# Health economic evaluation of continuous monitoring of vital signs
at Slingeland Hospital

A discrete event simulation study

**Final report**

23-01-2019

Jasper ten Dam

Master Thesis Industrial Engineering & Management

University of Twente

Slingeland Ziekenhuis

UNIVERSITY OF TWENTE.

| | |
|---|---|
| Graduation organization: | Slingeland Hospital<br>Kruisbergseweg 25<br>7009 BL Doetinchem<br>The Netherlands |
| University supervisors: | dr. D. Demirtas (Derya)<br>Faculty of Behavioural Management and Social Sciences<br>Dep. Industrial Engineering and Business Information Systems<br><br>dr. ir. H. Koffijberg (Erik)<br>Faculty of Behavioural Management and Social Sciences<br>Dep. Health Technology and Services Research |
| Organization supervisors: | drs. D. Winkeler (Daniel)<br>Change manager and organizational advisor<br><br>K. van Dulmen (Koen)<br>Change manager and organizational advisor |

University of Twente, Enschede
Faculty of Behavioural Management and Social Sciences
Study: Industrial Engineering and Management
Specialization: Healthcare Technology and Management

Jasper ten Dam
23-01-2019

# Preface

This thesis proposes the outcomes of the graduation project that I have been conducting for Slingeland Hospital in collaboration with my supervisors. When conducting my search for a graduation project at an organization for my study Industrial Engineering and Management in the field of health economic modelling in early 2018, I came into contact with my later external supervisor Daniel Winkeler. I am very grateful to Daniel and to his colleague Koen van Dulmen for the establishment of a graduation project that very well suited to my wishes and contained a high amount of complexity from which I learned a lot. Moreover, I want to thank Daniel and Koen for our productive, motivating and energetic conversations where I was always challenged and for always being ready to provide me with answers and the right resources when I needed them.

I want to thank my first supervisor Derya Demirtas for all the support, for the excellent feedback in writing my thesis and for being very motivated to be my supervisor throughout (and in particular already in the initial phase of) the project. I also want to thank my second supervisor Erik Koffijberg for dedicating time to share his large knowledge about health economics and modelling for this project and for inspiring me to explore this discipline.

With completing this research, I will also bring my invaluable student life to an end. Therefore, I also want to express gratitude to my friends who have been of great company during this unforgettable journey and hopefully will keep being this for some time. Finally, I want to mention my parents for their unconditional trust and support in every possible way during this time. Thank you.

I hope you enjoy your reading!

Enschede, 23-01-2019

Jasper ten Dam

# Management summary

Slingeland Hospital is a general hospital in Doetinchem. In the coming years, an increase demand of care is expected while, fewer organizational resources (such as hospital beds in the new hospital building) will be available. One of ways that Slingeland Hospital plans to cope with these challenges is by means of an innovation programme named “Sensing Clinic”, that concerns continuous monitoring of vital signs (CMVS). Via this technique, vital signs on non-acute wards can be measured continuously and monitored from distance whereas currently, these signs are measured manually and intermittently by health professionals. CMVS is expected to provide health gain for patients, shorten the Intensive Care Unit (ICU) length of stay (LOS), reduce the number of ICU transfers, reduce the number of readmissions, reduce the severity of complications and influence diagnostic costs and RRT interventions by means of early detection of deterioration and by analysing vital sign trends. Also, less time commitment of health professionals is expected.

Because of these expected outcomes, CMVS can result in health benefits and cost savings, due to reduction in supply of care. On the other hand, this reduction in supply of care results in fewer health services that are provided by the hospital, which leads to lower insurance reimbursement. The latter is rarely measured in health economic evaluations but very relevant given Slingeland Hospital’s position in the healthcare system. Therefore, our research question is as follows:

*“What is the impact of continuous monitoring of vital signs in Slingeland Hospital on costs, earnings and health for key target populations?”*

From literature and data, patients with a cerebrovascular accident (CVA patients), vascular surgery patients, patients with ischaemic heart disease and orthopaedic patients were designated as potential target populations for CMVS. We performed further analysis for CVA patients, to evaluate the health economic impact. For the effects of CMVS, we only considered (ICU-) LOS, ICU transfers, the number of readmissions and pneumonia (most relevant complication in this study’s context) incidence. Based on literature findings and expert opinions, we performed a scenario analysis.

| Outcome | Cautious | Standard | Optimistic |
|---|---|---|---|
| Length of stay | -5% | -10% | -20% |
| ICU transfers | -5% | -15% | -40% |
| ICU length of stay | -0% | -10% | -25% |
| Number of eadmissions | -5% | -10% | -25% |
| Pneumonia incidence | -5% | -25% | -40% |

These scenarios were simulated which resulted in changes in costs and earnings (total earnings and medical specialist company (MSB) earnings) as displayed below.[1] The costs of the intervention (approximately €200 - €250 per patient) were not included in this simulation model.

| | Cautious | Standard | Optimistic |
|---|---|---|---|
| Change in costs | -€62,414 ± €15,286 (-4.66% ± 0.77%) | -€123,145 ± €8,926 (-9.05% ± 0.75%) | -€251,311 ± €13,858 (-18.31% ± 0.61%) |
| Change in earnings | -€54,729 ± €15,875 (-3.57% ± 0.69%) | -€104,530 ± €11,081 (-7.08% ± 0.68%) | -€213,806 ± €14,851 (-14.20% ± 0.65%) |
| Change in MSB earnings | €7,388 ± €2,143 (-0.48% ± 0.09%) | €14,112 ± € 1,496 (-0.96% ± 0.09%) | €28,864 ± €2,005 -(1.9% ± 0.09%) |

In the simulation model, the hospital's costs decrease more than the earnings, leading to an increased margin between the hospital's earnings and costs. Length of stay has the largest influence on both costs and earnings.

Based on this work, the most important recommendations for Slingeland Hospital are:

- Extended the model by implementing the effects of CMVS that were not considered and by implementing other potential target populations.
- Improve data quality, in particular regarding complication incidence, and perform further validation, in particular regarding the hospital's earnings.
- Obtain data on the effectiveness of the intervention in terms of quality of life of patients who receive CMVS.
- When the increased margin between the hospital's earnings and costs and the intervention costs are considered, the hospital should decide, depending on the future scenario and intervention costs, whether a spending between approximately €90 (low intervention costs, optimistic scenario) and €215 (high intervention costs, cautious scenario) per patient is worth implementing CMVS. Here, the positive results on clinical outcomes for the patient, the innovative character and large opportunities to further study and improve CMVS should be considered. Moreover, the model's uncertainty and the complex health economic system that is described in this study should be taken into account.

[1] The values in the tables describe the uncertainty interval of the mean value due to variability between patients. For an interval, we are 95% certain that it contains the true mean.

# Management samenvatting

Slingeland Ziekenhuis is een algemeen ziekenhuis in Doetinchem. De komende jaren wordt een toename in vraag naar zorg verwacht terwijl er minder middelen (zoals minder bedden in de nieuwbouw) beschikbaar zullen zijn. Eén van de manieren waarop het ziekenhuis hiermee omgaat is door middel van een innovatieprogramma “Sensing Clinic” dat continue monitoren van vitale functies (CMVF) onderzoekt. Via deze techniek kunnen vitale functies op niet-acute afdelingen continue en vanaf afstand gemeten worden terwijl dit op dit moment handmatig enkele keren per dag gedaan wordt door verpleegkundigen. Van CMVF wordt verwacht dat het de Intensive Care (IC-) ligduur verkort, het aantal IC opnames vermindert, het aantal heropnames vermindert, de ernst van complicaties vermindert en diagnostiek en het aantal spoed interventies beïnvloedt door vroegtijdige detectie van achteruitgang en trendanalyse van vitale functies. Ook wordt verwacht dat de interventie verpleegkundigen tijd bespaart.

CMVF kan, vanwege deze verwachte uitkomsten, resulteren in gezondheidswinst en kostenbesparingen (door een reductie in vraag naar zorg). Anderzijds resulteert een vermindering in vraag naar zorg in minder diensten die worden verleend door het ziekenhuis, wat resulteert in een afname van de schadelast. Dit laatste is relevant voor Slingeland Ziekenhuis gezien haar positie in het zorgstelsel. Derhalve is de volgende onderzoeksvraag geformuleerd:

*“Wat is de invloed van continue meten van vitale functies in Slingeland Ziekenhuis op kosten, omzet en gezondheid voor relevante doelgroepen?*

Uit literatuur en data is gebleken dat patiënten met een cerebrovasculair accident (CVA-patiënten), vaatchirurgie patiënten, patiënten met ischemische hartziekte en orthopedische patiënten tot relevante doelgroepen voor CMVF behoren. Voor CVA-patiënten, zijn verdere analyses uitgevoerd om de gezondheids-economische impact te bepalen. Betreffende de verwachte effecten van CMVF zijn deze analyses gelimiteerd tot de (IC-) ligduur, IC opnames, het aantal heropnames en de incidentie van longontsteking (meest relevante complicatie in deze context). Gebaseerd op bevindingen in de literatuur en expert opinies is er een scenario analyse uitgevoerd.

| Uitkomst | Voorzichtig | Standaard | Optimistisch |
|---|---|---|---|
| Ligduur | -5% | -10% | -20% |
| IC opnames | -5% | -15% | -40% |
| IC ligduur | -0% | -10% | -25% |
| Aantal heropnames | -5% | -10% | -25% |
| Longonsteking incidentie | -5% | -25% | -40% |

Deze scenario's zijn gesimuleerd wat resulteerde in de verandering in kosten en omzet (totale opbrengsten en Medisch Specialistisch Bedrijf (MSB-) opbrengsten) zoals hieronder weergegeven.[1] De kosten van de interventie (ongeveer €200 - €250 per patiënt) zijn niet meegenomen in deze analyse.

| | Voorzichtig | Standaard | Optimistisch |
|---|---|---|---|
| Verandering in kosten | -€62.414 ± €15.286<br>(-4,66% ± 0,77%) | -€123.145 ± €8.926<br>(-9,05% ± 0,75%) | -€251.311 ± €13.858<br>-(18,31% ± 0,61%) |
| Verandering in omzet | -€54.729 ± €15.875<br>(-3,57% ± 0,69%) | -€104.530 ± €11.081<br>-(7,08% ± 0,68%) | -€213.806 ± €14.851<br>(-14,20% ± 0,65%) |
| Verandering in MSB omzet | €7.388 ± €2.143<br>(-0,48% ± 0,09%) | €14.112 ± € 1,496<br>(-0,96% ± 0,09%) | €28.864 ± €2.005<br>(-1,9% ± 0,09%) |

In de simulatie nemen de kosten van het ziekenhuis meer af dan de omzet, wat leidt tot een toename in de marge tussen omzet en kosten. De ligduur heeft de grootste invloed op kosten en opbrengsten.

