, some of the results might give a hint of what might be at play at a nursing department of a hospital.

The model reveals a boundary between a sustainable workload and a workload which results in escalation as discussed in section 5.3.7. The sensitivity tests conducted in 5.3.7 show a sustainable workload with an increase of *Patients Arrival Rate* of 10.75%, and a workload resulting in escalation at 11%, these numbers should not be interpreted as indicative for reality. This is merely an indication of the theoretical existence of a sustainable workload. In reality, many different factors are at play in preventing escalation that the model in this thesis does not take into account (e.g. management and leadership that serve as job resources).

Next to that, the model shows the possible effects that stress might have on performance. The model itself is merely a numerical construction, which gets only meaning when values and explanations from real life are associated with it. As described in section 2.5.1, Lupien (2007, p. 215) provides evidence for an inverted U-shaped curve between the amount of circulating glucocorticoids, a stress hormone, and memory performance. This relation can be projected on the model, in the effect that the *Schedule Pressure* has on the *Need for Recovery* and *Quality of Care*, showing a similar inverted U-shaped curve as portrayed in section 5.3.7. The two phenomena, the boundary of sustainable workload, and the stress-curve can together decrease organizational capabilities, such as the employee's well-being, over time. This poses a future threat since the best intentions of management can result in organizing the work as such that there is operated close to the sustainable workload. However, operating close to the sustainable workload also implies that there is a greater chance of getting above it, which might eventually lead to escalation in the form of burnout or disastrous mistakes in care (Morrison & Rudolph, 2011). The opportunities that HNL faces is to find an acceptable level of performance, which, together with the right job resources, is resilient enough to not lead to escalation or burnout .

Chapter 6. Conclusion and Discussion

6.1. Discussion central research question

The six sub-questions, as discussed under the analysis section of chapter 5, comprise of the findings to the central research question “How are changes in patient satisfaction related to employee well-being and work pressure over a time period of ten years?”. In summary, it can be expected that patient satisfaction is partially dependent on the number of patients, the intensity of care that these patients need, the number of nurses, and the nursing workforce characteristics such as experience, age, and skills. Next to that, feedback plays an important role in explaining how patients satisfaction relates to the work pressure and well-being of nurses. The development of patient satisfaction cannot be seen without the feedback effects responsible for it. Moreover, this research provides evidence that patient satisfaction is important not only to the performance of the hospital, and in negotiations with insurers, but also for the well-being of nurses. Since the well-being of nurses is, in turn, affecting the patient satisfaction there is a dynamic system at play. Furthermore, the ways of responding to lower levels of quality of care and patient satisfaction by management is to implement new sets of key performance indicators, which result in an administrative burden to nurses. Over a longer time-period this can erode the quality of care, and the well-being of the employees further, resulting in vicious cycles that can cause a decrease in the value of health care (Maarse et al., 2016; Pollitt et al., 2010; Porter & Teisberg, 2004).

The dynamic interactions amongst variables such as work pressure, fatigue, well-being and patient satisfaction are a major contribution of this thesis. Section 3.1 identifies various feedback loops that are grounded in theory and play an important role on a monthly and yearly basis. These feedback loops are either reinforcing feedback loops: virtues or vicious cycles, showing positive or negative ‘spirals’ of causal interaction. Or balancing feedback loops: limiting, counteracting measures which result in upper or lower limits, or in patterns of oscillations and wave effects.

The “Quality Erosion” loop is a reinforcing feedback loop, addressing the effect that quantities of workload have on the quality of work, and that better (or worse) quality eventually results in lower (or greater) quantities in work. The “Burnout” loop is a reinforcing feedback loop describing the effect that the demands and quantity of work have on the need for recovery. With a greater need for recovery the absenteeism rises. With less nurses less work is performed than would otherwise be the case, resulting in an even higher workload and thus need for recovery.

The “Work Availability” loop is a balancing feedback loop, which specifies that nurses will care for more patients when there are more patients. It means that nurses will not decide to leave patients behind, thus they adjust their care for the amount of patients that need care.

The “Challenge Resolvment” loop is a balancing feedback loop, in which tasks that are seen as challenges, are resolved quicker, which leaves less challenging task for later times. The “Self Undermining” reinforcing feedback loop shows the effect that fatigue causes more small mistakes and rework to be done, which is itself increasing fatigue. Another reinforcing feedback loop is named “Hindrance Drenching”, in which hindering, annoying work demands result in less enthusiasm for work, decreasing the employee well-being and the quality of work in the long run. This decrease in quality of work can again increase the amount of hindering tasks that have to be performed later. The same effect can work vice versa, in which actively coping with hindrance demands or reducing its amount can result in a better employee well-being, and quality of work. Another reinforcing feedback loop is called the “Work Engagement” loop, which states that employee well-being can be a job resource. For example, a greater (or lowered) well-being can result in job crafting activities (or less of these activities), that over time results in an even higher (or lower) level of employee well-being.

Furthermore, this thesis proposes a reinforcing feedback loop called “Patients’ Opinion”. In this feedback loop the patient satisfaction functions as a job resource to nurses, which affects the nurses well-being. Nurses in this research pointed out that patient satisfaction is indeed an important job resource to them in the way that it motivates them to work. Thus when patients are more satisfied, it is positive for the nurses well-being at work, and results in a higher quality of work. The higher quality of work in turn

has a positive effect on patient satisfaction. This virtuous cycle can also turn vicious when each of these variables moves in a downward direction. Closely related to the reinforcing effect of “Patients’ Opinion” is the balancing feedback loop “Expectations Adjustment”. The “Expectations Adjustment” loop prescribes that patients get used to the levels of quality of care over time, and are going to expect a higher (or lower) quality of care when the quality of care is high (or low) for some time. This results in a patient satisfaction to return to ‘normal’ levels, when on average the expectations match with reality. When the expectations are higher than reality, patient satisfaction is lower, and vice versa. Moreover, not only patients adjust their expectations of the work of nurses but also insurers and medical specialists do. The insurers and medical specialists can influence the work of nurses by imposing quality criteria and procedures. These quality criteria and procedures often imply registration procedures and rule-based working for nurses, which postulate as hindrance demands in their work. Hindrance demands can, in turn, result in lower levels of employee-wellbeing, reducing the quality of care. This evokes even more quality criteria and procedures prescribed by insurers and medical specialists. This effect is named the “Earning Autonomy” loop, and is a reinforcing feedback loop.

In addition, it is suggested that in the future insurers will also influence the work of nurses by controlling the number of patients that will arrive for certain treatments. This creates another balancing feedback loop called “Insurers Market Control”, which can increase the amount and intensity of fluctuations in workload and quality of care, due to its delay in information and decision making.

Finally the “Striving at Work” loop describes a reinforcing feedback loop through the well-being of nurses. Higher levels of well-being can result in better care and thus in slightly lower treatment times, decreasing the overall schedule pressure. The decrease in schedule pressure gives the opportunity to have an even higher level of well-being. The same is true in case this is a vicious cycle, in which well-being goes down and patients stay slightly longer than necessary due to small mistakes or rework.

6.2. Limitations and Future Research

The method that is conducted in this research is subject to many limitations. First, the literature research is shallow. The fields of research such as the biological effects of stress, and work and organizational psychology are broader than what is used in this thesis. Future research could start with a more structured approach to finding literature by using wider search terms and justifying why certain search results are filtered out.

Second, the boundaries of the model are the limitations of what it can explain. The effects related to the work-home interface and the interpersonal environment are excluded from the model, which might pose a weakness in its validity and predictive power (Sonnentag, 2015). Next to that, only a small amount of job resources is endogenously determined, and three job resources were added based on interviews with the nurses, and have no backing in the literature review. The effects of the other job resources: feedback, rewards, job control, participation, job security and supervisor support; are deemed to be constant in the simulation, contradicting with statements of nurses and earlier research (Demerouti et al., 2001). Moreover, the model currently does not take into account that the scheduling of personnel can be dependent on the amount of work. Furthermore, there is the possibility to send patients to other units or hospitals when the unit works at full capacity, which is also not accounted for in the model. Also, the model could be substantially improved by extensions incorporating the effects of the work-home interface and the interpersonal environment, the job resources currently not accounted for, the scheduling of personnel based on the workload, and including maximum numbers on patients. For example variables of the work-home interface that can be added might be related to the effect that time with the family has on the employees (Wu, Duan, Zuo, Yang, & Wen, 2016). Based on interviews I had at HNL, probably interesting variables related to the interpersonal environment which could be added are the socialization of newcomers (Kammeyer-mueller, Wanberg, Rubenstein, & Song, 2016), since these are also responsible for the trajectory of the development of employee well-being (Sonnentag, 2015, p. 267).

Third, during the Knowledge Elicitation Session some of the discussion points were answered by each participant individually, and others by the participants as a group together. It was found that brainstorming

tasks can best be performed by individuals or smaller groups, i.e. nominal groups, and evaluation tasks by structured group sessions (Vennix, Andersen, Richardson, & Rohrbaugh, 1992, p. 33). First making use of the nominal group technique in elicitation of mental models, and thereafter evaluating the results by a structured group session can increase the reliability of quantitative, as well as qualitative data. The nominal group technique was not used due to time constraints for the session. Although there have been firm discussions with opposing opinions on each of the topic, the obtained data might be subject to the biases of groupthink. Future research might structure their knowledge elicitation such that an individual brainstorming phase is scheduled prior to a structured group session, such that the possible bias of groupthink becomes more visible.

Fourth, the method of system dynamics modeling requires to transform all variables that are identified as relevant to the system in numerical values. Often there is no data available for the formulations used in the model, and numbers are found through calibration or best guesses. The numerical values of the model in this thesis are majorly best guesses, and few are calibrated. Future research could improve on providing better justifications for numerical values by performing more interviews, ask stakeholders directly or using scripts to find out what they think the values are as is used for working under pressure in section 5.2.4, or use the direct rating technique as a way to elicit numerical values as is used for the job resources and hindrance and challenge demands.

Fifth, the scope of this research was broad in its attempt to largely explain the underlying dynamic mechanisms responsible for changes in employee well-being and patient satisfaction. Moreover, the scope focused both on building theory and applying it to the nursing-cardiology department of HNL. This broad scope led to a large, complex model of which the behavior requires many factors to be described and underpinned. It would take a lot of time and resources to validate all variables of the model to a greater extent than is currently done in this thesis. Future research might opt for smaller parts of the system, and provide a more elaborate validity testing and discussion of the results related to that part.

As last point of reflection, the system dynamics method that is used provided for “more complex predictions” and for explicitly addressing the role of time in the linkages between long term outcomes and the dynamic and endogenous effects of job demands and resources (Ilies, Aw, et al., 2015, p. 9; Ilies, Pluut, et al., 2015, p. 849). The use of feedback loops fits with the current theory of loss and gain cycles, and their effects on employee well-being and job performance (Bakker, 2015). Although the system dynamics method is found to be suitable and useful, other methods of computational modelling, such as agent-based modeling, might be as useful and promising. An example is the work of Duggirala (2016), Silverman (2001), Singh (2016) and others in applying agent-based modeling for explaining absenteeism.

6.3. Managerial and theoretical implications

The findings of the model provide the idea that nurses are able to work sustainably under a greater than normal work pressure. However, operating continuously close to the upper sustainable limit, small and normal differences in workload might result in escalation. Moreover, the models behavior shows that it is possible to work above the sustainable limit for a relatively long time, without recognizing major changes. The analysis suggests time horizons of four to seven years of working above the sustainable workload, after which within only a few months escalation occurs. The escalation in the model is an exponential growth of the number of patients at the unit, however, in reality this might occur through nurses getting burned out, safety being reduced causing an increasing number of mistakes.

Next to that, it is recommended to closely monitor the development of the ‘state’ variables, such as the need for recovery, nurses well-being, and patient satisfaction. The combination of these state variables together with increasing work pressure calls for interventions such as investments in job resources. In general investing small amounts at earlier stages can prevent major escalations later. Waiting for problems to grow requires much higher investments later to return to normal circumstances.

This poses a challenge for managers. Operating as close as possible at the highest performance level results in a greater work output. However, this level of workload might fluctuate between just below and above the sustainable limit. This means that there is a very high risk of being above the sustainable

workload for some time, resulting in a loss cycle or disaster dynamic, which is spoken of in the literature and observed in reality over and over (Bakker, 2015; Morrison & Rudolph, 2011; Rudolph & Repenning, 2002). The activities of managing for the highest outcomes are honest attempts for reaching a greater job performance. This results in operating close to the sustainable workload, at which *small and normal* changes in the workload are then the causes for starting a loss cycle or vicious feedback loop, of which the results might take years to appear. Continuously proceeding in cost cutting activities, or increasing the workload, can reduce the quality of care which can eventually result in more intakes than would have been necessary. This has similarities to the 'adaptation trap' (Rahmandad & Repenning, 2016), which explains the erosion of organizational capabilities, and the path to worsening performance due to well-intended management efforts.

The notion of a sustainable workload, and the risks of erosion or disaster, is not only limited to nurses in hospitals but applies to each organization. Tasks which can pile up, the well-being of employees, challenging and hindering activities, and positive and negative reinforcement due to accomplishments and workload play a role in each team and organization. Hence, these findings can be generalized in its application to various other working teams.