Gebaseerd op deze studie zijn de belangrijkste aanbevelingen voor Slingeland Ziekenhuis:

- Breid het simulatiemodel uit door de effecten van CMVF mee te nemen die in deze studie buiten beschouwing zijn gelaten.
- Verbeter de datakwaliteit, met name betreffende de complicatie incidentie, en voer verdere validatie uit, met name betreffende de omzet.
- Verkrijg data die de effectiviteit van de interventie beschrijft door middel van kwaliteit van leven van patiënten die CMVF ondergaan.
- Wanneer de toename in de marge tussen omzet en kosten en de interventiekosten worden meegenomen, zal het ziekenhuis moeten besluiten of een besteding tussen ongeveer €90 (lage interventiekosten, optimistisch scenario) en €215 (hoge interventiekosten, voorzichtige scenario) per patiënt het waard is om CMVF te implementeren voor CVA-patiënten. Hierbij moet tevens de gezondheidswinst en het innovatieve karakter van CMVF (die grote mogelijkheden biedt voor verder onderzoek en ontwikkeling) beschouwd worden. Bovendien moet rekening gehouden worden met de onzekerheid van het model en de complexiteit van het economische systeem dat beschreven is in deze studie.

[1] De waarden in de tabellen betreffen het onbetrouwbaarheidsinterval van de gemiddelde waarde door variabiliteit tussen patiënten. Voor een interval zijn we er 95% zeker van dat het de werkelijke gemiddelde waarde bevat.

# List of Abbreviations

| | |
|---|---|
| **AMU** | Acute Medical Unit |
| **CMVS** | Continuous Monitoring of Vital Signs |
| **CI** | Confidence Interval |
| **CS** | Carotid Stenosis |
| **ER** | Emergency Room |
| **EWS** | Early Warning Score |
| **HR** | Heart Rate |
| **ICB** | Intracerebral- or intracranial bleeding |
| **ICU** | Intensive Care Unit |
| **LOS** | Length of stay |
| **MEWS** | Modified Early Warning Score |
| **MSB** | Medical Specialist Company |
| **OFAT** | One-factor-at-a-time |
| **QOL** | Quality of life |
| **RR** | Respiratory Rate |
| **RRT** | Rapid Response Team |
| **SCU** | Stroke Care Unit |
| **SKB** | Streekziekenhuis Koningin Beatrix |
| **STM** | State Transition Model |

# List of Figures

Figure 1: Triple Aim framework ..... 2
Figure 2: Changing focus of healthcare providers in the health pyramid ..... 3
Figure 3: Triangular relationship in healthcare economics. Adapted from *Bennett et al. (1997)* .... 6
Figure 4: Leading causes of amenable mortality in the EU, 2015. Modified from *Eurostat (2018)* 12
Figure 5: Number of RRT procedures per ward in Slingeland Hospital (2017) ..... 13
Figure 6: Costs and number of nursing days (Q1 through Q3 2018) for non-acute clinical specialisms in Slingeland Hospital ..... 15
Figure 7: Process for CVA patients. ..... 16
Figure 8: Example of a DBC care product derivation (DBC 099999017, the most frequent CVA care product in Slingeland Hospital). N&CN: Neurology & Clinical Neurophysiology ..... 18
Figure 9: A care trajectory can exist of one or multiple sub-trajectories ..... 18
Figure 10: Workflow of cost price calculation (LOGEX, 2018) ..... 19
Figure 11: Effects of CMVS. Dark boxes are not considered in the quantitative model. ..... 21
Figure 12: Earnings and costs for DBC care products of clinical CVA patients (sorted based on earnings) ..... 23
Figure 13: Branches in CVA care product decision tree with node probabilities (for dotted lines, in reality more nodes are present (mostly non-clinical) that are not needed in this study due to the level of detail of the study). n=345 patients (first admissions only). ICB: Intracerebral or intracranial bleeding; N&CN: Neurology & Clinical Neurophysiology. ..... 24
Figure 14: Empirical and geometric distribution for the length of stay of patients who did not have an intracranial or intracerebral bleeding (n=298) ..... 26
Figure 15: Empirical and geometric distribution for the length of stay of patients who had an intracranial or intracerebral bleeding (n=90) ..... 26
Figure 16: Complication incidence in Slingeland Hospital ..... 27
Figure 17: Cumulative distribution functions for the time to readmission for all CVA DBC's ..... 28
Figure 18: Ways to study a system *(Law, 2015)* ..... 29
Figure 19: Overview of the model for CVA patients. ICB: Intracranial or intracerebral bleeding; LOS: Length of Stay; N&CN: Neurology & Clinical Neurophysiology ..... 40
Figure 20: Empirical and uniform distribution for the length of stay of patients who had a pneumonia (n=7) ..... 42
Figure 21: Mean costs, mean earnings and the margin (Earnings – Costs) and 95% CI's for an increasing number of patients. The CI's for the first runs are not completely visible due to their large range. ..... 46
Figure 22: Costs and earnings for a decrease in length of stay (LOS). Error bars: 95% CI for first order uncertainty (barely visible in this figure). ..... 51
Figure 23: Costs for decreasing ICU Transfer rate and ICU length of stay. Error bars: 95% CI for first order uncertainty. Note the relatively small range of the Costs axis due to the subtitle changes. ..... 52
Figure 24: Earnings for decreasing ICU Transfer rate and ICU length of stay. Error bars: 95% CI for first order uncertainty. Note the relatively small range of the Earnings axis due to the very subtitle changes. ..... 53

Figure 25: Costs and earnings for decreasing number of readmissions. Error bars: 95% CI for first order uncertainty. ..... 53
Figure 26 Costs and earnings for decreasing pneumonia incidence. Error bars: 95% CI for first order uncertainty. ..... 54
Figure 27: Change in the margin between Costs and Earnings for a decrease in LOS, readmissions and pneumonia incidence. Error bars: 95% CI for first order uncertainty ..... 54
Figure 28: Costs and earnings for baseline, cautious, standard and optimistic scenario. Error bars: 95% CI for first order uncertainty. ..... 55
Figure 29: Change in the margin between costs and earnings for baseline, cautious, standard and optimistic scenario. Error bars: 95% CI for first order uncertainty. ..... 55
Figure 30: Search strategy ..... 66
Figure 31: Length of stay for readmitted non-ICB patients (n=28) ..... 69
Figure 32: Length of stay for readmitted ICB patients (n=16) ..... 69
Figure 33: Scatter plot and linear regression model for cost prediction of DBC 99999026. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$ ..... 70
Figure 34: Scatter plot and linear regression model for cost prediction of DBC 99999017. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$ ..... 70
Figure 35: Scatter plot and linear regression model for cost prediction of DBC 99999017 with removed outlier. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted R2 . 71
Figure 36: Scatter plot and linear regression model for cost prediction of DBC 99999045. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$ ..... 71
Figure 37: Scatter plot and linear regression model for cost prediction of DBC 99999008. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$ ..... 72
Figure 38: Scatter plot and linear regression model for cost prediction of DBC 99999027. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$ ..... 72
Figure 39: Exclusion of data ..... 74

# List of Tables

Table 1: Stratification of target patient populations in included studies of Downey et al. (2018) and Cardona-Morrell et al. (2016b) ..... 13
Table 2: Costs of diseases in the Netherlands (Zorgrekeningen CBS; excluding psychological disorders and not assignable care) *(Rijksinstituut voor Volksgezondheid en Milieu (RIVM), 2017)* ..... 14
Table 3: Fraction of patients who are readmitted per DBC. * Based on first admissions only. ICB: Intracerebral or intracranial bleeding; N&CN: Neurology & Clinical Neurophysiology..... 28
Table 4: Summary of identified studies that evaluated CMVS. None of the studies considered readmissions. LOS: Length of Stay; ICU TRF: ICU transfers; ICU LOS: ICU length of stay. ..... 35
Table 5: Summary of outcomes of interest of included studies..... 36
Table 6: Conditionality of the model's procedures. ICB: Intracranial or intracerebral bleeding; LOS: Length of Stay; N&CN: Neurology & Clinical Neurophysiology ..... 41
Table 7: OFAT experimental configuration ..... 48
Table 8: Scenario analysis design ..... 49
Table 9: 95% CI for absolute and percent change of costs and earnings for the scenarios compared to baseline..... 55
Table 10: 95% CI for change of the margin between costs and earnings ..... 56