Next to these managerial implications, this work has several theoretical implications. The theoretical background and loop descriptions as discussed in chapters 2 and 3 provide a comprehensive overview and descriptions of feedback loops that are responsible for non-linear changes over time. Moreover, it provides a first attempt on a quantitative system dynamics model for explaining changes in employee well-being and patient satisfaction due to these feedback loops. In the field of employee well-being Ilies, Aw, and Pluut (2015, p. 9; 2015, p. 849), argue for future research to address the linkages between long term outcomes and the dynamic and endogenous effects of job demands and resources. Next to that, they call for "more complex predictions", explicitly addressing the role of time, and the theoretical relevance of a long term perspective, with predictions over multiple years. This thesis serves as a first step towards more complex predictions, accounting for the role of time and feedback effects, with regards to employee well-being. In conclusion, system dynamics modeling is a promising method to substantiate the field of employee well-being, and its applications to health care. More research should be done to arrange for more valid and reliable models, of which the results could provide for more accurate and useful predictions.

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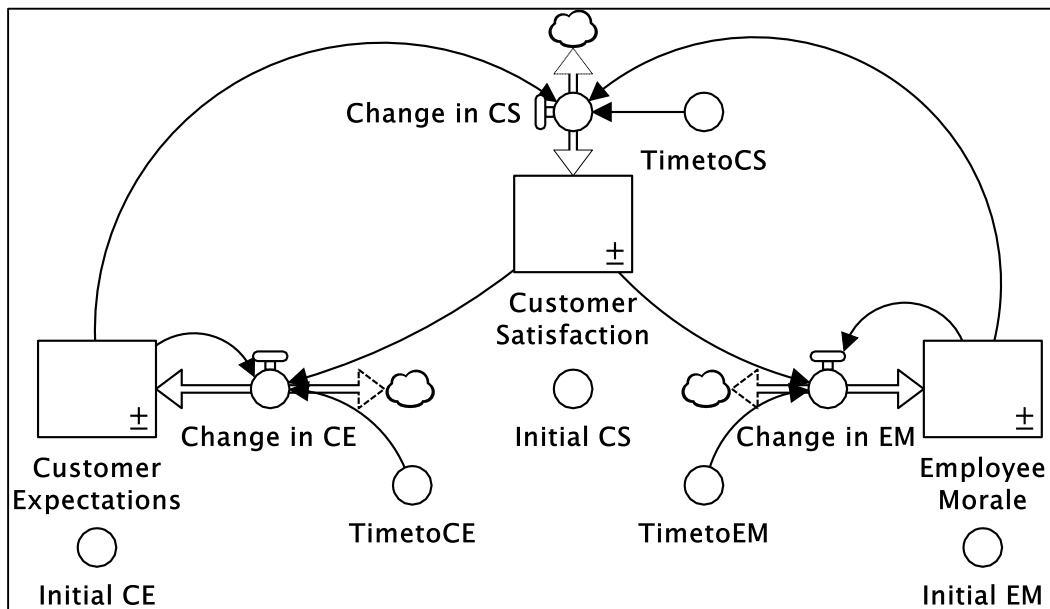
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Appendices

A1. Example Customer Satisfaction model; Stock-and-Flow diagram and equations



$$\text{Customer_Expectations}(t) = \text{Customer_Expectations}(t - dt) + (\text{Change_in_CE}) * dt$$

$$\text{INIT Customer_Expectations} = \text{Initial_CE}$$

INFLOWS:

$$\text{Change_in_CE} = (\text{Customer_Satisfaction} - \text{Customer_Expectations}) / \text{TimetoCE}$$

$$\text{Customer_Satisfaction}(t) = \text{Customer_Satisfaction}(t - dt) + (\text{Change_in_CS}) * dt$$

$$\text{INIT Customer_Satisfaction} = \text{Initial_CS}$$

INFLOWS:

$$\text{Change_in_CS} = (\text{Employee_Morale} - \text{Customer_Expectations}) / \text{TimetoCS}$$

$$\text{Employee_Morale}(t) = \text{Employee_Morale}(t - dt) + (\text{Change_in_EM}) * dt$$

$$\text{INIT Employee_Morale} = \text{Initial_EM}$$

INFLOWS:

$$\text{Change_in_EM} = (\text{Customer_Satisfaction} - \text{Employee_Morale}) / \text{TimetoEM}$$

$$\text{Initial_CE} = 1$$

$$\text{Initial_CS} = 1$$

$$\text{Initial_EM} = 7$$

$$\text{TimetoCE} = 2$$

$$\text{TimetoCS} = 2$$

$$\text{TimetoEM} = 2$$

A2. Equations List

Formulation and comments

Units

"SW_Reference-Start2012_Equilibrium" = 1

Dimensionless

SW (switch; either 0 or 1), set to 1 forces exogenous variables to an equilibrium starting with close to 2012 values. Set to 0 uses historical data for relevant exogenous variables.

A2.1.Care Intensity

Formulation and comments

Units

$High_Intensity_Diagnosis_Type(t) = High_Intensity_Diagnosis_Type(t - dt) + (HI_Patients_Arrival_Rate - HI_Patients_Treated_Rate) * dt$

Stocks Initial Value: $High_Intensity_Diagnosis_Type = Initial_High_Intensity_Diagnosis_Type_Patients$

Patients

Each stock in this description starts with its equation, after which the equation for the initial value is provided. For the above formula the initial value of the stock refers to a separate variable. The units are outlined at the right side. The stock of patients with a high intensity diagnosis depends on the initial value (ending with (t-dt)), and the arrival rate and treated rate of patients.

$HI_Patients_Arrival_Rate = Patient_Flow.Patients_Arrival_Rate * Fraction_High_Intensity_Diagnosis_Type_Patients_Arriving$

Patients/Months

$HI_Patients_Treated_Rate = Fraction_HI_Patients * Patient_Flow.Patients_Treated_Rate$

Patients/Months

The stock of patients with a high intensity diagnosis type increases due to its arrival rate, and decreases by its treated rate. The arrival rate is a fraction of all the patients, exogenously determined by historical values. This is mostly equal for the Low Intensity Diagnosis Type, Patients Aged > 70, Patients with Multiple Diagnosis, and Total Registration Procedures.

$Low_Intensity_Diagnosis_Type(t) = Low_Intensity_Diagnosis_Type(t - dt) + (LI_Patients_Arrival_Rate - LI_Patients_Treated_Rate) * dt$

Stocks Initial Value: $Low_Intensity_Diagnosis_Type = Initial_Low_Intensity_Diagnosis_Type_Patients$

Patients

$LI_Patients_Arrival_Rate = Fraction_Low_Intensity_Diagnosis_Type_Patients_Arriving * Patient_Flow.Patients_Arrival_Rate$

Patients/Months

$LI_Patients_Treated_Rate = Patient_Flow.Patients_Treated_Rate * Fraction_LI_Patients$

Patients/Months

$Norm_Fraction_High_Intensity_Diagnosis_Type_Patients(t) = Norm_Fraction_High_Intensity_Diagnosis_Type_Patients(t - dt) + (Change_in_Norm_High_Intensity_Diagnosis_Type_Patients) * dt$

Stocks Initial Value: $Norm_Fraction_High_Intensity_Diagnosis_Type_Patients = Fraction_HI_Patients$

Dimensionless

$Change_in_Norm_High_Intensity_Diagnosis_Type_Patients = (Fraction_HI_Patients - Norm_Fraction_High_Intensity_Diagnosis_Type_Patients) / Time_to_Change_Norm_of_High_Intensity_Diagnosis_Type_Patients$

Per Month

The fraction of patients with a high intensity diagnosis is compared to the normal fraction, which updates over time. This is equal for the Low Intensity Diagnosis Type, Patients Aged > 70, Patients with Multiple Diagnosis, and Total Registration Procedures.

$Norm_Fraction_of_Patients_Aged_>_70(t) = Norm_Fraction_of_Patients_Aged_>_70(t - dt) + (Change_in_Norm_Old_Patients) * dt$

Stocks Initial Value: $Norm_Fraction_of_Patients_Aged_>_70 = .SW_Reference-Start2012_Equilibrium$

$* Fraction_of_Patients_Aged_>_70 + (1 - .SW_Reference-Start2012_Equilibrium) * Reference-$

$1st3Months_Fraction_of_Patients_Aged_>_70$

Dimensionless

The normal fraction updates over time. The initial value is different in equilibrium or in historical values mode. In equilibrium it is equal to the actual fraction, in historical mode it is the average of the first 3 months. The use of the switch is similar in other equations.

Change_in_Norm_Old_Patients = ("Fraction_Patients_Aged_>_70"-
"Norm_Fraction_of_Patients_Aged_>_70")/Time_to_Change_Norm_of_Old_Patients

Per Month

Norm_Fraction_Patient_Multiple_Diagnosis(t) = Norm_Fraction_Patient_Multiple_Diagnosis(t - dt) +
(Change_in_Norm_Registration_Procedures_1) * dt

Stocks Initial Value: Norm_Fraction_Patient_Multiple_Diagnosis = ".SW_Reference-Start2012_Equilibrium"
*Fraction_of_Patients_with_Multiple_Diagnosis + (1-.SW_Reference-Start2012_Equilibrium)"*Reference-
1st3Months_Fraction_of_Patients_with_Multiple_Diagnoses"

Dimensionless

Change_in_Norm_Registration_Procedures_1 = (Current_Fraction_Patients_Multiple_Diagnosis-
Norm_Fraction_Patient_Multiple_Diagnosis)/Time_to_Change_Norm_of_Multiple_Diagnosis

Per Month

Norm_Registration_Procedures(t) = Norm_Registration_Procedures(t - dt) + (Change_in_Norm_Registration_Procedures) * dt

Stocks Initial Value: Norm_Registration_Procedures = ".SW_Reference-Start2012_Equilibrium" * "Reference-
Start2012Equilibrium_Perceived_Proportion_of_Registration_Procedures_per_Patient" + (1-.SW_Reference-
Start2012_Equilibrium)"* ("Reference-1stMonth_Perceived_Proportion_of_Registration_Procedures_per_Patient"-
Correction_for_Linear_Increase_in_Registration_procedures)

RegProcDemands/Patients

Change_in_Norm_Registration_Procedures = (Actual_Registration_Procedures_per_Patient-
Norm_Registration_Procedures)/Time_to_Change_Norm_of_Registration_Procedures

RegProcDemands/Patients/Months

"Patients_Aged_>_70"(t) = "Patients_Aged_>_70"(t - dt) + ("Patients_Aged_>_70_Arrival_Rate" -
"Patients_Aged_>_70_Treated_Rate") * dt

Stocks Initial Value: "Patients_Aged_>_70" = ".SW_Reference-Start2012_Equilibrium" * "Fraction_of_Patients_Aged_>_70"
*Patient_Flow.Patients_at_the_Unit + (1-.SW_Reference-Start2012_Equilibrium)"*Start_Number_of_Arriving_Patients*
"Reference-1st3Months_Fraction_of_Patients_Aged_>_70"*Initial_Average_Time_at_Unit

Patients

"Patients_Aged_>_70_Arrival_Rate" = "Fraction_of_Patients_Aged_>_70"*Patient_Flow.Patients_Arrival_Rate

Patients/Months

"Patients_Aged_>_70_Treated_Rate" = Patient_Flow.Patients_Treated_Rate*"Fraction_Patients_Aged_>_70"

Patients/Months

Patients_with_Multiple_Diagnoses(t) = Patients_with_Multiple_Diagnoses(t - dt) + (Patients_Multiple_Diagnosis_Arrival_Rate -
Patients_Multiple_Diagnosis_Treatedl_Rate) * dt

Stocks Initial Value: Patients_with_Multiple_Diagnoses = ".SW_Reference-Start2012_Equilibrium"
*Fraction_of_Patients_with_Multiple_Diagnosis*Patient_Flow.Patients_at_the_Unit + (1-.SW_Reference-
Start2012_Equilibrium)"* Start_Number_of_Arriving_Patients* "Reference-
1st3Months_Fraction_of_Patients_with_Multiple_Diagnoses" *Initial_Average_Time_at_Unit

Patients

Patients_Multiple_Diagnosis_Arrival_Rate = Fraction_of_Patients_with_Multiple_Diagnosis*Patient_Flow.Patients_Arrival_Rate

Patients/Months

Patients_Multiple_Diagnosis_Treatedl_Rate =

Patient_Flow.Patients_Treated_Rate*Current_Fraction_Patients_Multiple_Diagnosis

Patients/Months

Recent_Time_to_Treat_an_HI_Patient(t) = Recent_Time_to_Treat_an_HI_Patient(t - dt) +
(Change_in_Recent_Time_to_Treat_an_HI_Patient) * dt

Stocks Initial Value: Recent_Time_to_Treat_an_HI_Patient =

Reference_Mode_Monthly_Average_Needed_Time_to_Treat_HI_Patient

Months

The time of treatment for high intensity and low intensity diagnosis types of patients is based on historical data, and also updates over the historical data. It is assumed that the historical data gives a fair estimation for the actual desired time to treat the patients.