# Contents

**Preface** ..... **v**

**Management summary** ..... **vii**

**Management samenvatting** ..... **ix**

**List of Abbreviations** ..... **xi**

**List of Figures** ..... **xii**

**List of Tables** ..... **xiv**

**Contents** ..... **xv**

1. **Introduction** ..... **1**

1.1 Organization of Slingeland Hospital ..... 1

1.2 Sensing Clinic programme ..... 3

1.3 Continuous monitoring of vital signs ..... 4

1.4 Health economic evaluation ..... 6

1.5 Intention of study ..... 7

1.5.1 Problem formulation and study objective ..... 7

1.5.2 Research question ..... 8

1.5.3 Sub-questions ..... 8

1.5.4 Scope ..... 8

1.6 Outline of report ..... 9

2. **System analysis** ..... **10**

2.1 Impact of intervention on the rapid response system ..... 10

2.2 Selecting high-risk high-cost populations ..... 11

2.2.1 Amenable mortality ..... 11

2.2.2 Populations in comparable research ..... 12

2.2.3 RRT interventions ..... 12

2.2.4 High-cost patients ..... 14

2.3 Selected high-risk high-cost patients ..... 14

2.4 Process ..... 15

2.5 Financial planning and control ..... 16

2.5.1 Insurance reimbursement ..... 16

2.5.2 MSB ..... 18

2.5.3 Cost allocation ..... 19

2.6 Conclusion ..... 19

3. **Study design** ..... **20**
3.1 The effects of CMVS ..... 20
3.2 Available data ..... 21
3.3 Dependent variables ..... 22
3.3.1 Costs ..... 22
3.3.2 Earnings ..... 23
3.3.3 Health ..... 23
3.4 Care pathways ..... 24
3.5 Independent variables ..... 24
3.6 Conclusion ..... 28
4. **Literature** ..... **29**
4.1 Modelling techniques ..... 29
4.1.1 Simulation ..... 30
4.1.2 Simulation modelling techniques in healthcare ..... 31
4.2 Effectiveness of continuous monitoring of vital signs ..... 33
4.2.1 Length of stay ..... 33
4.2.2 ICU transfers ..... 34
4.2.3 ICU length of stay ..... 34
4.3 Avoidable illness ..... 34
4.3.1 CVA complications ..... 36
4.3.2 Length of stay ..... 37
4.3.3 ICU transfers and length of stay ..... 37
4.3.4 Avoidable readmissions ..... 37
4.4 Conclusion ..... 38
4.4.1 Modelling techniques ..... 38
4.4.2 Continuous monitoring of vital signs ..... 38
5. **Simulation model** ..... **39**
5.1 DES in R ..... 39
5.2 Design of the baseline model ..... 39
5.2.1 Care pathways and complications ..... 41
5.2.2 Length of stay ..... 42
5.2.3 ICU transfers and LOS ..... 42
5.2.4 Readmissions ..... 42
5.2.5 DBC handling ..... 43
5.2.6 Costs ..... 43
5.2.7 Earnings ..... 43
5.3 List of assumptions ..... 44
5.4 Input ..... 44
5.5 Output ..... 44
5.6 Uncertainty ..... 45
5.6.1 Stochastic uncertainty and number of simulated patients ..... 45
5.6.2 Parameter uncertainty ..... 46
5.6.3 Heterogeneity ..... 46

5.6.4 Structural uncertainty ..... 47
5.7 Verification ..... 47
5.8 Validation ..... 47
5.9 Experimental design ..... 47
5.9.1 Sensitivity analysis ..... 48
5.9.2 Scenario analysis ..... 49
5.10 Conclusion ..... 50
6. **Results ..... 51**
6.1 Results OFAT simulation ..... 51
6.1.1 Length of stay ..... 51
6.1.2 ICU Transfers and LOS ..... 52
6.1.3 Readmissions ..... 53
6.1.4 Pneumonia incidence ..... 53
6.2 Scenarios ..... 54
6.3 Conclusion ..... 56
7. **Discussion ..... 57**
7.1 Conclusions ..... 57
7.2 Limitations ..... 58
7.3 Future directions ..... 60
7.4 Recommendations ..... 61
**References ..... 62**
**Search strategy ..... 66**
**Logic flowchart ..... 67**
**Length of stay of readmitted patients ..... 69**
**Linear regression models for cost prediction ..... 70**
**Establishment of confidence intervals ..... 73**
**Exclusion of data ..... 74**

# *Chapter 1*

# Introduction

In this chapter, background information for the grounds of this research is provided. Also, the intention of the study is provided via the outline of the problem, study objective, research question and sub questions. The chapter concludes with an outline of the report.

## 1.1 Organization of Slingeland Hospital

Slingeland Hospital is a general hospital in the Netherlands, containing almost all specializations. The hospital has 420 beds and 1,700 employees and is located in Doetinchem, in the province Gelderland. On January 1st, 2017, the hospital was merged at an organizational level with Streekziekenhuis Koningin Beatrix (SKB) in Winterswijk via the umbrella organization Santiz. Currently, Slingeland Hospital is also preparing for a new building, planned to be finished in 2022. (*Slingeland Ziekenhuis, 2016*)

Because of multiple factors in the coming years, an increase in demand of care is expected and fewer organizational resources will be available for the hospital. The increase in demand of care is mainly caused by the increasing number of chronically ill patients and elderly patients, and an expected increase in (highly) complex care. In terms of organizational resources, Slingeland Hospital will structurally have fewer beds (10-20%) available in the new building. Also, the proportion of young persons in the region is decreasing. This contributes to a future nurse shortage. The problem of aging and a decreasing proportion of young persons in the region that Slingeland Hospital serves are above average, compared to the Netherlands.

To cope with the future new building, the more intensive collaboration with the SKB, external (demographic) developments and changes in the healthcare system, some important and large-scale developments are put in motion. One of these developments is a vision to make healthcare in the region future-proof. Here, the base is the triple aim framework, as advocated by the Institute

for Healthcare Improvement (Cambridge, Massachusetts). This framework advocates to optimize health system performance by simultaneously pursuing three dimensions: 1) improving the health of populations, 2) improving individual experience of care, and 3) reducing the per capita costs of care for populations *(Berwick et al., 2008)* (Figure 1).

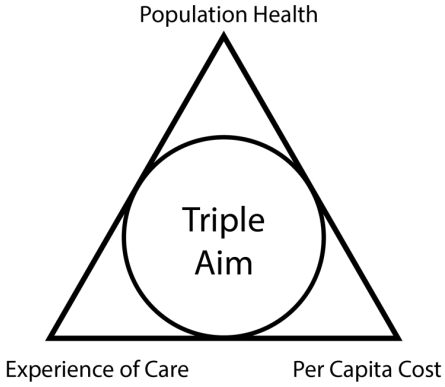



**Figure 1: Triple Aim framework**

To achieve the triple aim targets, Santiz has constructed a vision on the future provision of healthcare. This vision is shown in the "health pyramid" (Figure 2). In different levels in the pyramid, different care is provided. In the base of the pyramid, welfare provision is located. When moving up, the focus goes to provision of (specialized) care (1st and 2nd line treatment). On the top of the pyramid, cure is provided. The goal of the health pyramid is to have to be provided care as much as possible as low as possible in the pyramid. The vision of the pyramid is that giving more attention to health and care in the chain will result in less demand for specialized care and cure by providing the right care at the right time by the right person. Slingeland Hospital wants to realize this by organizing care as close as possible to the patient (at home). Therefore, the hospital will become smaller whilst having a greater range because of the shift to care at home. To achieve this, collaboration and exchange of information between care providers in the chain is necessary. Technological innovation (E-health) plays an increasingly important role in making this possible on multiple levels in the pyramid. One of these innovations is the introduction of continuous monitoring of vital signs (CMVS). The programme that concerns this innovation is named "Sensing Clinic".


**Figure 2: Changing focus of healthcare providers in the health pyramid**

## 1.2 Sensing Clinic programme

The Sensing Clinic programme is a precursor in the establishment of a new command & control centre when Slingeland Hospital's new building is opened. This command & control centre is an innovative ICT-health infrastructure that supports the health trajectory of individual patients both at home (for a certain period after hospital discharge) and at the hospital itself by performing sensor measurements 24/7 or at certain intervals to measure and monitor multiple vital functions. The goal of the command & control centre is to increase quality of life (QOL) and safety of care for patients, to provide efficient care, to diminish the complications of patients (which helps to decrease the demand for more complex care) and to realize cost savings. The command & control centre is expected to reduce the number of readmissions, shorten the length of stay (LOS), reduce the number of ICU (Intensive Care Unit) admissions and provide health gain for patients. It is presumed that this will be reached by early detection of deterioration and performing preventive interventions. Also, the command & control centre could make work processes both more efficient and effective. This is because CMVS takes over a significant amount of time of health professionals.

The Sensing Clinic programme is a precursor in establishing this command & control centre because (clinical) CMVS is believed to initiate intervening from distance. The goals of the Sensing Clinic programme are to test the process and innovation and to calculate the health economic impact. In 2017, phase 1 of the Sensing Clinic project took place. This phase concerned the testing of effectiveness of the technique regarding the measurement of vital functions and the analysis of the data. The vital functions that have been included were: heartrate (HR), respiratory rate (RR), skin temperature and heart rhythm (VitalPatch) and blood pressure (iHealthLabs Blood Pressure

Monitor). The measurements were conducted on 30 CVA (cerebrovascular accident) patients from the neurology department. In this phase, the technical functioning of the monitoring system was investigated. Also, experiences of patients and employees were mapped. Phase 2 of the project has the goal to implement automatic continuous monitoring in the medical process. In this phase, patients who underwent vascular surgery are also included and the vital signs that are measured were extended with saturation measurement (iHealthLabs Pulse Oximeter) and a sleep score (Emfit).

In the Sensing Clinic program, the company Fujitsu and Slingeland Hospital co-create the sensor technology. The Sensing Clinic study is the first trial of research outcomes from Fujitsu's healthcare research project KIDUKU: a three-year project to understand how best to integrate sensing solutions into clinical and community-based settings.

## 1.3 Continuous monitoring of vital signs

Vital signs of hospitalized patients are measured to assess the general physical health of a patient, to give clues to possible diseases, to show progress toward recovery or to detect clinical deterioration. Usually, the monitoring of these vital signs is performed manually by nurses, and includes blood pressure, heart rate, respiratory rate, blood oxygen saturation and core temperature. Typically, this is performed 3 times per day. *(Cardona-Morrell et al., 2016a; Weenk et al., 2017)*

The early detection of deterioration can prevent or reduce harm resulting from serious adverse events *(Ludikhuize et al., 2012)*. To facilitate the early identification and management of at-risk or deteriorating patients, and to predict adverse clinical outcomes, early warning systems, such as the early warning score (EWS) have been developed. These systems are based on vital signs. There are two types of EWS: single-parameter criteria and aggregated weighted scores. In the case of a single-parameter EWS, one abnormal physiologic threshold (e.g., respiratory rate > 36) would trigger the system. In contrast, aggregate weighted EWS allocate points to abnormal thresholds in a weighted manner. Here, the sum of the allocated points represents the EWS. The modified early warning system (MEWS) is a version of an aggregate weighted EWS that is often used in hospitals. *(M. Churpek, 2016; Smith et al., 2008; Weenk et al., 2017)*.

Early detection of deterioration is essential to improve patient safety outcomes and reduce the cost of care. Although the EWS provides relevant data on patients' health status, they are limited by their intermittent and user-dependent nature *(Downey et al., 2017; Ludikhuize et al., 2012) (Tarassenko et al., 2005)*. For example, patients show signs of deteriorations in the 6-8 hours that precede a cardiac or respiratory arrest *(Morgan J.A., 2010)*. Such signs might be overlooked due to a lack of documentation of vital signs in the hours preceding life-threatening adverse effects in hospitalized patients *(Ludikhuize et al., 2012)*. Here, a lack of measurements during the night also

plays an important role *(Beckett et al., 2009)*. Also, the full range of measures of vital signs are rarely obtained, which is expected to be due to nurses' clinical judgements or competing demands (causing nonadherence to mandated policies) *(Cardona-Morrell et al., 2016a)*. Such incomplete and not frequently measured sets of vital signs might lead to missing signs of early deterioration. In addition, most early warning scores only utilize a patient's current vital signs. Using vital sign trends in intermittent monitoring of vital signs was found to increase the accuracy for detecting critical illness on wards *(M. M. Churpek et al., 2016)*.

To obtain more adequate measurements of vital signs, these signs can be measured continuously. Here, wireless devices are used to monitor patients from distance. *Downey et al. (2018)* conducted a systematic review and narrative synthesis on the impact of continuous versus intermittent monitoring of vital signs outside the critical care setting in hospitals. Twenty-four studies were included. The majority of studies showed benefits in terms of critical care use and length of hospital stay. Larger studies were more likely to demonstrate clinical benefit, particularly critical care use and length of hospital stay. *Cardona-Morrell et al. (2016b)* conducted a systematic review and meta-analysis and found no conclusive confirmation of improvements in prevention of cardiac arrest, reduction in length of hospital stay, or prevention of other neurological or cardiovascular adverse effects. The evidence found at the moment of publication was insufficient to recommend CMVS in general wards as routine practise. However, studies were identified that did obtain significant results in favour of continuous vital signs monitoring. Also, studies assessed different combinations of vital signs and some of the included studies only assessed one vital sign. Also, studies were not limited by specific technologies and various early warning systems were used in the included studies. In addition, studies were included that had a low the number of participants.

Concluding, despite potential advantages of CMVS, devices for remote monitoring are underutilized in healthcare. The review of *Downey et al. (2018)* indicates nursing engagement and alarm burden as main barriers to implementation and the review of *Cardona-Morrell et al. (2016b)* found insufficient evidence to recommend continuous vital signs monitoring. Other studies point out technical dysfunction, adverse psychological effects increasing anxiety of patients for disturbances of vital signs *(Appelboom et al., 2014)* and lack of prove on an infrastructure of evidence regarding reliability, validity and responsiveness for each application *(Appelboom et al., 2014; Ludikhuize et al., 2012)*. Also, the impact of continuous monitoring technology on nurse-patient interaction should be evaluated *(Cardona-Morrell et al., 2016a)*.

## 1.4 Health economic evaluation

As stated, CMVS is expected to provide health gain for patients, to shorten the (ICU) length of stay and to reduce the number of ICU transfers and the number of readmissions by early detection of deterioration and by using vital sign trends. Also, the command & control centre could make work processes both more efficient and effective. Therefore, CMVS can result in health benefits and cost savings, due to reduction in supply of care. On the other hand, this reduction in supply of care results in fewer health services that are provided by the hospital, which leads to lower insurance reimbursement. Here, the interaction between consumers, payers and providers of the healthcare system is of importance (Figure 3). Investments for the Sensing Clinic programme are made by the hospital. For the internal business administration of Slingeland Hospital, it is important to know how the investments and possible changes in costs and earnings relate to each other. Also, benefits of the Sensing Clinic programme (and the future monitoring unit) are found for all stakeholders in the healthcare system.

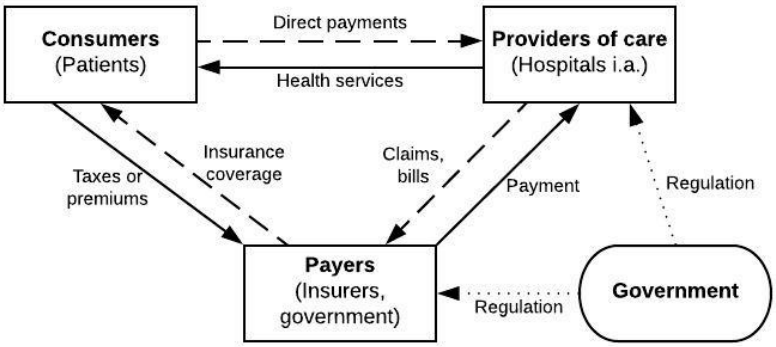



**Figure 3: Triangular relationship in healthcare economics. Adapted from *Bennett et al. (1997)***

Literature is identified that studied the economic evaluation of CMVS. The search strategy can be found in appendix A. The system prices of continuous monitoring are around $1500 and the cost of the wearable sensors varies *(Hofmann & Welch, 2017)*. Although there is limited evidence on healthcare economics of patient monitoring *(Downey et al., 2018)*, some studies were performed that analysed the cost effectiveness of implementing continuous monitoring. *Slight et al. (2014)* performed a multiway sensitivity analyses on the return on investment of continuous monitoring. They found a return on investment of 127% for the least favourable conditions, with the most optimistic model returning up to 1739%. *Ochroch et al. (2006)* examined the costs of patients that required an ICU transfer and found a difference of $28,195 (p = 0.04) in favour of patients who received (single parameter) continuous monitoring. *Morgan J.A. (2010)* implemented continuous monitoring in a 36-bed orthopaedic unit with 10,938 patient days and 3,207 patient discharges per year. A decision tree was applied to evaluate cost effectiveness for the hospital. The cost savings per patient were $255 per patient for the implementation year and were projected to be $404 for

subsequent years. Annual cost savings were about $817,000 in the first year and were projected to be $1,295,000 thereafter. Sensitivity analysis showed that cost-effectiveness was driven by reduced ICU transfers. *(Morgan J.A., 2010)*

Of all the studies that considered cost effectiveness, cost savings (i.e. expenditure of a hospital) were the primary outcome. No studies were identified that looked at the economic consequences of reduction in the demand of care in terms of lower insurance reimbursement.

## 1.5 Intention of study

The following sections will discuss the intention of the study via the problem formulation and study objective, research questions and scope of this research.

### 1.5.1 Problem formulation and study objective

Aging of the population and the increase of chronical illness are expected to cause a higher demand of care and more complex care for Slingeland Hospital in the future. On the other hand, fewer qualified personnel, (financial) changes in the healthcare system and a reduction of beds in Slingeland Hospital's new building are expected to cause resources for the supply of care to be limited. To cope with this future imbalance between demand and supply, SH must provide more efficient and effective care in the future. CMVS is expected to reduce the demand of care by more effective emergency interventions, better provision of medication, improvement of the treatment plan and more adequate handling which will result in a lower length of stay, fewer ICU days and fewer readmissions. Also, the expectation is that less nurse time will be needed because of the continuous and automatic monitoring of vital signs. Currently, monitoring of vital signs is done an intermitted and manual way. Therefore, CMVS is a way for Slingeland Hospital to improve efficiency and effectiveness in the healthcare chain.

A reduction in demand of care results in fewer and lower insurance reimbursement. On the other hand, higher efficiency and effectiveness in the healthcare chain can lead to cost savings. For Slingeland Hospital, higher efficiency and reduction in demand of care is one of the requisites via the triple aim framework. However, this could lead to an imbalance in terms of earnings and costs for a hospital. Therefore, is important to map the expected reduction in insurance reimbursement (earnings from the perspective of Slingeland Hospital) in relation to the cost savings. If such an imbalance is realistic while CMVS achieves the triple aim requisites (Figure 1), this imbalance should be altered to optimize healthcare in the whole system. This possible imbalance depends on the extent of implementing CMVS.

Systematic reviews on CMVS conclude that evidence on healthcare economics of patient monitoring is limited *(Cardona-Morrell et al., 2016b; Downey et al., 2018)*. Some studies are identified that have mapped the cost effectiveness of continuous monitoring based on cost savings

*(Hofmann & Welch, 2017; Morgan J.A., 2010; Ochroch et al., 2006; Slight et al., 2014)*, but none did consider a change in insurance reimbursement. The effect on the insurance reimbursement (i.e. a hospital's earnings) needs to be identified to obtain a better overview of the health economic impact of CMVS in the Dutch healthcare system. Besides the impact on earnings and costs, it is also important to evaluate QOL via health outcomes of CMVS.