Change_in_Recent_Time_to_Treat_an_HI_Patient = (Reference_Mode_Monthly_Average_Needed_Time_to_Treat_HI_Patient-
Recent_Time_to_Treat_an_HI_Patient)/Time_to_Change_Recent_Time_to_Treat_an_HI_Patient

Dimensionless

$Recent_Time_to_Treat_an_LI_Patient(t) = Recent_Time_to_Treat_an_LI_Patient(t - dt) + (Change_in_Recent_Time_to_Treat_an_LI_Patient) * dt$
Stocks Initial Value: $Recent_Time_to_Treat_an_LI_Patient =$
 $Reference_Mode_Monthly_Average_Needed_Time_to_Treat_LI_Patient$

Months

$Change_in_Recent_Time_to_Treat_an_LI_Patient = (Reference_Mode_Monthly_Average_Needed_Time_to_Treat_LI_Patient - Recent_Time_to_Treat_an_LI_Patient) / Time_to_Change_Recent_Time_to_Trwat_an_LI_Patient$

Dimensionless

$Total_Registration_Procedures(t) = Total_Registration_Procedures(t - dt) + (Registration_Procedures_Arrival_Rate - Registration_Procedures_Fulfilled_Rate) * dt$
Stocks Initial Value: $Total_Registration_Procedures = . "SW_Reference-Start2012_Equilibrium" * "Reference-Start2012Equilibrium_Perceived_Proportion_of_Registration_Procedures_per_Patient" * Patient_Flow.Patients_at_the_Unit + (1 - . "SW_Reference-Start2012_Equilibrium") * "Reference-1stMonth_Perceived_Proportion_of_Registration_Procedures_per_Patient" * Patient_Flow.Patients_at_the_Unit$

RegProcDemands

$Registration_Procedures_Arrival_Rate = SW_R7_Expectations_Build_Registrations * Perceived_Proportion_of_Registration_Procedures_per_Patient * Patient_Flow.Patients_Arrival_Rate * Expectations.Effect_of_Expectations_on_Registration_Procedures + (1 - SW_R7_Expectations_Build_Registrations) * Perceived_Proportion_of_Registration_Procedures_per_Patient * Patient_Flow.Patients_Arrival_Rate$

RegProcDemands/Months

$Registration_Procedures_Fulfilled_Rate = Patient_Flow.Patients_Treated_Rate * Actual_Registration_Procedures_per_Patient$

RegProcDemands/Months

$Actual_Registration_Procedures_per_Patient = Total_Registration_Procedures / Patient_Flow.Patients_at_the_Unit$

RegProcDemands/Patients

$Correction_for_Linear_Increase_in_Registration_procedures = 0.01$

RegProcDemands/Patients

In the non-equilibrium setting the registration procedures are based on the values provided by participants in the knowledge elicitation session. With use of the most conservative hindsight numbers a linear increase in the registration procedures was assumed. Since the registration procedures is compared with a normal amount of registration procedures, the initial value of the normal amount is adjusted to provide for an assumed linear development before the simulation time.

$Current_Fraction_Patients_Multiple_Diagnosis = Patients_with_Multiple_Diagnoses / Patient_Flow.Patients_at_the_Unit$

Dimensionless

$Desired_Treatment_Rate = Desired_Treatment_Rate_HI_Patients + Desired_Treatment_Rate_LI_Patients$

Patients/Months

$Desired_Treatment_Rate_HI_Patients = High_Intensity_Diagnosis_Type / Target_Time_to_Treat_an_HI_Patient$

Patients/Months

$Desired_Treatment_Rate_LI_Patients = Low_Intensity_Diagnosis_Type / Target_Time_to_Treat_an_LI_Patient$

Patients/Months

$Effect_of_Patients_Age_on_Target_Times_for_Treatment = ("Fraction_Patients_Aged_>_70" / "Norm_Fraction_of_Patients_Aged_>_70") ^ POLICY_Power_of_Extra_Time_for_Older_Patients$

Dimensionless

The last variable in the above equation, starting with POLICY, makes it possible to create and change the effect of patients age on target times for treatment (e.g. a value of 0 keeps the variable at 1, regardless of the fractions; a value of 1 lets the actual ratio determine the effect size).

$Equilibrium_Start_Number_of_Arriving_Patients = 200$

Patients/Months

$Fraction_HI_Patients = High_Intensity_Diagnosis_Type / Patient_Flow.Patients_at_the_Unit$

Dimensionless

$Fraction_High_Intensity_Diagnosis_Type_Patients_Arriving = . "SW_Reference-Start2012_Equilibrium" * "Reference-Start2012_Fraction_HI" + (1 - . "SW_Reference-Start2012_Equilibrium") * "Reference-5yr_Fraction_HI_Diagnosis_Type"$

Dimensionless

$Fraction_LI_Patients = Low_Intensity_Diagnosis_Type / Patient_Flow.Patients_at_the_Unit$

Dimensionless
Fraction_Low_Intensity_Diagnosis_Type_Patients_Arriving = 1-*Fraction_High_Intensity_Diagnosis_Type_Patients_Arriving*

Dimensionless
"Fraction_of_Patients_Aged_>_70" = *"SW_Reference-Start2012_Equilibrium"* * *"Reference-Start2012Equilibrium_Fraction_Patients_Aged_>_70"* + (1-*"SW_Reference-Start2012_Equilibrium"*) * *"Reference-5yr-Fraction_of_Patients_Aged_>_70"* + STEP(*"STEP2_Fraction_of_Patients_Aged_>_70_Arriving"*, 70)

Dimensionless
Fraction_of_Patients_with_Multiple_Diagnosis = *"SW_Reference-Start2012_Equilibrium"* * *"Reference-Start2012Equilibrium_Fraction_Patients_with_Multiple_Diagnoses"* + (1-*"SW_Reference-Start2012_Equilibrium"*) * *"Reference-5yr_Fraction_of_Patients_with_Multiple_Diagnoses"* + STEP(*STEP_Fraction_of_Patients_Multiple_Diagnoses*, 70)

Dimensionless
"Fraction_Patients_Aged_>_70" = *"Patients_Aged_>_70"/Patient_Flow.Patients_at_the_Unit*

Dimensionless
Initial_Average_Time_at_Unit = *"SW_Reference-Start2012_Equilibrium"* * *References_Start_Norm_Time_to_Treat_Patient* + (1-*"SW_Reference-Start2012_Equilibrium"*) * *Reference_Mode_Monthly_Average_Needed_Time_to_Treat_Patients*

Months
Initial_High_Intensity_Diagnosis_Type_Patients = *"SW_Reference-Start2012_Equilibrium"* * (*Equilibrium_Start_Number_of_Arriving_Patients* * *Fraction_High_Intensity_Diagnosis_Type_Patients_Arriving* * *Initial_Average_Time_at_Unit*) + (1-*"SW_Reference-Start2012_Equilibrium"*) * *Start_Number_of_Arriving_Patients* * *Fraction_High_Intensity_Diagnosis_Type_Patients_Arriving* * *Initial_Average_Time_at_Unit*

Patients
 The initial value of the stock of high intensity diagnosis type patients depends on the setting for equilibrium or non-equilibrium. This is equal for the similar types of stocks in this sub-model; Low Intensity Diagnosis Type, Patients Aged > 70, Patients with Multiple Diagnosis, and Total Registration Procedures.

Initial_Low_Intensity_Diagnosis_Type_Patients = *"SW_Reference-Start2012_Equilibrium"* * (*Equilibrium_Start_Number_of_Arriving_Patients* * *Fraction_Low_Intensity_Diagnosis_Type_Patients_Arriving* * *Initial_Average_Time_at_Unit*) + (1-*"SW_Reference-Start2012_Equilibrium"*) * *Start_Number_of_Arriving_Patients* * *Fraction_Low_Intensity_Diagnosis_Type_Patients_Arriving* * *Initial_Average_Time_at_Unit*

Patients
Norm_Time_to_Treat_an_HI_Patient = *"SW_Reference-Start2012_Equilibrium"* * *References_Start_Norm_Time_to_Treat_Patient* + (1-*"SW_Reference-Start2012_Equilibrium"*) * *Recent_Time_to_Treat_an_HI_Patient*

Months
Norm_Time_to_Treat_an_LI_Patient = *"SW_Reference-Start2012_Equilibrium"* * *References_Start_Norm_Time_to_Treat_Patient* + (1-*"SW_Reference-Start2012_Equilibrium"*) * *Recent_Time_to_Treat_an_LI_Patient*

Months
Perceived_Proportion_of_Registration_Procedures_per_Patient = *"SW_Reference-Start2012_Equilibrium"* * *"Reference-Start2012Equilibrium_Perceived_Proportion_of_Registration_Procedures_per_Patient"* + (1-*"SW_Reference-Start2012_Equilibrium"*) * *"Reference-5yr_Perceived_Proportion_of_Registration_Procedures_per_Patient"* + STEP(*STEP_Perceived_Proportion_of_Registration_Procedures_per_Patient*, 13)

RegProcDemands/Patients
 The proportion of registration procedures is dependent on the number of patients at the unit. Over time, the amount of registration procedures might change. However, in the model the amount of registration procedures that have to be conducted depends on the moment the patients arrived at the unit. Hence, there is a stock of 'total registration procedures'

POLICY_Power_of_Extra_Time_for_Older_Patients = 0

Dimensionless
Ratio_of_Aged_Patients = *"Fraction_Patients_Aged_>_70"/Norm_Fraction_of_Patients_Aged_>_70"*

Dimensionless
 The model uses ratio's to affect other variables in the model (e.g. ratio of older patients affects the hindrance demands in the *Job-Demands* sub-model)

Ratio_of_High_Intensity_Diagnosis_Type_Patients = *Fraction_HI_Patients/Norm_Fraction_High_Intensity_Diagnosis_Type_Patients*

Dimensionless

$Ratio_of_Multiple_Diagnosis = Current_Fraction_Patients_Multiple_Diagnosis / Norm_Fraction_Patient_Multiple_Diagnosis$

Dimensionless

$Ratio_of_Registration_Procedures = Actual_Registration_Procedures_per_Patient / Norm_Registration_Procedures$

Dimensionless

$Recent_Weighted_Time_to_Treat_Patients =$
 $Fraction_LI_Patients * Target_Time_to_Treat_an_LI_Patient + Target_Time_to_Treat_an_HI_Patient * Fraction_HI_Patients$

Months

$Reference_Mode_Monthly_Average_Needed_Time_to_Treat_HI_Patient = GRAPH(TIME)$
 (1.00, 0.11), (2.00, 0.108), (3.00, 0.124), (4.00, 0.126), (5.00, 0.103), (6.00, 0.115), (7.00, 0.124), (8.00, 0.115), (9.00, 0.135),
 (10.00, 0.123), (11.00, 0.113), (12.00, 0.116), (13.00, 0.109), (14.00, 0.115), (15.00, 0.111), (16.00, 0.104), (17.00, 0.107), (18.00,
 0.102), (19.00, 0.09), (20.00, 0.106), (21.00, 0.084), (22.00, 0.111), (23.00, 0.122), (24.00, 0.093), (25.00, 0.097), (26.00, 0.098),
 (27.00, 0.101), (28.00, 0.123), (29.00, 0.113), (30.00, 0.144), (31.00, 0.129), (32.00, 0.093), (33.00, 0.115), (34.00, 0.117), (35.00,
 0.106), (36.00, 0.117), (37.00, 0.113), (38.00, 0.105), (39.00, 0.111), (40.00, 0.112), (41.00, 0.133), (42.00, 0.106), (43.00, 0.1),
 (44.00, 0.101), (45.00, 0.106), (46.00, 0.09), (47.00, 0.099), (48.00, 0.123), (49.00, 0.117), (50.00, 0.111), (51.00, 0.124), (52.00,
 0.117), (53.00, 0.117), (54.00, 0.112), (55.00, 0.11), (56.00, 0.104), (57.00, 0.101), (58.00, 0.124), (59.00, 0.107), (60.00, 0.092)

Months

This variable specifies a numerical value for each month, 1 to 60. All variables starting with 'reference mode' are related to exogenous values, which is the historical data that the model runs on. This variable specifies the average needed time to treat a patient from the high intensity category, for each month.