The effect of CMVS on Slingeland Hospitals earnings and costs and patient's health will depend on characteristics of the population that is targeted (i.e. distinguished based on specialty or risk level of patients) and the size of this population. Therefore, these effects of CMVS need to be identified for multiple target populations.

Following from the problem formulation, the objective of this study is to identify the impact on costs, earnings[1] and health outcomes of CMVS on key target populations for Slingeland Hospital. Key target populations are defined as high-risk high-cost groups where CMVS is hypothesised to be effective in terms of health and/or economic outcomes.

### 1.5.2 Research question

Following from the study objective, the following research question is formulated:
"What is the impact of continuous monitoring of vital signs in Slingeland Hospital on costs, earnings and health for key target populations?"

### 1.5.3 Sub-questions

To answer the research question, the following sub-questions are formulated:

1. How can the impact of CMVS on costs and earnings be measured?
2. What are key target populations and how is the care for these groups organized?
3. What is the current performance of Slingeland Hospital for a key target population?
4. How can the impact of CMVS be evaluated for a key target population?
5. What is the expected impact of CMVS for a key target population?
6. What insights does this research give?

### 1.5.4 Scope

The study is limited to: 1) health outcomes; 2) internal costs and 3) earnings for a key target population for CMVS in Slingeland Hospital.

[1] In this study, 'earnings' is chosen as terminology to represent the insurer's reimbursement to the hospital (i.e. revenue, turnover, insurer reimbursement or income have the same definition in this study's scope)

## 1.6 Outline of report

The report contains multiple chapters that are needed to answer the research questions. An outline is provided:

In Chapter 2 (System analysis), first, the impact of the intervention on the rapid response system is discussed. Then, based on high-risk high-cost populations, key target populations are selected and the process and planning and control for this study's key target population is given.

Chapter 3 (Study design) will illustrate design of the study. Here, dependent and independent variables are identified. When applicable, a baseline measurement is performed.

Chapter 4 (Literature) discusses the literature findings with the respect to clinical effects of CMVS and models used in similar studies.

In Chapter 5 (Simulation model), the simulation model that is used to assess the economic impact of CMVS will be introduced.

Chapter 6 (Results) discusses the results of the experiments that are performed.

Chapter 7 (Discussion) will complete the report with the conclusions, limitations and recommendations of the study.

# *Chapter 2*

# System analysis

In this chapter, the health economic context of continuous monitoring will be analysed, and potential target populations will be chosen. First, the organisation of care for a deteriorating patient is discussed in Section 2.1 by means of the rapid response system. Following, Section 2.2 will specify high-risk high-cost populations. In Section 2.3, we choose the key target populations. Then, in Section 2.4, the process is given for the main key target population of this research. Section 2.5 discusses the financial planning and control for this key target population.

## 2.1 Impact of intervention on the rapid response system

To consider the micro-economic evaluation at treatment level of CMVS, the organization of care for the deteriorating patient must be known. By organizing adequate care for deteriorating patients, the chance of survival increases. Since 2011, a rapid response system is mandatory in the Netherlands. The goal of a rapid response system is to reduce damage in critically ill patients. In a rapid response system, a Rapid Response Team (RRT) intervenes when the value of one or multiple vital parameter of a patient is outside the safe margins (EWS system) or when an aggregated score based on the vital parameters is too high (MEWS system). In Slingeland Hospital, a MEWS is used. Normally, a nurse is the person who identifies the deteriorating patient and this person is the one that starts the procedure to request an RRT by calling the (head) practitioner. In Slingeland Hospital, this is the case for an EWS higher or equal then 5. In case of an EWS of 3 or 4, a practitioner is consulted. The practitioner drafts a treatment plan within 30 minutes. This treatment plan can be to start a specific treatment, to directly call the RRT or to consult the intensivist. Within 1 hour, the treatment plan is evaluated. When there is not enough improvement of the patient's condition based on the EWS or MEWS, the (head) practitioner calls the RRT. Different codes are used to indicate procedures for deteriorating patients in Slingeland Hospital. In case of an RRT intervention, code yellow is used.

To obtain the early warning scores, vital signs are measured three to four times per day by nurses. For post-OR (operating room) patients, this is every hour until the patient is stable. Multiple factors can influence these measurements. Due to transmission of shifts, the measurements can be performed by multiple individuals. This can influence the outcomes of these manual measurements. Also, despite an early warning system is used, initiating an alarm relies on the response of medical professionals. Despite the focus in the education of the medical professionals, such a response can vary between medical professionals.

## 2.2 Selecting high-risk high-cost populations

The goal of this section is to identify high-risk high-cost populations in order to choose key target populations where CMVS is hypothesised to be effective in terms of health and/or economic outcomes. First, amenable mortality numbers will be consulted. Then, literature is consulted to outline the target populations in studies that already have been conducted. Following, RRT intervention data of Slingeland Hospital is consulted and cost data of The Netherlands and Slingeland Hospital are given. Finally, conclusions are drawn regarding the key target populations for CMVS at Slingeland Hospital.

### 2.2.1 Amenable mortality

Amenable mortality is defined as premature deaths that could have been avoided through timely and effective (or optimal quality) health care *(Eurostat, 2018; OECD & European Observatory on Health System and Policies, 2017)*. CMVS is hypothesised to provide such health care, and thus to decrease the amenable mortality rate. Therefore, amenable mortality numbers per disease/condition gives an insight in the high-risk populations when choosing key target populations for CMVS.

In 2015, there were 90.55 amenable deaths per 100,000 inhabitants in The Netherlands. The number of amenable deaths per 100,000 inhabitants was higher for men (98.02) then for women (83.42). Figure 4 shows the leading causes in terms of diseases or conditions of amenable mortality in the EU for 2015. These numbers were obtained by defining a list of diseases and conditions by health care experts, followed by summation of all deaths by using causes of death data. More detailed information about the calculation of these amenable death numbers is unknown.

Ischemic heart diseases, with distance, is the biggest cause of amenable mortality and is responsible for 31% of all amenable deaths in the EU. Within this group of patients, men (responsible for 66% of deaths) have a higher mortality risk than women (responsible for 34% of deaths). Other high-risk groups are cerebrovascular diseases, colorectal cancer, breast cancer, hypertensive diseases and pneumonia. For breast cancer patients, 99% of the amenable deaths are women. *(Eurostat, 2018)*

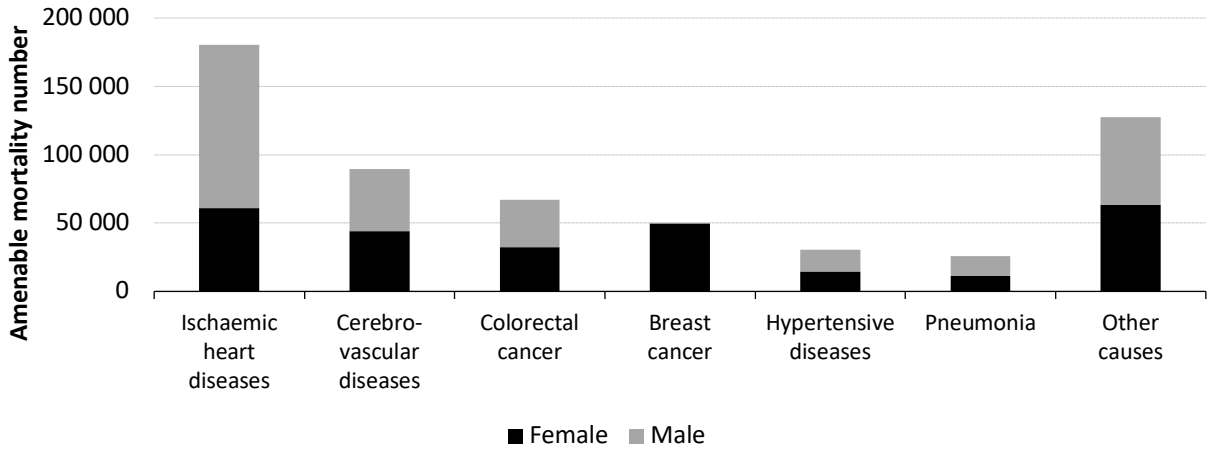



**Figure 4: Leading causes of amenable mortality in the EU, 2015. Modified from *Eurostat (2018)***

### 2.2.2 Populations in comparable research

The systematic reviews of *Downey et al. (2018)* and *Cardona-Morrell et al. (2016b)* show that continuous monitoring outside a critical care setting has been conducted for target populations within a large variety of settings. Both single and multi-parameter continuous monitoring of vital signs studies are performed, where a variety of interventions were used. Also, different participant populations were used.

Specialities that concern the studies include orthopaedics, cardiology, surgery, neurology/neurosurgery, trauma, colorectal and urology (studies regarding paediatric, obstetric or neonatal patients were excluded). In general, choosing the participant populations for continuous monitoring is based on three strategies: 1) by including all patients admitted on specific wards; 2) by including all patient with a specific diagnose and/or treatment; 3) by self-defining high-risk populations.

Table 1 shows a stratification of the target populations of the included studies of *Downey et al. (2018)* and *Cardona-Morrell et al. (2016b)* by the different strategies for the inclusion criteria.

In general, often was chosen for surgical, trauma, stroke and myocardial patients. The high-risk studies choose for the most sophisticated ways to include patients, based on multiple inclusion criteria.