$Reference_Mode_Monthly_Average_Needed_Time_to_Treat_LI_Patient = GRAPH(TIME)$
 (1.00, 0.11), (2.00, 0.12), (3.00, 0.12), (4.00, 0.138), (5.00, 0.126), (6.00, 0.115), (7.00, 0.088), (8.00, 0.09), (9.00, 0.11), (10.00,
 0.146), (11.00, 0.119), (12.00, 0.105), (13.00, 0.081), (14.00, 0.139), (15.00, 0.098), (16.00, 0.107), (17.00, 0.074), (18.00, 0.118),
 (19.00, 0.075), (20.00, 0.08), (21.00, 0.077), (22.00, 0.068), (23.00, 0.106), (24.00, 0.079), (25.00, 0.096), (26.00, 0.086), (27.00,
 0.076), (28.00, 0.077), (29.00, 0.123), (30.00, 0.129), (31.00, 0.097), (32.00, 0.091), (33.00, 0.09), (34.00, 0.098), (35.00, 0.104),
 (36.00, 0.095), (37.00, 0.077), (38.00, 0.1), (39.00, 0.094), (40.00, 0.096), (41.00, 0.094), (42.00, 0.087), (43.00, 0.074), (44.00,
 0.084), (45.00, 0.085), (46.00, 0.096), (47.00, 0.085), (48.00, 0.097), (49.00, 0.111), (50.00, 0.093), (51.00, 0.093), (52.00, 0.105),
 (53.00, 0.092), (54.00, 0.086), (55.00, 0.1), (56.00, 0.097), (57.00, 0.08), (58.00, 0.092), (59.00, 0.117), (60.00, 0.093)

Months

$Reference_Mode_Monthly_Average_Needed_Time_to_Treat_Patients = GRAPH(TIME)$
 (1.00, 0.123), (2.00, 0.12), (3.00, 0.139), (4.00, 0.14), (5.00, 0.126), (6.00, 0.121), (7.00, 0.119), (8.00, 0.113), (9.00, 0.138), (10.00,
 0.144), (11.00, 0.123), (12.00, 0.124), (13.00, 0.115), (14.00, 0.133), (15.00, 0.12), (16.00, 0.116), (17.00, 0.104), (18.00, 0.118),
 (19.00, 0.091), (20.00, 0.104), (21.00, 0.089), (22.00, 0.105), (23.00, 0.122), (24.00, 0.098), (25.00, 0.107), (26.00, 0.103), (27.00,
 0.097), (28.00, 0.112), (29.00, 0.123), (30.00, 0.149), (31.00, 0.126), (32.00, 0.1), (33.00, 0.115), (34.00, 0.118), (35.00, 0.118),
 (36.00, 0.116), (37.00, 0.107), (38.00, 0.112), (39.00, 0.106), (40.00, 0.106), (41.00, 0.119), (42.00, 0.098), (43.00, 0.092), (44.00,
 0.097), (45.00, 0.102), (46.00, 0.093), (47.00, 0.096), (48.00, 0.114), (49.00, 0.118), (50.00, 0.107), (51.00, 0.113), (52.00, 0.115),
 (53.00, 0.108), (54.00, 0.104), (55.00, 0.107), (56.00, 0.101), (57.00, 0.095), (58.00, 0.115), (59.00, 0.11), (60.00, 0.093)

Months

"Reference-1st3Months_Fraction_of_Patients_Aged_>_70" = 0.514

Dimensionless

"Reference-1st3Months_Fraction_of_Patients_with_Multiple_Diagnoses" = 0.086

Dimensionless

"Reference-1stMonth_Perceived_Proportion_of_Registration_Procedures_per_Patient" = 0.2

RegProcDemands/Patients

$"Reference-5yr_Fraction_HI_Diagnosis_Type" = GRAPH(TIME)$
 (1.00, 0.69), (2.00, 0.7), (3.00, 0.67), (4.00, 0.66), (5.00, 0.63), (6.00, 0.76), (7.00, 0.73), (8.00, 0.65), (9.00, 0.73), (10.00, 0.7),
 (11.00, 0.71), (12.00, 0.72), (13.00, 0.71), (14.00, 0.71), (15.00, 0.77), (16.00, 0.71), (17.00, 0.66), (18.00, 0.64), (19.00, 0.65),
 (20.00, 0.64), (21.00, 0.59), (22.00, 0.64), (23.00, 0.62), (24.00, 0.66), (25.00, 0.59), (26.00, 0.56), (27.00, 0.59), (28.00, 0.58),
 (29.00, 0.64), (30.00, 0.6), (31.00, 0.63), (32.00, 0.58), (33.00, 0.59), (34.00, 0.62), (35.00, 0.65), (36.00, 0.71), (37.00, 0.58),
 (38.00, 0.62), (39.00, 0.57), (40.00, 0.59), (41.00, 0.6), (42.00, 0.56), (43.00, 0.6), (44.00, 0.6), (45.00, 0.64), (46.00, 0.64), (47.00,
 0.64), (48.00, 0.62), (49.00, 0.61), (50.00, 0.66), (51.00, 0.62), (52.00, 0.62), (53.00, 0.59), (54.00, 0.59), (55.00, 0.56), (56.00, 0.6),
 (57.00, 0.62), (58.00, 0.65), (59.00, 0.63), (60.00, 0.65)

Dimensionless

"Reference-5yr_Fraction_of_Patients_with_Multiple_Diagnoses" = GRAPH(TIME)

(1.00, 0.093), (2.00, 0.09), (3.00, 0.074), (4.00, 0.079), (5.00, 0.102), (6.00, 0.08), (7.00, 0.079), (8.00, 0.086), (9.00, 0.062), (10.00, 0.08), (11.00, 0.055), (12.00, 0.067), (13.00, 0.07), (14.00, 0.038), (15.00, 0.073), (16.00, 0.057), (17.00, 0.068), (18.00, 0.103), (19.00, 0.09), (20.00, 0.056), (21.00, 0.061), (22.00, 0.069), (23.00, 0.059), (24.00, 0.045), (25.00, 0.072), (26.00, 0.06), (27.00, 0.056), (28.00, 0.109), (29.00, 0.085), (30.00, 0.075), (31.00, 0.068), (32.00, 0.094), (33.00, 0.083), (34.00, 0.095), (35.00, 0.086), (36.00, 0.098), (37.00, 0.092), (38.00, 0.121), (39.00, 0.101), (40.00, 0.093), (41.00, 0.099), (42.00, 0.111), (43.00, 0.072), (44.00, 0.142), (45.00, 0.092), (46.00, 0.097), (47.00, 0.082), (48.00, 0.087), (49.00, 0.093), (50.00, 0.075), (51.00, 0.074), (52.00, 0.095), (53.00, 0.099), (54.00, 0.097), (55.00, 0.1), (56.00, 0.128), (57.00, 0.081), (58.00, 0.106), (59.00, 0.099), (60.00, 0.114)

Dimensionless

"Reference-5yr_Perceived_Proportion_of_Registration_Procedures_per_Patient" = GRAPH(TIME)

(1.00, 0.200), (12.80, 0.210), (24.60, 0.220), (36.40, 0.230), (48.20, 0.23875), (60.00, 0.250)

RegProcDemands/Patients

"Reference-5yr-Fraction_of_Patients_Aged_>_70" = GRAPH(TIME)

(1.00, 0.51), (2.00, 0.53), (3.00, 0.5), (4.00, 0.48), (5.00, 0.48), (6.00, 0.52), (7.00, 0.54), (8.00, 0.54), (9.00, 0.49), (10.00, 0.47), (11.00, 0.53), (12.00, 0.53), (13.00, 0.5), (14.00, 0.55), (15.00, 0.55), (16.00, 0.52), (17.00, 0.53), (18.00, 0.51), (19.00, 0.45), (20.00, 0.46), (21.00, 0.44), (22.00, 0.44), (23.00, 0.47), (24.00, 0.51), (25.00, 0.46), (26.00, 0.47), (27.00, 0.43), (28.00, 0.48), (29.00, 0.49), (30.00, 0.49), (31.00, 0.46), (32.00, 0.43), (33.00, 0.49), (34.00, 0.49), (35.00, 0.46), (36.00, 0.46), (37.00, 0.52), (38.00, 0.54), (39.00, 0.48), (40.00, 0.51), (41.00, 0.49), (42.00, 0.47), (43.00, 0.5), (44.00, 0.49), (45.00, 0.5), (46.00, 0.49), (47.00, 0.48), (48.00, 0.47), (49.00, 0.51), (50.00, 0.52), (51.00, 0.53), (52.00, 0.5), (53.00, 0.52), (54.00, 0.46), (55.00, 0.46), (56.00, 0.53), (57.00, 0.5), (58.00, 0.5), (59.00, 0.45), (60.00, 0.53)

Dimensionless

"Reference-Start2012_Fraction_HI" = 0.62

Dimensionless

"Reference-Start2012Equilibrium_Fraction_Patients_Aged_>_70" = 0.5

Dimensionless

"Reference-Start2012Equilibrium_Fraction_Patients_with_Multiple_Diagnoses" = 0.1

Dimensionless

"Reference-Start2012Equilibrium_Perceived_Proportion_of_Registration_Procedures_per_Patient" = 0.25

RegProcDemands/Patients

References_Start_Norm_Time_to_Treat_Patient = 0.1

Months

Start_Number_of_Arriving_Patients = 198

Patients/Months

STEP_Fraction_of_Patients_Multiple_Diagnoses = 0

Dimensionless

STEP_Perceived_Proportion_of_Registration_Procedures_per_Patient = 0

RegProcDemands/Patients

"STEP2_Fraction_of_Patients_Aged_>_70_Arriving" = 0

Dimensionless

SW_Exogenous_Treatment_Time = 1

Months

SW_R7_Expectations_Build_Registrations = 0

Dimensionless

Target_Time_to_Treat_an_HI_Patient = Norm_Time_to_Treat_an_HI_Patient

Months

Target_Time_to_Treat_an_LI_Patient =

Norm_Time_to_Treat_an_LI_Patient*Effect_of_Patients_Age_on_Target_Times_for_Treatment

Months

Test_Mutual_Exclusive =

Fraction_High_Intensity_Diagnosis_Type_Patients_Arriving+Fraction_Low_Intensity_Diagnosis_Type_Patients_Arriving

Dimensionless

Time_to_Change_Norm_of_High_Intensity_Diagnosis_Type_Patients = 12

Months

Time_to_Change_Norm_of_Multiple_Diagnosis = 12

Months

Time_to_Change_Norm_of_Old_Patients = 3

$Time_to_Change_Norm_of_Registration_Procedures = 24$	Months
$Time_to_Change_Recent_Time_to_Treat_an_HI_Patient = SW_Exogenous_Treatment_Time * 3 + (1 - SW_Exogenous_Treatment_Time) * 999999$	Months
$Time_to_Change_Recent_Time_to_Trwat_an_LI_Patient = SW_Exogenous_Treatment_Time * 3 + (1 - SW_Exogenous_Treatment_Time) * 999999$	Months
	Months

A2.2. Patient Flow

Formulation and comments	Units
$Patients_at_the_Unit(t) = Patients_at_the_Unit(t - dt) + (Patients_Arrival_Rate - Patients_Treated_Rate) * dt$ Stocks Initial Value: $Patients_at_the_Unit = Initial_Total_Patients$	Patients
<p>This stock represents the average number of patients at the unit for that month, based on financial data. This might not coincide with the actual average, dependent on the accuracy of the financial data. Moreover, this average is a very rough estimate of how busy it was on the unit that month, and no inferences should be made based on exact numbers.</p>	
$Patients_Arrival_Rate = Expectations.Effect_of_Insurers_Expectation_on_Norm_Arrival_Rate * ("SW_Reference-Start2012_Equilibrium" * Reference_Start_Patients_Arrival_Rate + (1 - "SW_Reference-Start2012_Equilibrium") * Reference_Patients_Arrival_Rate) + STEP(STEP_amount_Patients_Arrival_Rate, STEP_Time_Patients_Arrival_Rate) + PULSE(PULSE_amount_Patients_Arrival_Rate, PULSE_Time_Nr_Patients_Arrival_Rate, PULSE_Interval_Nr_Patients_Arrival_Rate_1)$	Patients/Months
$Patients_Treated_Rate = MIN(Maximum_Treatment_Rate, Potential_Treatment_Rate)$	Patients/Months
$Recent_Patients_per_Employee(t) = Recent_Patients_per_Employee(t - dt) + (Change_in_Recent_Patients_per_Employee) * dt$ Stocks Initial Value: $Recent_Patients_per_Employee = "SW_Reference-Start2012_Equilibrium" * Reference_Start_Patients_per_Employee + (1 - "SW_Reference-Start2012_Equilibrium") * "Reference-1st3Months_Patients_per_Employee"$	Patients/FTE
$Change_in_Recent_Patients_per_Employee = (Actual_Patients_per_Employee - Recent_Patients_per_Employee) / Time_to_Change_Recent_Patients_per_Employee$	Patients/FTE/Months
$Stock_1(t) = Stock_1(t - dt) + (Flow_1) * dt$ Stocks Initial Value: $Stock_1 = 0$	Patients
$Flow_1 = ABS(Difference)$	Patients/Months
$Stock_2(t) = Stock_2(t - dt) + (Flow_2) * dt$ Stocks Initial Value: $Stock_2 = 0$	Patients
$Flow_2 = Difference$	Patients/Months
$Absenteeism = (1 - Effect_of_Need_for_Recovery_on_FTE)$	Dimensionless
$Actual_Average_Treatment_Time = SAFEDIV(Patients_at_the_Unit, Patients_Treated_Rate, 1)$	Months
$Actual_Patients_per_Employee = Patients_at_the_Unit / Workforce.Employees$	Patients/FTE
$Amount_STEP = 0$	

$Difference = Patients_Treated_Rate - Potential_Treatment_Rate$	Patients/Months
$Direct_Care_Time = Standard_Direct_Care_Time * Effect_of_Schedule_Pressure_on_Direct_Care_Time$	Patients/Months
$Effect_of_Care_Quality_on_Treatment_Rate = GRAPH(Care_Quality.Ratio_of_Actual_Care)$ (0.000, 1.1000), (0.250, 1.0954), (0.500, 1.0799), (0.750, 1.0553), (1.000, 1.0000), (1.250, 0.9393), (1.500, 0.9146), (1.750, 0.9037), (2.000, 0.9000)	Minutes
$Effect_of_Direct_Care_Time_on_Care_Quality =$ $(Direct_Care_Time / Standard_Direct_Care_Time)^{SW_R1_Effect_of_Care_Quality_on_Time_per_Treatment}$	Dimensionless
$Effect_of_Need_for_Recovery_on_FTE =$ $GRAPH(Job_Demands.Ratio_of_Need_for_Recovery^{SW_R6_Effect_of_Need_for_Recovery_on_FTE})$ (1.000, 1.000), (1.250, 0.945), (1.500, 0.800), (1.750, 0.600), (2.000, 0.400), (2.250, 0.200), (2.500, 0.100), (2.750, 0.050), (3.000, 0.030), (3.250, 0.020), (3.500, 0.010), (3.750, 0.005), (4.000, 0.001)	Dimensionless
$Effect_of_Quality_of_Work_on_Care_Quality =$ $(Quality_of_Work / Standard_Quality_of_Work)^{SW_R1_Effect_of_Care_Quality_on_Time_per_Treatment}$	Dimensionless
$Effect_of_Schedule_Pressure_on_Direct_Care_Time = GRAPH(Schedule_Pressure)$ (0.250, 3.770), (0.500, 1.920), (0.750, 1.280), (1.000, 1.000), (1.250, 0.860), (1.500, 0.750), (1.750, 0.700), (2.000, 0.650), (2.250, 0.600), (2.500, 0.570)	Dimensionless
$Effect_of_Schedule_Pressure_on_Quality_of_Work = GRAPH(Schedule_Pressure)$ (0.250, 1.0950), (0.500, 1.0950), (0.750, 1.0490), (1.000, 1.0000), (1.250, 0.9550), (1.500, 0.9100), (1.750, 0.8050), (2.000, 0.6990), (2.250, 0.6440), (2.500, 0.5880)	Dimensionless
$Initial_Total_Patients =$ $Care_Intensity.Initial_High_Intensity_Diagnosis_Type_Patients + Care_Intensity.Initial_Low_Intensity_Diagnosis_Type_Patients$	Patients
$Maximum_Treatment_Rate = Patients_at_the_Unit / Minimum_Treatment_Time$	Patients/Months
$Minimum_Treatment_Time = 0.05$	Months
$Norm_Patients_per_Employee = . "SW_Reference-Start2012_Equilibrium" * Reference_Start_Patients_per_Employee + (1 - . "SW_Reference-Start2012_Equilibrium") * (Recent_Patients_per_Employee)$	Patients/FTE
$Number_of_FTEmployees = Workforce.Employees * Effect_of_Need_for_Recovery_on_FTE$	FTE
$Patients_per_Employee = Standard_Patients_per_Employee * (Schedule_Pressure^{SW_B1})$	Patients/FTE
$Potential_Treatment_Rate = Number_of_FTEmployees * Patients_per_Employee / Time_per_Treatment$	Patients/Months
$Proxy_Absenteeism = 0.4626 * DELAY(Job_Demands.Ratio_of_Need_for_Recovery, 5) - 0.4055$	Dimensionless
$PULSE_amount_Patients_Arrival_Rate = 0$	Patients
$PULSE_Interval_Nr_Patients_Arrival_Rate_1 = 0$	Months
$PULSE_Time_Nr_Patients_Arrival_Rate = 13$	Months
$Quality_of_Work = Effect_of_Schedule_Pressure_on_Quality_of_Work * Standard_Quality_of_Work$	SelfGrade
$Reference_Absenteeism = GRAPH(TIME)$	

(1.00, 0.0797), (2.00, 0.0791), (3.00, 0.0837), (4.00, 0.0876), (5.00, 0.0885), (6.00, 0.0897), (7.00, 0.0936), (8.00, 0.0955), (9.00, 0.0962), (10.00, 0.0965), (11.00, 0.0995), (12.00, 0.1007), (13.00, 0.1007), (14.00, 0.1046), (15.00, 0.1089), (16.00, 0.1133), (17.00, 0.1131), (18.00, 0.1077), (19.00, 0.1009), (20.00, 0.094), (21.00, 0.0876), (22.00, 0.0808), (23.00, 0.0718), (24.00, 0.0617), (25.00, 0.0528), (26.00, 0.0443), (27.00, 0.0384), (28.00, 0.0326), (29.00, 0.0305), (30.00, 0.0275), (31.00, 0.0262), (32.00, 0.0253), (33.00, 0.029), (34.00, 0.0344), (35.00, 0.0409), (36.00, 0.0518), (37.00, 0.0582), (38.00, 0.0629), (39.00, 0.0674), (40.00, 0.0704), (41.00, 0.0764), (42.00, 0.0876), (43.00, 0.0973), (44.00, 0.1038), (45.00, 0.1068), (46.00, 0.1068), (47.00, 0.1039), (48.00, 0.0983), (49.00, 0.0979), (50.00, 0.0995), (51.00, 0.0996), (52.00, 0.1003), (53.00, 0.0952), (54.00, 0.087), (55.00, 0.0811), (56.00, 0.0801), (57.00, 0.0789), (58.00, 0.0778), (59.00, 0.0774), (60.00, 0.0748)

Dimensionless

Reference_Patients_Arrival_Rate = GRAPH(TIME)

(1.00, 215.0), (2.00, 189.0), (3.00, 230.0), (4.00, 242.0), (5.00, 216.0), (6.00, 251.0), (7.00, 214.0), (8.00, 257.0), (9.00, 241.0), (10.00, 225.0), (11.00, 237.0), (12.00, 255.0), (13.00, 284.0), (14.00, 265.0), (15.00, 247.0), (16.00, 283.0), (17.00, 279.0), (18.00, 262.0), (19.00, 290.0), (20.00, 302.0), (21.00, 360.0), (22.00, 333.0), (23.00, 288.0), (24.00, 310.0), (25.00, 362.0), (26.00, 318.0), (27.00, 354.0), (28.00, 320.0), (29.00, 284.0), (30.00, 268.0), (31.00, 266.0), (32.00, 278.0), (33.00, 303.0), (34.00, 327.0), (35.00, 313.0), (36.00, 276.0), (37.00, 349.0), (38.00, 281.0), (39.00, 307.0), (40.00, 302.0), (41.00, 282.0), (42.00, 316.0), (43.00, 321.0), (44.00, 274.0), (45.00, 251.0), (46.00, 321.0), (47.00, 293.0), (48.00, 287.0), (49.00, 302.0), (50.00, 306.0), (51.00, 296.0), (52.00, 295.0), (53.00, 283.0), (54.00, 309.0), (55.00, 289.0), (56.00, 296.0), (57.00, 335.0), (58.00, 292.0), (59.00, 304.0), (60.00, 308.0)

Patients/Months

Reference_Start_Patients_Arrival_Rate = 200

Patients/Months

Reference_Start_Patients_per_Employee = 8/3

Patients/FTE

"Reference-1st3Months_Patients_per_Employee" = 3.342

Patients/FTE

Schedule_Pressure = (SAFEDIV(Care_Intensity.Desired_Treatment_Rate, Standard_Treatment_Rate, 1))

Dimensionless

Standard_Direct_Care_Time = 5.3

Minutes

Standard_Patients_per_Employee = Norm_Patients_per_Employee

Patients/FTE

Standard_Quality_of_Work = 7.58

SelfGrade

Standard_Time_per_Treatment = ".SW_Reference-Start2012_Equilibrium"*Care_Intensity.References_Start_Norm_Time_to_Treat_Patient + (1-.SW_Reference-Start2012_Equilibrium")*(Care_Intensity.Recent_Weighted_Time_to_Treat_Patients)

Months

Standard_Treatment_Rate = Workforce.Employees*Norm_Patients_per_Employee/Standard_Time_per_Treatment

Patients/Months

StandDev_STEP = 0

Dimensionless

STEP_amount_Patients_Arrival_Rate = NORMAL(Amount_STEP, StandDev_STEP)

Patients/Months

STEP_Time_Patients_Arrival_Rate = 13

Months

SW_B1 = 1

Dimensionless

SW_R1_Effect_of_Care_Quality_on_Time_per_Treatment = 1

Dimensionless

SW_R6_Effect_of_Need_for_Recovery_on_FTE = 1

Dimensionless

Time_per_Treatment = Standard_Time_per_Treatment*Effect_of_Care_Quality_on_Treatment_Rate

Months

Time_to_Change_Recent_Patients_per_Employee = 4

Months

A2.3. Workforce

Formulation and comments	Units
$\text{Norm_Employees_Average_Age}(t) = \text{Norm_Employees_Average_Age}(t - dt) + (\text{Change_in_Norm_Employees_Average_Age}) * dt$ <p>Stocks Initial Value: Norm_Employees_Average_Age = "Reference-5yr_Employees_Average_Age"</p>	EmployeeAge
$\text{Change_in_Norm_Employees_Average_Age} = (\text{"Reference-5yr_Employees_Average_Age"} - \text{Norm_Employees_Average_Age}) / \text{Time_to_Change_Norm_Employees_Average_Age}$	EmployeeAge/Months
$\text{Norm_Fraction_of_Telemetric_Employees}(t) = \text{Norm_Fraction_of_Telemetric_Employees}(t - dt) + (\text{Change_in_Norm_Fraction_of_Telemetric_Employees}) * dt$ <p>Stocks Initial Value: Norm_Fraction_of_Telemetric_Employees = Fraction_of_Telemetric_Employees</p>	Dimensionless
$\text{Change_in_Norm_Fraction_of_Telemetric_Employees} = (\text{Fraction_of_Telemetric_Employees} - \text{Norm_Fraction_of_Telemetric_Employees}) / \text{Time_to_Change_Norm_Fraction_of_Telemetric_Employees}$	Per Month
$\text{Employees} = ((\text{"SW_Reference-Start2012_Equilibrium"} * \text{"Reference-Start2012_Employees"} + (1 - \text{"SW_Reference-Start2012_Equilibrium"}) * (\text{IF}(\text{TIME} \leq 60) \text{ THEN } (\text{"Reference-5yr_FTE"}) \text{ ELSE } (\text{"Reference-Av5yr_Employees_per_Month"})))) * (1 + \text{STEP}(\text{Percentage_STEP_Employees}, 13))$	FTE
$\text{Fraction_of_Telemetric_Employees} = .\text{"SW_Reference-Start2012_Equilibrium"} * \text{"Reference-Start2012_Ratio_of_Total_Hours_Worked_by_Telemetricians_over_Total_Hours_Worked_1"} + (1 - \text{"SW_Reference-Start2012_Equilibrium"}) * \text{"Reference-5yr_Ratio_of_Total_Hours_Worked_by_Telemetricians_over_Total_Hours_Worked"}$	Dimensionless
Percentage_STEP_Employees = 0	Dimensionless
$\text{Ratio_of_Employee_Age} = .\text{"SW_Reference-Start2012_Equilibrium"} * \text{"Reference-Start2012_Employees_Average_Age"} / \text{Norm_Employees_Average_Age} + (1 - \text{"SW_Reference-Start2012_Equilibrium"}) * (\text{IF}(\text{TIME} \leq 60) \text{ THEN } (\text{"Reference-5yr_Employees_Average_Age"} / \text{Norm_Employees_Average_Age}) \text{ ELSE } (\text{Start2017_Employees_Average_Age} / \text{Norm_Employees_Average_Age}))$	Dimensionless
$\text{Ratio_of_Experience} = .\text{"SW_Reference-Start2012_Equilibrium"} * \text{"Reference-Start2012_Experience"} / \text{"Reference-Start2012_Experience"} + (1 - \text{"SW_Reference-Start2012_Equilibrium"}) * (\text{IF}(\text{TIME} \leq 60) \text{ THEN } (\text{"Reference-5yr_Experience"} / \text{"Reference-Start2012_Experience"}) \text{ ELSE } (\text{Start2017_Experience} / \text{"Reference-Start2012_Experience"}))$	Dimensionless
Ratio_of_Telemetricians = Fraction_of_Telemetric_Employees / Norm_Fraction_of_Telemetric_Employees	Dimensionless
<p>"Reference-5yr_Employees_Average_Age" = GRAPH(TIME)</p> <p>(1.00, 36.95), (2.00, 36.44235226), (3.00, 36.20771429), (4.00, 35.96043893), (5.00, 35.78841238), (6.00, 36.06102753), (7.00, 36.6988568), (8.00, 36.62507481), (9.00, 36.26095972), (10.00, 35.88496105), (11.00, 35.82537313), (12.00, 35.6750365), (13.00, 37.18667861), (14.00, 37.98805513), (15.00, 37.86327889), (16.00, 37.83811851), (17.00, 37.18671349), (18.00, 37.44732089), (19.00, 37.85057821), (20.00, 37.36808937), (21.00, 37.21049661), (22.00, 37.28005579), (23.00, 37.57223957), (24.00, 37.37008979), (25.00, 38.86298215), (26.00, 38.41552256), (27.00, 38.21099144), (28.00, 38.41305571), (29.00, 37.58948824), (30.00, 37.25963197), (31.00, 38.24554515), (32.00, 37.43650342), (33.00, 37.35529679), (34.00, 37.50575043), (35.00, 37.49649737), (36.00, 37.34049871), (37.00, 37.99273134), (38.00, 37.65865119), (39.00, 37.99004834), (40.00, 38.2281106), (41.00, 38.03076923), (42.00, 38.60617647), (43.00, 39.32371007), (44.00, 39.65146783), (45.00, 39.53725244), (46.00, 38.181032), (47.00, 37.37092316), (48.00, 36.90924092), (49.00, 37.7169222), (50.00, 37.10519088), (51.00, 36.93783784), (52.00, 37.01984235), (53.00, 36.77171828), (54.00, 37.64628194), (55.00, 38.79216695), (56.00, 38.6777117), (57.00, 37.73305556), (58.00, 37.38216907), (59.00, 37.6546862), (60.00, 37.4651036)</p>	EmployeeAge
<p>"Reference-5yr_Experience" = GRAPH(TIME)</p> <p>(1.00, 115.2818316), (2.00, 112.7050985), (3.00, 111.7922857), (4.00, 113.6687843), (5.00, 112.833286), (6.00, 113.8841896), (7.00, 120.3637184), (8.00, 120.7100539), (9.00, 117.8827014), (10.00, 115.7588376), (11.00, 116.3629851), (12.00, 116.6242336), (13.00, 121.3548387), (14.00, 124.267075), (15.00, 124.7056866), (16.00, 124.9386072), (17.00, 121.4761487), (18.00, 124.6201084), (19.00, 127.356056), (20.00, 122.6044113), (21.00, 119.8896727), (22.00, 119.8867503), (23.00,</p>	