### 2.2.3 RRT interventions

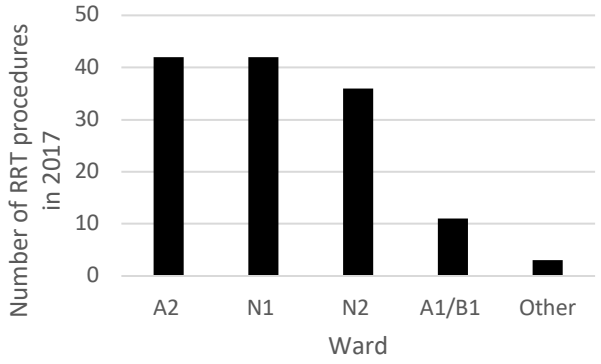
To map the high-risk patients of Slingeland Hospital, RRT interventions are considered. Figure 5 shows the number of RRT interventions per ward for the year 2017. Besides the patient journeys, no hospital system data is available concerning the diagnose of patients that have an RTT intervention. Therefore, in 2017, an analysis of patient journeys was performed that mapped frequent diseases of patients with an RRT procedure.

**Table 1: Stratification of target patient populations in included studies of Downey et al. (2018) and Cardona-Morrell et al. (2016b)**

| Ward admission (5 studies) | Diagnose and/or treatment (6 studies) | High risk (7 studies) |
|---|---|---|
| (Subacute) medical/surgical ward *(Gross et al., 2011; Slight et al., 2014)* | Ischemic stroke *(Cavallini et al., 2003; Sulter et al., 2002)* | Patients monitored after myocardial infarct/with severe heart failure/with acute respiratory problems/with hip fracture monitored both pre- and post-operatively *(Tarassenko et al., 2005)* |
| Surgical ward *(Brown et al., 2014; Ochroch et al., 2006)* | Ischemic or haemorrhagic stroke *(Langhorne et al., 2010; Yong & Kaste, 2008)* | Patients on general medicine ward with pyrexia >38C in previous 24 h *(Varela et al., 2011)* |
| Trauma step down unit *(Hravnak et al., 2011)* | Post coronary artery bypass grafting ± valve surgery *(Kisner et al., 2009)* | Patients admitted as medical or surgical emergencies or undergoing major elective surgery with high expected rate of complications (including death) *(Watkinson et al., 2006)* |
| | Long bone fractures and healthy controls *(Wong et al., 2004)* | Patients requiring intensive surveillance monitoring, but no intensive nursing care *(Banks et al., 2000)* |
| | | Adult trauma patients *(Parimi et al., 2016)* |
| | | Post-operative orthopaedic patients *(Morgan J.A., 2010)* |

From this analysis, it was concluded that for surgical patients, the most frequent diseases were: 1) vascular disease; 2) kidney function disorders; 3) diabetes mellitus; 4) atrial fibrillation; 5) oncological disease. For medical patients, these were: 1) oncological disease; 2) diabetes mellitus; 3) vascular disease and kidney function disorders; 4) angina pectoris and COPD; 5) heart failure. *(Eijkelkamp, 2017)* However, Figure 5 shows that medical wards contribute to only a small part of the total RTT interventions.

For medical patients, it is remarkable that CVA is not included among the most frequent diseases in the analysis of patient journeys of 2017 while being ranked 2nd in leading cause of amenable mortality. This is because in case deterioration occurs in a CVA patient, a practitioner is directly consulted (often without an RRT procedure). Moreover, CVA patients are for the first 24 hours admitted to the stroke care unit, an acute ward for stroke patients. Here, RRT interventions are not applicable.




| Ward | Specialism(s) |
|---|---|
| A2 | Dental surgery, ENT surgery, orthopaedics, plastic surgery, traumatology, vascular surgery |
| N1 | Cardiology, neurology, neurosurgery |
| N2 | Gastroenterological surgery, urology |
| A1/B1 | Lung and internal medicine: endocrinology, hematology, diseases, nephrology, oncology, rheumatology |
| Other | Dialysis, Day care, Gynecology, Coronary Care Unit, ER |

**Figure 5: Number of RRT procedures per ward in Slingeland Hospital (2017)**

From the RRT interventions, we can conclude that surgical patients are a high-risk group. Within surgical patients, patients with vascular disease occur most frequent in RRT interventions. For CVA patients, the RRT data is not reliable regarding the risk level of patients.

### 2.2.4 High-cost patients

Table 2 shows the total costs as well as hospital and medical specialist care costs for the five most costly groups of diseases in the Netherlands. Both in terms of total costs in the Netherlands and hospital and medical specialist care, cardiovascular diseases are among the costliest groups of diseases. Neoplasms are relatively costlier for hospital and medical specialist care compared to the total costs. The opposite is true for digestive system diseases. Other costly groups of diseases are musculoskeletal system and connective tissue, nervous system and senses, and urogenital system diseases.

Figure 6 shows the costs and number of nursing days for all non-acute clinical specialisms in Slingeland Hospital. Internal medicine and general surgery generate the highest costs. The level of aggregation for these specialisms however is high since they contain many sub specialisms (legend Figure 5). Considering the number of nursing days for the specialism, it can be observed that internal medicine and orthopaedics have relatively high costs in contrast to the number of nursing days.

**Table 2: Costs of diseases in the Netherlands (Zorgrekeningen CBS; excluding psychological disorders and not assignable care)** ***(Rijksinstituut voor Volksgezondheid en Milieu (RIVM), 2017)***

| No. | Total costs (million euro/year) | Hospital and medical specialist care costs (million euro/year) |
|---|---|---|
| 1 | Cardiovascular (€11,572.8) | Neoplasms (€4708.1) |
| 2 | Musculoskeletal system and connective tissue (€6303.9) | Cardiovascular (€4175.6) |
| 3 | Digestive system (€5915.6) | Musculoskeletal system and connective tissue (€2747.6) |
| 4 | Nervous system and senses (€5870.2) | Nervous system and senses (€2055.1) |
| 5 | Neoplasms (€5618.7) | Urogenital system (€1905.8) |

## 2.3 Selected high-risk high-cost patients

In this study, the strategy to choose key target populations is to select a group based on diagnosis because in this way, the process and planning and control can be mapped for a specific group of patients, which makes simulating the pathways more feasible.

Based on amenable mortality numbers, ischaemic heart diseases jump out as a high-risk group. Also, cerebrovascular diseases, colorectal cancer and breast cancer patients are at high risk of mortality that could have been avoided through timely and effective health care. When concerning studies that applied CMVS, target populations are often surgical, trauma, stroke, orthopaedic and

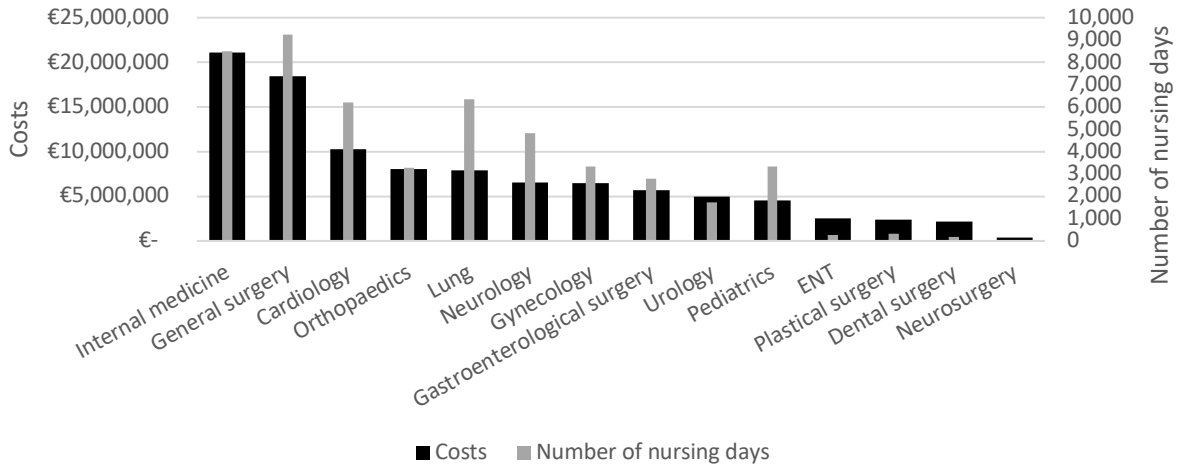



**Figure 6: Costs and number of nursing days (Q1 through Q3 2018) for non-acute clinical specialisms in Slingeland Hospital**

ischaemic heart disease patients. RRT interventions in Slingeland Hospital show that surgical wards are responsible for most RRT interventions in non-acute care wards. Considering the surgical group of patients, vascular diseases are the most frequent diseases among RRT procedures in surgical specialisms. In this data, CVA patients are under-represented due to a different work procedure knowing that in case deterioration occurs in a CVA patient, a practitioner is directly consulted (often without an RRT procedure).

Neoplasms and cardiovascular diseases are responsible for high spending in hospitals and medical specialist care. In Slingeland Hospital, internal medicine and general surgery disciplines account for high costs. Internal medicine and orthopaedic wards have high costs in contrast to the number of nursing days.

The first and second phase of the Sensing Clinic project already focussed on cerebral vascular accident (CVA) and vascular surgery patients. These diseases correspond with the high-risk high-cost profile that we obtained from data and from literature and therefore are legitimate key-target populations for CMVS. For the remaining quantitative analysis in this study, CVA patients will be identified as main key target population because this are the most important group for CMVS in Slingeland Hospital at this moment. For near-future research, a model for vascular surgery patients is also desired. Other key target populations are ischaemic heart disease patients and orthopaedic patients.

## 2.4 Process

Figure 7 shows the process of CVA patients. A patient arrives at Slingeland Hospital in the emergency room (ER) where a patient is evaluated, and the course of treatment is determined. When thrombectomy (emergency removal of the thrombus which is blocking blood circulation) is needed, the patient is discharged to another (specialized) hospital. Otherwise, the patient is

admitted to the stroke care unit (SCU). This is a specialized ward for patients who undergo a stroke and is part of the neurology ward. A patient is admitted to the SCU for less than 48 hours and is then either admitted to the regular neurology ward or discharged from the hospital. During the process, a patient can also be admitted to the ICU when deterioration occurs. After dismission, a patient can either be re-admitted or not be re-admitted at Slingeland Hospital.