126.6721544), (24.00, 126.214927), (25.00, 130.5066206), (26.00, 128.510227), (27.00, 127.8196631), (28.00, 129.8733821), (29.00, 126.4899032), (30.00, 122.6046578), (31.00, 130.8474781), (32.00, 124.6292711), (33.00, 123.916501), (34.00, 125.9102933), (35.00, 128.7845884), (36.00, 128.6256807), (37.00, 127.0684932), (38.00, 125.8825318), (39.00, 129.4890532), (40.00, 132.1298963), (41.00, 131.6558405), (42.00, 136.8670588), (43.00, 143.6136364), (44.00, 146.9878201), (45.00, 146.2565231), (46.00, 135.6445662), (47.00, 130.2012161), (48.00, 125.0847085), (49.00, 125.5993754), (50.00, 122.6099973), (51.00, 121.6418919), (52.00, 123.2750747), (53.00, 121.706769), (54.00, 130.3241459), (55.00, 138.0005718), (56.00, 137.672614), (57.00, 130.6047222), (58.00, 128.806741), (59.00, 131.9543821), (60.00, 130.5588877)

ExperienceMonths

"Reference-5yr_FTE" = GRAPH(TIME)

(1.00, 7.284262295), (2.00, 7.525081967), (3.00, 7.299180328), (4.00, 7.380163934), (5.00, 7.505901639), (6.00, 7.508032787), (7.00, 7.083934426), (8.00, 7.122295082), (9.00, 7.194754098), (10.00, 7.145737705), (11.00, 7.154262295), (12.00, 7.335409836), (13.00, 7.173442623), (14.00, 7.115901639), (15.00, 6.913442623), (16.00, 6.977377049), (17.00, 7.450491803), (18.00, 7.079672131), (19.00, 7.00295082), (20.00, 7.439836066), (21.00, 7.578360656), (22.00, 7.65295082), (23.00, 7.294918033), (24.00, 7.595409836), (25.00, 7.403606557), (26.00, 7.606065574), (27.00, 7.723278689), (28.00, 7.574098361), (29.00, 7.725409836), (30.00, 7.412131148), (31.00, 7.079672131), (32.00, 7.484590164), (33.00, 7.503770492), (34.00, 7.412131148), (35.00, 7.301311475), (36.00, 7.43557377), (37.00, 7.714754098), (38.00, 7.710491803), (39.00, 7.495245902), (40.00, 7.399344262), (41.00, 7.512295082), (42.00, 7.403606557), (43.00, 6.968852459), (44.00, 6.823934426), (45.00, 6.779180328), (46.00, 7.582622951), (47.00, 7.710491803), (48.00, 7.772295082), (49.00, 7.505901639), (50.00, 7.759508197), (51.00, 7.885245902), (52.00, 7.840491803), (53.00, 7.78295082), (54.00, 7.484590164), (55.00, 7.501639344), (56.00, 7.525081967), (57.00, 7.778688525), (58.00, 7.870327869), (59.00, 7.81704918), (60.00, 7.836229508)

FTE

"Reference-5yr_Ratio_of_Total_Hours_Worked_by_Telemetricians_over_Total_Hours_Worked" = GRAPH(TIME)

(1.00, 0.645), (2.00, 0.612), (3.00, 0.637), (4.00, 0.64), (5.00, 0.625), (6.00, 0.643), (7.00, 0.687), (8.00, 0.662), (9.00, 0.634), (10.00, 0.627), (11.00, 0.595), (12.00, 0.616), (13.00, 0.637), (14.00, 0.611), (15.00, 0.591), (16.00, 0.574), (17.00, 0.591), (18.00, 0.571), (19.00, 0.562), (20.00, 0.556), (21.00, 0.558), (22.00, 0.582), (23.00, 0.587), (24.00, 0.663), (25.00, 0.612), (26.00, 0.645), (27.00, 0.627), (28.00, 0.648), (29.00, 0.647), (30.00, 0.642), (31.00, 0.677), (32.00, 0.642), (33.00, 0.578), (34.00, 0.598), (35.00, 0.588), (36.00, 0.597), (37.00, 0.563), (38.00, 0.537), (39.00, 0.555), (40.00, 0.594), (41.00, 0.576), (42.00, 0.581), (43.00, 0.565), (44.00, 0.629), (45.00, 0.529), (46.00, 0.546), (47.00, 0.531), (48.00, 0.513), (49.00, 0.498), (50.00, 0.494), (51.00, 0.481), (52.00, 0.513), (53.00, 0.51), (54.00, 0.494), (55.00, 0.556), (56.00, 0.612), (57.00, 0.534), (58.00, 0.583), (59.00, 0.577), (60.00, 0.593)

Dimensionless

"Reference-Av5yr_Employees_per_Month" = 7.43

FTE

"Reference-Start2012_Employees" = 7.5

FTE

"Reference-Start2012_Employees_Average_Age" = 36.95

EmployeeAge

"Reference-Start2012_Experience" = 115.28

ExperienceMonths

"Reference-Start2012_Ratio_of_Total_Hours_Worked_by_Telemetricians_over_Total_Hours_Worked_1" = 0.645

Dimensionless

Start2017_Employees_Average_Age = 37.48

EmployeeAge

Start2017_Experience = 125.9

ExperienceMonths

Time_to_Change_Norm_Employees_Average_Age = 9999

Months

Time_to_Change_Norm_Fraction_of_Telemetric_Employees = 12

Months

A2.4. Job Demands

Formulation and comments

Units

Need_for_Recovery(t) = Need_for_Recovery(t - dt) + (Adjustment_of_Need_for_Recovery) * dt

Stocks Initial Value: Need_for_Recovery = Initial_Need_for_Recovery

Dimensionless

$Adjustment_of_Need_for_Recovery = (Potential_Need_for_Recovery - Need_for_Recovery) / Fatigue_Onset_Time$

Per Month

$Actual_Challenge_Demands = 1/2 * Effect_of_Multiple_Diagnoses_on_Challenge_Demands * Norm_Challenge_Demands + 1/2 * Effect_of_High_Intensity_Diagnoses_on_Challenge_Demands * Norm_Challenge_Demands$

ChallengeDemands

$Actual_Hindrance_Demands = 1/3 * Effect_of_Need_for_Recovery_on_Hindrance_Demands * Norm_Hindrance_Demands + 1/3 * Effect_of_Older_Patients_on_Hindrance_Demands * Norm_Hindrance_Demands + 1/3 * Effect_of_Registration_Procedures_on_Hindrance_Demands * Norm_Hindrance_Demands$

HindranceDemands

$Effect_of_Challenge_Demands_on_Need_for_Recovery = GRAPH(Ratio_of_Challenge_Demands)$
 (0.000, 0.9000), (0.250, 0.9037), (0.500, 0.9146), (0.750, 0.9393), (1.000, 1.0000), (1.250, 1.0553), (1.500, 1.0799), (1.750, 1.0954), (2.000, 1.1000)

Dimensionless

$Effect_of_Employee_Age_on_Fatigue_Onset_Time = GRAPH(Workforce.Ratio_of_Employee_Age^{SW_Effect_of_Age_on_Fatigue})$
 (0.9000, 1.500), (0.9250, 1.463), (0.9500, 1.390), (0.9750, 1.272), (1.0000, 1.000), (1.0250, 0.751), (1.0500, 0.605), (1.0750, 0.527), (1.1000, 0.500)

Dimensionless

$Effect_of_High_Intensity_Diagnoses_on_Challenge_Demands = GRAPH(Care_Intensity.Ratio_of_High_Intensity_Diagnosis_Type_Patients)$
 (0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)

Dimensionless

$Effect_of_Hindrance_Demands_on_Need_for_Recovery = GRAPH(Ratio_of_Hindrance_Demands)$
 (0.000, 0.9000), (0.250, 0.9037), (0.500, 0.9146), (0.750, 0.9393), (1.000, 1.0000), (1.250, 1.0553), (1.500, 1.0799), (1.750, 1.0954), (2.000, 1.1000)

Dimensionless

$Effect_of_Multiple_Diagnoses_on_Challenge_Demands = GRAPH(Care_Intensity.Ratio_of_Multiple_Diagnosis)$
 (0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)

Dimensionless

$Effect_of_Need_for_Recovery_on_Hindrance_Demands = GRAPH((Ratio_of_Need_for_Recovery^{SW_R2_Effect_of_Need_for_Recovery_on_Hindrance_Demands}))$
 (0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)

Dimensionless

$Effect_of_Older_Patients_on_Hindrance_Demands = GRAPH(Care_Intensity.Ratio_of_Aged_Patients)$
 (0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)

Dimensionless

$Effect_of_Registration_Procedures_on_Hindrance_Demands = GRAPH(Care_Intensity.Ratio_of_Registration_Procedures)$
 (0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)

Dimensionless

$Fatigue_Onset_Time = Standard_Fatigue_Onset_Time * Effect_of_Employee_Age_on_Fatigue_Onset_Time$

Months

$Initial_Need_for_Recovery = Patient_Flow.Schedule_Pressure$

Dimensionless

$Maximum_Need_for_Recovery = 4$

Dimensionless

$Need_for_Personal_Recovery_Right_after_work = GRAPH(TIME)$
 (3.00, 21.2), (27.00, 15.2), (58.00, 39.3)

percentage Yes answers

"Need_for_Recovery_-_Questionnaire" = GRAPH(TIME)
(3.00, 30.0), (27.00, 33.0), (58.00, 50.0)

percentage scoring lowest 20%

"Needs_to_Hurry_(item)" = GRAPH(TIME)
(3.00, 47.1), (27.00, 52.9), (58.00, 74.2)

QuestionnaireScore

Norm_Challenge_Demands = 0.5

ChallengeDemands

The value 0.5 is chosen as a representation of an average value of that variable. This value is found in all of the variables with non-physical units such as Job Demands, Satisfaction, and Quality of Care

Norm_Hindrance_Demands = 0.5

HindranceDemands

Norm_Need_for_Recovery = 1

Dimensionless

Potential_Need_for_Recovery = Patient_Flow.Schedule_Pressure *Norm_Need_for_Recovery
*(1/2*Effect_of_Hindrance_Demands_on_Need_for_Recovery + 1/2*Effect_of_Challenge_Demands_on_Need_for_Recovery)
Dimensionless

Ratio_of_Challenge_Demands = (Actual_Challenge_Demands/Norm_Challenge_Demands)

Dimensionless

Ratio_of_Hindrance_Demands = (Actual_Hindrance_Demands/Norm_Hindrance_Demands)

Dimensionless

Ratio_of_Hindrance_Demands_Inverse = Norm_Hindrance_Demands/Actual_Hindrance_Demands

Dimensionless

Ratio_of_Need_for_Recovery = (Need_for_Recovery/Norm_Need_for_Recovery)

Dimensionless

Standard_Fatigue_Onset_Time = 2

Months

SW_Effect_of_Age_on_Fatigue = 1

Dimensionless

SW_R2_Effect_of_Need_for_Recovery_on_Hindrance_Demands = 1

Dimensionless

"Too_Much_Work_(item)" = GRAPH(TIME)
(3.00, 79.4), (27.00, 64.7), (58.00, 83.9)

QuestionnaireScore

"Too_Much_Work_(item)_Time_Adjusted" = GRAPH(TIME)
(3.00, 79.4), (27.00, 64.7), (58.00, 83.9)

QuestionnaireScore

Too_Much_Work_for_Theil = ("Too_Much_Work_(item)_Time_Adjusted"-74.5)/43

QuestionnaireScore

"Workload_(scale)_-_Questionnaire" = GRAPH(TIME)
(3.00, 4.400), (27.00, 4.200), (58.00, 4.900)

QuestionnaireScore

A2.5. Job Resources

Formulation and comments

Units

Effect_of_Excluded_Resources = 1*(1+STEP(STEP_Resources, 13))

Dimensionless

Effect_of_Patient_Satisfaction_on_Resources = GRAPH(Expectations.Ratio_of_Patient_Satisfaction)
(0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)

Dimensionless

"Effect_of_Well-being_on_Resources" = GRAPH("Well-being"."Ratio_of_Well-being")
(0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)

Dimensionless

Effect_of_Workforce_Experience_on_Resources =
GRAPH(1/2*Workforce.Ratio_of_Experience+1/2*Workforce.Ratio_of_Telemetricians)
(0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)

Dimensionless

Norm_Resources = 0.5

Resources

Ratio_of_Resources = (Resources/Norm_Resources)

Dimensionless

Resources = 0.16*Norm_Resources*(^"Effect_of_Well-being_on_Resources"SW_R4_Effect_of_Well-being_on_Resources") +
0.13*Norm_Resources*(Effect_of_Patient_Satisfaction_on_Resources^SW_R5_Effect_of_Patient_Satisfaction_on_Resources) +
0.13*Norm_Resources*Effect_of_Workforce_Experience_on_Resources + 0.58*Norm_Resources*Effect_of_Excluded_Resources
Resources

The results of discussion point 8 from the Knowledge Elicitation Session are used to distinguish the effects of different job resources. Here only additional effects are assumed.

STEP_Resources = 0

Dimensionless

"SW_R4_Effect_of_Well-being_on_Resources" = 1

Dimensionless

SW_R5_Effect_of_Patient_Satisfaction_on_Resources = 1

Dimensionless

A2.6. Well-being

Formulation and comments

Units

"Well-being"(t) = "Well-being"(t - dt) + ("Change_in_Well-being") * dt

Stocks Initial Value: "Well-being" = 0.5

Well-being

"Change_in_Well-being" = ("Potential_Well-being"-"Well-being")/"Time_to_Change_Well-being"

Well-being/Months

Effect_of_Challenge_Demands = GRAPH(Job_Demands.Ratio_of_Challenge_Demands)
(0.000, 0.000), (0.250, 0.050), (0.500, 0.200), (0.750, 0.350), (1.000, 0.500), (1.250, 0.650), (1.500, 0.800), (1.750, 0.950), (2.000, 1.000)

Dimensionless

Effect_of_Hindrance_Demands = GRAPH(Job_Demands.Ratio_of_Hindrance_Demands)
(0.000, 1.000), (0.250, 0.950), (0.500, 0.800), (0.750, 0.650), (1.000, 0.500), (1.250, 0.350), (1.500, 0.200), (1.750, 0.050), (2.000, 0.000)

Dimensionless

Effect_of_Job_Resources_on_Interaction_with_Demands = GRAPH(Job_Resources.Ratio_of_Resources)
(0.000, 0.000), (0.250, 0.037), (0.500, 0.183), (0.750, 0.457), (1.000, 1.000), (1.250, 1.452), (1.500, 1.753), (1.750, 1.900), (2.000, 2.000)

Dimensionless

"Effect_of_Need_for_Recovery_on_Well-being" = GRAPH((Job_Demands.Ratio_of_Need_for_Recovery))
(0.000, 1.000), (0.500, 1.000), (1.000, 1.000), (1.500, 0.922), (2.000, 0.658), (2.500, 0.365), (3.000, 0.174), (3.500, 0.055), (4.000, 0.000)

Dimensionless

"Norm_Well-being" = 0.5

Well-being

"Potential_Well-being" = 1/2*Target_Effect_of_CD + 1/2*Target_Effect_of_HD	Well-being
"Ratio_of_Well-being" = "Well-being"/"Norm_Well-being"	Dimensionless
"SW_B2_Effect_of_Challenge_Demands_on_Well-being" = 1	Dimensionless
"SW_R3_Effect_of_Hindrance_Demands_on_Well-being" = 1	Dimensionless
Target_Effect_of_CD = ((Effect_of_Challenge_Demands*"SW_B2_Effect_of_Challenge_Demands_on_Well-being" +0.5*(1-"SW_B2_Effect_of_Challenge_Demands_on_Well-being"))*Effect_of_Job_Resources_on_Interaction_with_Demands*"Norm_Well-being" +(1-((Effect_of_Challenge_Demands*"SW_B2_Effect_of_Challenge_Demands_on_Well-being" +0.5*(1-"SW_B2_Effect_of_Challenge_Demands_on_Well-being"))))*Effect_of_Need_for_Recovery_on_Well-being*"Norm_Well-being"	Well-being
Target_Effect_of_HD = (Effect_of_Hindrance_Demands*"SW_R3_Effect_of_Hindrance_Demands_on_Well-being" +0.5*(1-"SW_R3_Effect_of_Hindrance_Demands_on_Well-being"))*Effect_of_Job_Resources_on_Interaction_with_Demands*"Norm_Well-being" +(1-((Effect_of_Hindrance_Demands*"SW_R3_Effect_of_Hindrance_Demands_on_Well-being" +0.5*(1-"SW_R3_Effect_of_Hindrance_Demands_on_Well-being"))))*Effect_of_Need_for_Recovery_on_Well-being*"Norm_Well-being"	Well-being
"Time_to_Change_Well-being" = 1	Months

A2.7. Care Quality

Formulation and comments	Units
Actual_Quality_of_Care = 1/2*"Potential_Quality_of_Care_due_to_Well-being"*Patient_Flow.Effect_of_Quality_of_Work_on_Care_Quality + 1/2*"Potential_Quality_of_Care_due_to_Well-being"*Patient_Flow.Effect_of_Direct_Care_Time_on_Care_Quality	QualityofCare
"Effect_of_Well-being_on_Quality_of_Care" = GRAPH("Well-being"."Ratio_of_Well-being") (0.000, 0.000), (0.250, 0.046), (0.500, 0.183), (0.750, 0.466), (1.000, 1.000), (1.250, 1.479), (1.500, 1.753), (1.750, 1.918), (2.000, 2.000)	Dimensionless
"Potential_Quality_of_Care_due_to_Well-being" = "Effect_of_Well-being_on_Quality_of_Care"*Standard_Quality_of_Care	QualityofCare
Ratio_of_Actual_Care = (Actual_Quality_of_Care/Standard_Quality_of_Care)	Dimensionless
Standard_Quality_of_Care = 0.5	QualityofCare

A2.8. Expectations

Formulation and comments	Units
Insurers_Expectations(t) = Insurers_Expectations(t - dt) + (Change_in_Insurers_Expectations) * dt	
Stocks Initial Value: Insurers_Expectations = Initial_Insurers_Expected_Quality	QualityofCare

$\text{Change_in_Insurers_Expectations} = \text{DELAY}(\text{Adjustment_Insurers_Perceived_Quality},$
 $\text{Fixed_Time_Delay_in_Adjustment_of_Insurers_Expected_Quality}, 0) + \text{PULSE}(\text{PULSE_Amount_Insurers_Expectations},$
 $\text{PULSE_Time_Insurers_Expectations}, \text{PULSE_Interval_Insurers_Expectations})$
QualityofCare/Months

$\text{Insures_Perceived_Quality}(t) = \text{Insures_Perceived_Quality}(t - dt) + (\text{Adjustment_Insurers_Perceived_Quality}) * dt$
 $\text{Stocks Initial Value: Insures_Perceived_Quality} = \text{Care_Quality.Actual_Quality_of_Care}$
QualityofCare

$\text{Adjustment_Insurers_Perceived_Quality} = (\text{Potential_Insurers_Quality_Perception} -$
 $\text{Insures_Perceived_Quality}) / \text{Time_to_Adjust_Insurers_Perceived_Quality}$
QualityofCare/Months

$\text{"Patients_\"Total\"_Expected_Quality"}(t) = \text{"Patients_\"Total\"_Expected_Quality"}(t - dt) +$
 $(\text{Total_Patients_Expected_Quality_Arrival_Rate} - \text{Total_Patients_Expected_Quality_Treated_Rate}) * dt$
 $\text{Stocks Initial Value: "Patients_\"Total\"_Expected_Quality"} =$
 $\text{Initial_Patients_Expected_Quality} * \text{Patient_Flow.Initial_Total_Patients}$
QualityofCare*Patients

$\text{Total_Patients_Expected_Quality_Arrival_Rate} =$
 $\text{SW_B3_Potential_Patients_Quality_Expectations} * (0.5 * \text{Patient_Flow.Patients_Arrival_Rate} * \text{Insurers_Expectations} + 0.5 * \text{Potential}$
 $\text{_Patients_Quality_Expectations} * \text{Patient_Flow.Patients_Arrival_Rate}) + (1 -$
 $\text{SW_B3_Potential_Patients_Quality_Expectations}) * \text{Patient_Flow.Patients_Arrival_Rate} * \text{Insurers_Expectations}$
QualityofCare*Patients/Months

$\text{Total_Patients_Expected_Quality_Treated_Rate} = \text{Patients_Expected_Quality} * \text{Patient_Flow.Patients_Treated_Rate}$
QualityofCare*Patients/Months

$\text{Potential_Patients_Quality_Expectations}(t) = \text{Potential_Patients_Quality_Expectations}(t - dt) +$
 $(\text{Change_in_Potential_Patients_Quality_Expectations}) * dt$
 $\text{Stocks Initial Value: Potential_Patients_Quality_Expectations} = \text{Initial_Potential_Patients_Expectations}$
QualityofCare

$\text{Change_in_Potential_Patients_Quality_Expectations} = (\text{Potential_Quality_Expectations} -$
 $\text{Potential_Patients_Quality_Expectations}) / \text{Time_to_Change_Potential_Patients_Quality_Expectations}$
QualityofCare/Months

$\text{Recent_Patients_Satisfaction}(t) = \text{Recent_Patients_Satisfaction}(t - dt) + (\text{Adjustment_Recent_Patients_Satisfaction}) * dt$
 $\text{Stocks Initial Value: Recent_Patients_Satisfaction} = \text{Norm_Recent_Patients_Satisfaction}$
Satisfaction

$\text{Adjustment_Recent_Patients_Satisfaction} = (\text{Potential_Patient_Satisfaction} - \text{Recent_Patients_Satisfaction})$
 $/ \text{Time_to_Adjust_Recent_Patients_Satisfaction}$
Satisfaction/Months

$\text{Effect_of_Disconfirmation_on_Patient_Satisfaction} =$
 $\text{GRAPH}(\text{"Patients_Disconfirmation_ (Ratio_of_Quality_of_Care_over_the_Patients_Expected_Quality_of_Care)"})$
 $(0.000, 0.275), (0.200, 0.400), (0.400, 0.550), (0.600, 0.700), (0.800, 0.850), (1.000, 1.000), (1.200, 1.150), (1.400, 1.300), (1.600,$
 $1.450), (1.800, 1.600), (2.000, 1.725)$
Dimensionless

$\text{Effect_of_Expectations_on_Registration_Procedures} = \text{GRAPH}(\text{"Insurers_Disconfirmation_ (Ratio_of_Expectations)"})$
 $(0.000, 1.991), (0.125, 1.954), (0.250, 1.845), (0.375, 1.644), (0.500, 1.374), (0.625, 1.183), (0.750, 1.078), (0.875, 1.037), (1.000,$
 $1.000)$
Dimensionless

$\text{Effect_of_Insurers_Expectation_on_Norm_Arrival_Rate} =$
 $\text{GRAPH}(\text{"Insurers_Disconfirmation_ (Ratio_of_Expectations)"})^{\text{SW_B4_Effect_of_Insurers_on_Patients_Arrival_Rate}}$
 $(0.000, 0.000), (0.125, 0.027), (0.250, 0.228), (0.375, 0.630), (0.500, 0.831), (0.625, 0.904), (0.750, 0.950), (0.875, 0.977), (1.000,$
 $1.000), (1.125, 1.000), (1.250, 1.000), (1.375, 1.041), (1.500, 1.096), (1.625, 1.196), (1.750, 1.297), (1.875, 1.342), (2.000, 1.361)$
Dimensionless

$\text{Fixed_Time_Delay_in_Adjustment_of_Insurers_Expected_Quality} = 6$
Dimensionless