After discharge, it may be that a patient needs a new place in for example a rehabilitation centre. When there is no place available yet, a patient stays in the hospital while this is medically not needed. Such a day is called a wrong bed day and are not considered in this study.

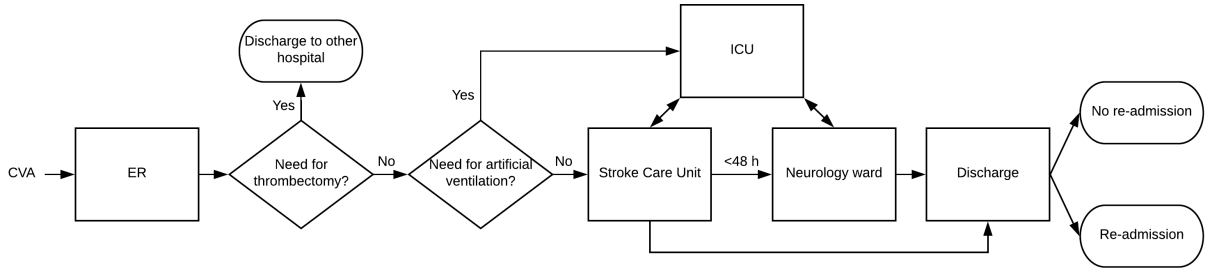



**Figure 7: Process for CVA patients.**

## 2.5 Financial planning and control

In this section, planning and control of financial processes in Slingeland Hospital will be discussed. This information is necessary to evaluate the impact of CMVS on Slingeland Hospital's financial system. *Hans et al. (2011)* propose a framework for health care planning and control. This framework describes all managerial areas (medical, resource capacity, materials and financial planning) and all hierarchical levels of control (strategic, tactical, and operation levels). Here, the planning and control of Slingeland Hospital within financial planning will be discussed. Financial planning in health care concerns functions such as investment planning, contracting (with e.g. health care insurers), budget and cost allocation, accounting, cost allocation calculation and billing. First, an introduction to the finance of the Dutch healthcare system is provided.

### 2.5.1 Insurance reimbursement

Each year, hospitals and insurers negotiate and agree upon the price and volume of the provided care of the hospital. These agreements are laid down in a contract. Subsequently, hospitals bill the provided care to the insurer.

#### DBC billing

To bill the provided care, the Dutch government has defined diagnose treatment combinations (DBC care products). Such a product is a 9-number code that contains classes of care that are used

for different treatments, for example for a hip fracture. Here, the price of the care product is the average of the costs for the treatment this hip fracture. Therefore, not every treatment is billed separately, but instead is billed as a bundle containing multiple treatments. DBC care products are divided into two segments: the A segment and the B segment. DBC care products in the A segment are in the regulated segment and for these products, maximum prices are provided by the NZa. DBC care products in the B segment are in the free segment.

The DBC system does not apply to all operations that are performed by the hospital. Some operations are defined as "other" care product (OVP) by the NZa. Here, exceptional care products are listed, such as children medicines, expensive medications and treatments and ICU-days.

**Insurance negotiations**

For both the A- and B-segments of DBC care products, hospitals must negotiate with insurers to determine prices. Three types of agreements are made regarding the billing of the DBC care products. First, there can be agreed to bill DBC care products until a maximum budget is reached. Second, the budgets can be decreased or increased in steps when fewer or more DBC care products are billed. Finally, the freest approach "P * Q" can be chosen where insurers reimburse all DBC care products for the corresponding price. The latter approach is not common.

**Operational DBC decisions**

To determine the height of an invoice for a treatment that is provided, the DBC care product must be determined. This depends on the following factors:

- The costs of the average treatment at the moment of the diagnosis
- The burden of the treatment (e.g. the need for hospital hospitalization)
- The need for an operation
- Number of visits to a doctor

All these factors are administrated by the hospital in the DBC. A DBC contains all activities of a hospital and a medical professional as a result of a demand for care: the diagnosis of the health professional, hospital treatments and, if needed, follow-up. A doctor or care provider determines which DBC care product is chosen.

The Dutch Healthcare Authority has published a care product application, where all care products can be derived via the factors that are mentioned. Also, for all care products, the place in a care product decision tree can be viewed. Within the top tree of this decision tree, there are multiple care product groups. An example of the derivation of a care product for a CVA patient can be seen in Figure 8.

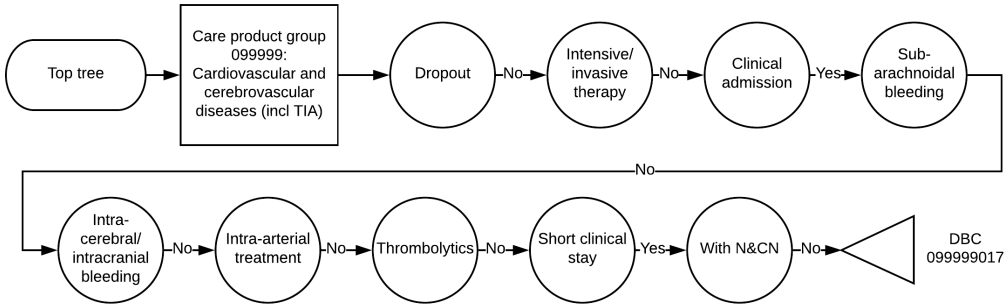



**Figure 8: Example of a DBC care product derivation (DBC 099999017, the most frequent CVA care product in Slingeland Hospital). N&CN: Neurology & Clinical Neurophysiology**

The DBC represents a sub-trajectory within a care trajectory. Figure 9 shows that a care trajectory can consist of multiple sub-trajectories. A sub-trajectory remains valid for a maximum of 120 days. In some cases, the DBC is closed earlier, for example after 42 days after an operation or clinical admission or after 90 days for outpatient treatments without an operation. The initial sub-trajectory remains valid for a maximum of 90 days. When this period has elapsed, the hospital sends an invoice to the insurer or to the patient. This means that if a patient is re-admitted with the same diagnosis before a sub-trajectory is closed, the existing DBC remains valid and the new admission is not billed separately. However, if there is a new diagnosis, treatment or demand for other care in this readmission, a parallel DBC is created, besides the existing one. If a patient is re-admitted after the validity of the prior DBC, a new follow-up trajectory with corresponding DBC is created. This DBC is billed separately.

A care trajectory is closed if after a period of three times 120 days after closing a sub-trajectory, no care activities have been registered.

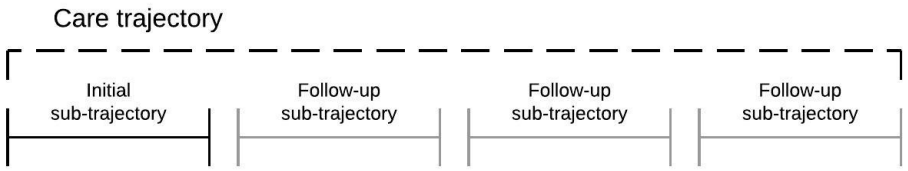



**Figure 9: A care trajectory can exist of one or multiple sub-trajectories**

### 2.5.2 MSB

All medical specialists in Slingeland Hospital are a member of the medical specialist company (MSB) via a personal holding. The earnings of the MSB are a fraction of the reimbursement resulting from the DBC's of Slingeland Hospital.

### 2.5.3 Cost allocation

The costs of Slingeland Hospital are allocated to operations via a cost price model of an external company, LOGEX. First, data is obtained, cost places are clustered, and the organizational structure is analysed. Then, costs are allocated to wards via distribution keys. Following, costs are allocated to products, such as care products and health activities, also via distribution keys. Finally, the output of this model are cost prices (DBC-) care product or per care activity. A care activity are units of care that are part of the treatment of a patient, such as a medical consult or an MRI-scan. This workflow is displayed in Figure 10

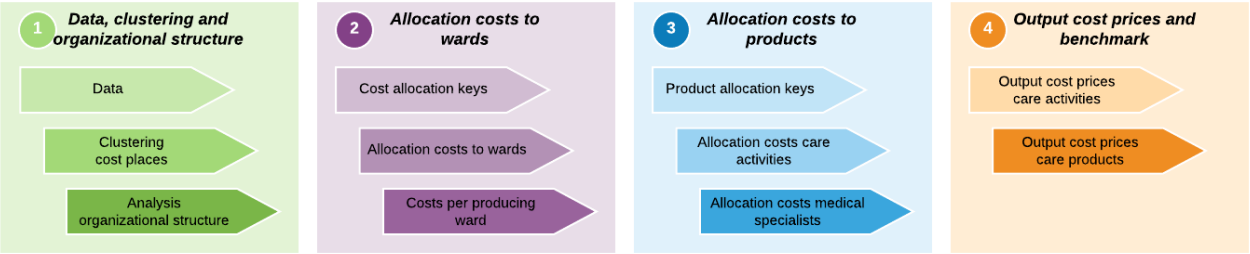



**Figure 10: Workflow of cost price calculation (LOGEX, 2018)**

Cost prices represent average costs for a unit of care (i.e. care activity or care product). An important care unit is that of the care activity nursing day, which is the same for all non-acute clinical, but different for acute wards such as the AAD and SCU. Within care units, a distinction can be made direct and indirect costs and for different cost types (personnel, materials, capital + other).

## 2.6 Conclusion

From our analysis of high-risk high cost patient populations, we select ischaemic heart disease, orthopaedic, CVA and vascular patients as key target populations for CMVS. For further analysis in this study, only CVA patients are considered due to the current scope of the Sensing Clinic programme. By mapping the main processes of CVA patients, CMVS on the nursing wards of these patient groups is placed in a context of the care for these patients. Financial planning and control operations are mapped to obtain background information on evaluating the impact of CMVS on Slingeland Hospital's financial system. We conclude that there is a high complexity in financial strategy and billing and cost analysis of operations for CVA patients due to a large number of rationing rules.