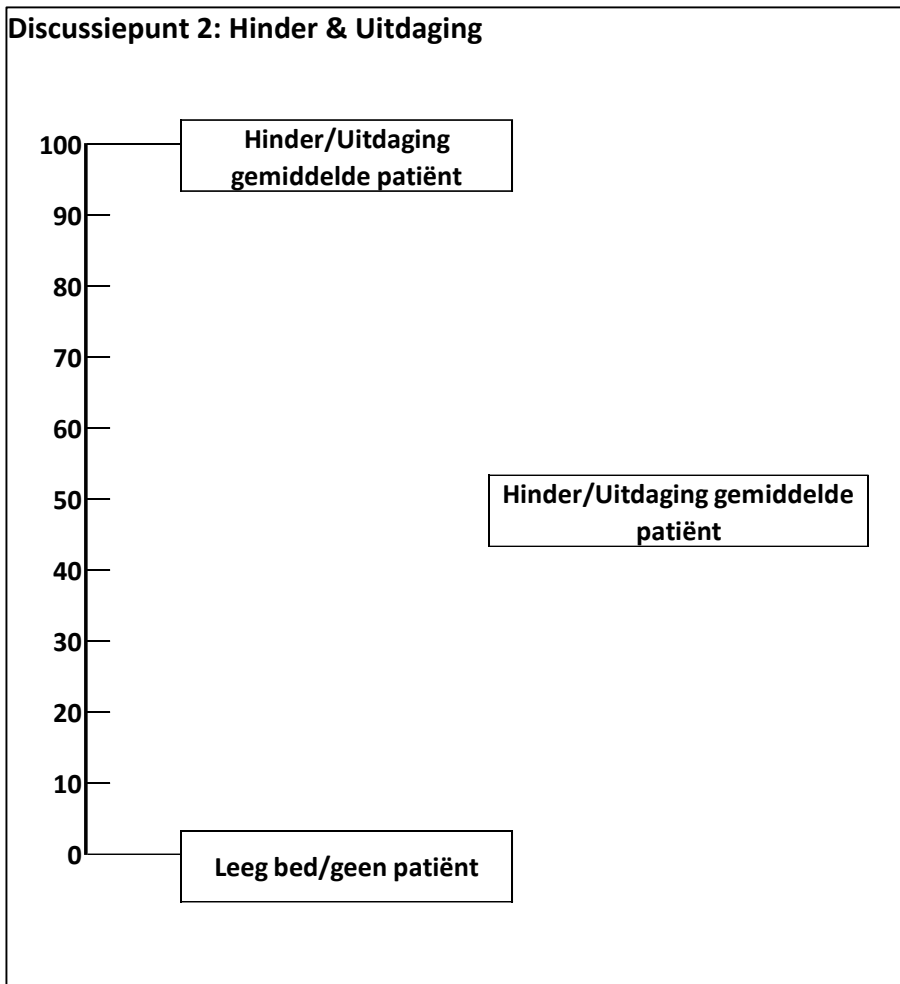
$\text{Initial_Insurers_Expected_Quality} = 0.5$
QualityofCare

$\text{Initial_Patients_Expected_Quality} = 0.5$
QualityofCare

$Initial_Potential_Patients_Expectations = 0.5$	
$"Insurers_Disconfirmation_ (Ratio_of_Expectations)" = Insurers_Expectations / Norm_Expectations$	QualityofCare
$Norm_Expectations = 0.5 + STEP(0, 13)$	Dimensionless
$Norm_Potential_Patients_Quality_Expectations = 0.5$	QualityofCare
$Norm_Recent_Patients_Satisfaction = 0.5$	QualityofCare
$"Patients_Disconfirmation_ (Ratio_of_Quality_of_Care_over_the_Patients_Expected_Quality_of_Care)" = (Care_Quality.Actual_Quality_of_Care / Patients_Expected_Quality)^{SW_B3_Patients_Disconfirmation}$	Satisfaction
$Patients_Expected_Quality = "Patients_Total_Expected_Quality" / Patient_Flow.Patients_at_the_Unit$	Dimensionless
$Potential_Insurers_Quality_Perception = Care_Quality.Actual_Quality_of_Care$	QualityofCare
$Potential_Patient_Satisfaction = Norm_Recent_Patients_Satisfaction * Effect_of_Disconfirmation_on_Patient_Satisfaction$	QualityofCare
$Potential_Quality_Expectations = Norm_Potential_Patients_Quality_Expectations * Ratio_of_Patient_Satisfaction$	Satisfaction
$PULSE_Amount_Insurers_Expectations = 0$	QualityofCare
$PULSE_Interval_Insurers_Expectations = 0$	QualityofCare
$PULSE_Time_Insurers_Expectations = 13$	Months
$Ratio_of_Patient_Satisfaction = Recent_Patients_Satisfaction / Norm_Recent_Patients_Satisfaction$	Months
$"Reference_Bi-Annual_Reported_Patient_Satisfaction" = GRAPH(TIME)$ (3.00, 10.2162), (9.00, 10.4615), (15.00, 10.2364), (21.00, 10.7595), (27.00, 10.1882), (33.00, 10.3069), (39.00, 9.8641), (51.00, 10.3421)	Dimensionless
$SW_B3_Patients_Disconfirmation = 1$	Satisfaction
$SW_B3_Potential_Patients_Quality_Expectations = 1$	Dimensionless
$SW_B4_Effect_of_Insurers_on_Patients_Arrival_Rate = 0$	Dimensionless
$Time_to_Adjust_Insurers_Perceived_Quality = 3$	Dimensionless
$Time_to_Adjust_Recent_Patients_Satisfaction = 1$	Months
$Time_to_Change_Potential_Patients_Quality_Expectations = 48$	Months
	Months

A3. Knowledge Elicitation Session – Materials and unedited results

A3.2. Discussion Point 2: Hindrance and Challenge Demands



Average Patients Proportions of Hindrance and Challenge Demands

Raw Scores						
Demand	P1	P2	P3	P4	P5	
Hindrance Demands	100	100	100	43	50	
Challenge Demands	70	90	70	100	100	
Empty bed/No patient	0	0	0	0	0	
Calculated Scores						
Total	170	190	170	143	150	Average
Proportion Hindrance Demands	0.59	0.53	0.59	0.30	0.33	0.47
Proportion Challenge Demands	0.41	0.47	0.41	0.70	0.67	0.53

A3.3. Discussion Point 3: Multiple Diagnoses

Multiple and Single Diagnoses Patients Swing of Intensity of Care

Raw Scores					
Patient type	P1	P2	P3	P4	P5
Multiple Diagnoses	100	100	100	100	100

Single Diagnosis	60	85	80	70	90	
Empty bed/No patient	0	0	0	0	0	
Calculated Scores						
Total	160	185	180	170	190	Average
Multiple Diagnoses Weight	0.63	0.54	0.56	0.59	0.53	0.57
Single Diagnosis Weight	0.38	0.46	0.44	0.41	0.47	0.43
Intensity of Care of Multiple Diagnosis (with Single Diagnosis = 1)						
Multiple Diagnoses Weight/Single Diagnosis Weight	1.31					

Average Patients with Multiple Diagnosis Proportions of Hindrance and Challenge Demands

Raw Scores						
Demand	P1	P2	P3	P4	P5	
Hindrance Demands	70	70	60	100	60	
Challenge Demands	100	100	100	50	100	
Empty bed/No patient	0	0	0	0	0	
Calculated Scores						
Total	170	170	160	150	160	Average
Proportion Hindrance Demands	0.41	0.41	0.38	0.67	0.38	0.45
Proportion Challenge Demands	0.59	0.59	0.63	0.33	0.63	0.55

A3.4. Discussion Point 4: Older Patients

Older Patients Swing of Intensity of Care

Intensity of Care of Older Patients (with Younger Patients = 1)						
Raw Scores						
Patient type	P1	P2	P3	P4	P5	
Age 70+ Patients	100	100	100	100	100	
Age 69- Patients	80	85	60	80	100	
Empty bed/No patient	0	0	0	0	0	
Calculated Scores						
Total	180	185	160	180	200	Average
Age 70+ Patients Weight	0.56	0.54	0.63	0.56	0.50	0.56
Age 69- Weight	0.44	0.46	0.38	0.44	0.50	0.44
Intensity of Care of Older Patients (with Younger Patients = 1)						
Age 70+ Weight/Age 69- Weight						1.25

Older Patients Proportions of Hindrance and Challenge Demands

Order Patients Reports on Hindrance and Challenge Demands						
Raw Scores						
Demand	P1	P2	P3	P4	P5	
Hindrance Demands	100	85	100	100	100	
Challenge Demands	80	100	70	100	50	
Empty bed/No patient	0	0	0	0	0	
Calculated Scores						
Total	180	185	170	200	150	Average
Proportion Hindrance Demands	0.56	0.46	0.59	0.50	0.67	0.55
Proportion Challenge Demands	0.44	0.54	0.41	0.50	0.33	0.45

A3.5. Discussion Point 5: Registration Procedures

Registration Procedures Proportion of Hindrance Demands						
Raw Scores						
Demand	P1	P2	P3	P4	P5	
All Hindrance Demands	100	100	100	100	100	
Current Reg. Proc.	60	70	50	20	50	
2012 Reg. Proc. Proportion	50	20	30	10	5	
No Hindrance	0	0	0	0	0	
Calculated Scores						
Demand						Average
Current Reg. Proc. Proportion	0.6	0.7	0.5	0.2	0.5	0.50
2012 Reg. Proc. Proportion	0.5	0.2	0.3	0.1	0.05	0.23

A3.6 Discussion Point 6: High and Low Intensity Diagnosis Groups

Direct Rating Results for Diagnosis Groups					
Intensity of Care		Challenge Demands		Hindrance Demands	
Raw Scores					
Diagnosis group	Group Rating		Group Rating		Group Rating
G1. Angina Pectoris	30		70		40
G2. Angina Pectoris Unstable	80		90		75
G3. Dyspnea	95		80		60
G4. Rhythm disorder	90		100		20
G5. Chronic heart disorder	10		40		10
G6. Inflammation	50		40		70
G7. Follow-up A	70		60		30
G8. Follow-up B	20		20		10
G9. Follow-up C	35		25		35
G10. Miscellaneous	100		30		100
Weighted Scores					
Total	580	Intensity Group	555		450
G1. Angina Pectoris	0.05	LI	0.13		0.09
G2. Angina Pectoris Unstable	0.14	HI	0.16		0.17
G3. Dyspnea	0.16	HI	0.14		0.13
G4. Rhythm disorder	0.16	HI	0.18		0.04
G5. Chronic heart disorder	0.02	LI	0.07		0.02
G6. Inflammation	0.09	LI	0.07		0.16
G7. Follow-up A	0.12	HI	0.11		0.07
G8. Follow-up B	0.03	LI	0.04		0.02
G9. Follow-up C	0.06	LI	0.05		0.08
G10. Miscellaneous	0.17	HI	0.05		0.22
Intensity Group	Weight		Weight		Weight
HI	0.75		0.65		0.63
LI	0.25		0.35		0.37

A3.7. Discussion Point 7: Working under Pressure

Minutes of Direct Care per Hour when Working under Pressure

Raw Values						
Pat./Emp.	Direct Care Minutes per Hour					Average
	P1	P2	P3	P4	P5	
1	40	20	17	20	5	20.4
2	30	20	20	20	10	20
3	25	20	22	20	15	20.4
4	20	20	26	20	20	21.2
5	20	17.5	28	23	25	22.7
6	20	15	30	25	30	24
7	20	13.5	33	28	35	25.9
8	20	12	35	30	40	27.4
9	20	11	35	33	45	28.8
10	20	10	35	35	50	30

Calculated Values			
Patients (4=norm)	Ave. Minutes Adj.	Time per Pat.	Time (5.3 = norm)
0.25	20.0	20.00	3.77
0.50	20.4	10.20	1.92
0.75	20.4	6.80	1.28
1.00	21.2	5.30	1.00
1.25	22.7	4.54	0.86
1.50	24.0	4.00	0.75
1.75	25.9	3.70	0.70
2.00	27.4	3.43	0.65
2.25	28.8	3.20	0.60
2.50	30.0	3.00	0.57

Graded Care Quality when Working under Pressure

Raw Values						Calculated Values		
Pat./Emp.	Grade Care Quality					Patients (4 = norm)	Average	Effect (7.58 = norm)
	P1	P2	P3	P4	P5			
1	8.5	7	10	8.5	7.5	0.25	8.30	1.095
2	8.5	7	10	8.5	7.5	0.5	8.30	1.095
3	8	7	9.5	7.75	7.5	0.75	7.95	1.049
4	7.5	7	9	7	7.4	1	7.58	1.000
5	7	6.75	8.5	6.75	7.2	1.25	7.24	0.955
6	6.5	6.5	8	6.5	7	1.5	6.90	0.910
7	5.25	6	7	5.75	6.5	1.75	6.10	0.805
8	4	5.5	6	5	6	2	5.30	0.699
9	4	5.25	5	4.25	5.9	2.25	4.88	0.644
10	4	5	4	3.5	5.8	2.5	4.46	0.588

A3.8. Discussion Point 8: Job Resources

Job Resources Ranking		
Raw Scores		Weighted Scores
Resource	Group Rating	
Well-being	100	0.16
Autonomy	95	0.15
Participation	90	0.14
Work-experience	85	0.13
Patient Satisfaction	80	0.13
Supervisor Support	60	0.09
Feedback	50	0.08
Reward	40	0.06
Job Safety	40	0.06
No Resource	0	0.00
Total	640	1