# *Chapter 3*

# Study design

In this chapter, we propose the design of the study to evaluate the health economic impact of CMVS and we perform baseline measurements. Section 3.1 summarizes the effects of CMVS and presents a framework for analysing the effects. Section 3.2 gives information about the data that is available. In Section 3.3, the depended variables of the study are discussed and based on baseline measurements, we decide upon the level of detail for further baseline measurements. Section 3.4 discusses the care pathways of the key target population. In Section 3.5, all independent variables are discussed, and baseline measurements are performed when relevant. Section 3.6 states the conclusions from the chapter.

## 3.1 The effects of CMVS

In Section 1, the expected effects of CMVS for Slingeland hospital were discussed. We concluded in the problem formulation that a reduction in demand of care results in fewer and lower insurance reimbursement. On the other hand, higher efficiency and effectiveness in the healthcare chain can lead to cost savings. To better understand how hospital costs, earnings and health can be assessed, effectiveness and efficiency in this context is of importance.

We define effectiveness as a reduction in the average demand of care per patient. Examples are fewer (re-)admissions or less demand for diagnostics. Efficiency is defined as making the hospital's processes more efficient to make the supply of care cheaper. Examples are: reduction of length of stay and reduction of time commitment of health professionals. Figure 11 summarizes the effects of CMVS and connects them to efficiency and effectiveness via independent variables However, the variables (and thus efficiency and effectiveness) are not independent. I.e. there are statistical relationships, whether causal or not, between the variables. For example, a reduction in the number of complications (more effective care) can result in a lower length of stay (more

efficient care). In general, more efficient care directly reduces the costs of a hospital, whilst more effective affects a hospital's demand for care: its earnings. In this study, it is important to measure this imbalance. Both more efficient as more effective processes are expected to improve population health.

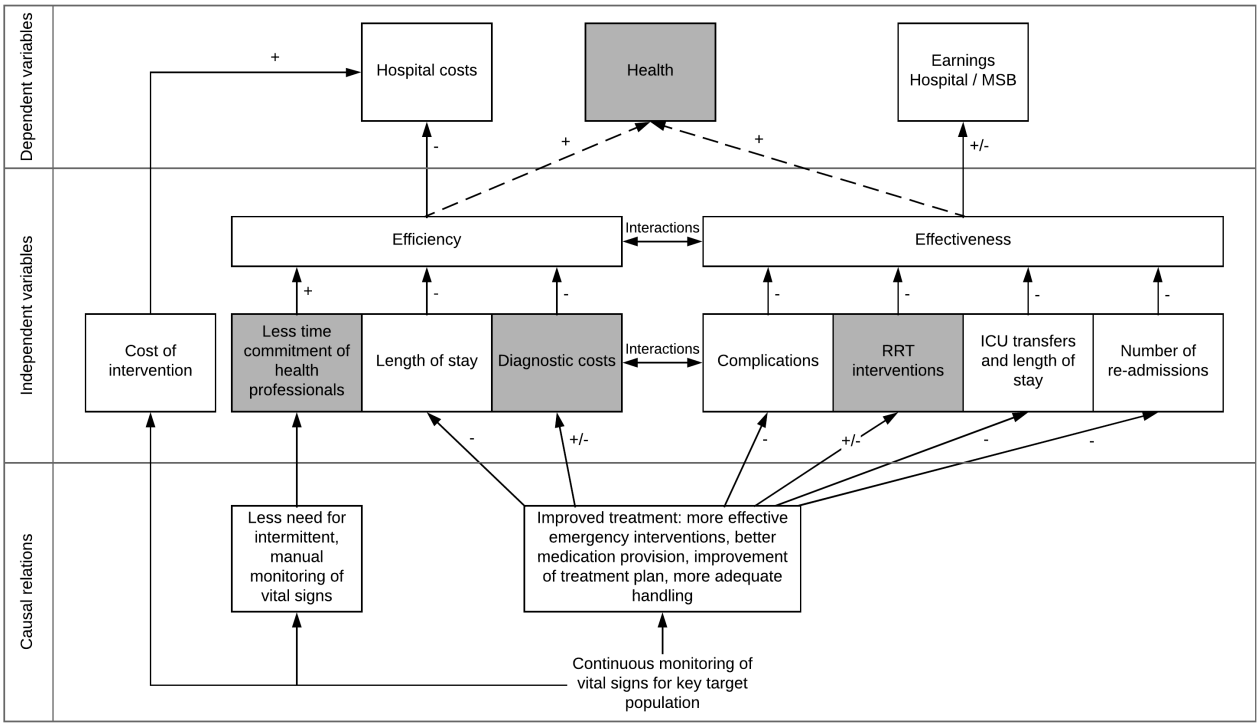



**Figure 11: Effects of CMVS. Dark boxes are not considered in the quantitative model.**

## 3.2 Available data

Via the hospital's internal information system (Hix) data is available regarding all the care products and care activities that an individual patient has had on a particular date. HiX also provides information regarding the complications. Cost prices per care unit are available via a cost price model for cost allocation (LOGEX; Section 2.5.3). We use the cost price per care activity which includes both direct and indirect costs. Turnover and volume per care product per insurer are available via a forecast model (LOGEX).

For the Hix data, data from January 2017 to March 2018 (November 2018 for complications) is used. Care unit prices are used via point estimates per care product and care activity that the cost price model of LOGEX provided in October 2018. For the turnover and volume per care product per insurer data, data from 2017 is used.

## 3.3 Dependent variables

We use the indicators, or dependent variables, costs, earnings and health to assess performance. The following sections describe the way these indicators will be measured and the scope and level of detail to assess these indicators are discussed. For costs and earnings, a baseline measurement is performed from which we decide upon the level of detail of our model.

### 3.3.1 Costs

To evaluate the costs of Slingeland Hospital, all relevant DBC care products and care activities that are involved in the diagnosis and treatment of the key target populations will be identified. Following, care unit prices will be used to map the total costs of the key target populations.

**Scope**

To limit the scope of the assessment of the costs, only costs of Slingeland Hospital will be considered. Thus, no costs of other healthcare organizations outside the hospital (e.g. revalidation care outside the hospital) are considered. Since this study is limited to hospitalized patients (Section 1.5.4), only costs of hospitalized patients will be considered. Also, costs outside the healthcare sector (i.e. the costs of patients and family or costs in other sectors) are not part of the scope of this research. No costs of life prolonging effects (also known as indirect medical costs) will be considered

**Level of aggregation**

In this study, care unit prices obtained from the LOGEX cost prize model (Section 2.5.3) are used. In this model, the level of aggregation in identifying the units of care is high. For example, units such as pain medication and antibiotics are accommodated within the care unit ‘nursing day’, instead of being identified separately. The LOGEX cost prize model values these aggregated costs of average care units on other aggregated sources (Figure 10). Therefore, for determining the costs, a top down grosscosting approach is used. In this study, care units are distinguished as care products and care activities (Section 2.5).

**Baseline measurement**

In 2017, hospitalized CVA patients accounted for 95.0% of the costs of all CVA patients. Figure 12 shows the costs per care product of hospitalized CVA patients. The five biggest care products account for 91.1% of the costs of hospitalized CVA patients.

### 3.3.2 Earnings

The earnings of Slingeland Hospital are derived via the negotiated price of individual (DBC) care products between Slingeland Hospital and insurers. For the calculation of total earnings, we assume that all types of agreement that are made between hospital and insurer for care products are “P * Q” (Section 2.5.1). Because the study is limited to hospitalized patients (Section 1.5.4), only care products that concern ward admission are included. In 2017, hospitalized CVA patients accounted for 94.8% of the earnings of all CVA patients. Figure 12 shows the earnings per care products for these CVA patients. Based on earnings, the five most valuable care products account for 91.5% of the total earnings of hospitalized CVA patients. For further analysis, only these five care products are considered.

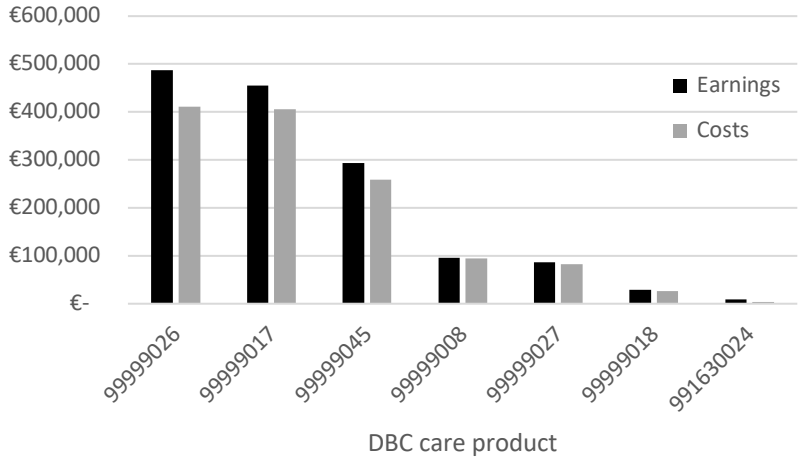



**Figure 12: Earnings and costs for DBC care products of clinical CVA patients (sorted based on earnings)**

Because the MSB, representing the medical professionals, is also an important stakeholder, the impact on MSB earnings will also be measured. Due to confidentiality of the actual percentage, a fraction of the total reimbursement of 13.5% is assumed in this study.

### 3.3.3 Health

The benefits of continuous monitoring for patients can be found in health gain or gain in QOL. QOL is an important parameter to consider when evaluating how a patient is affected on an individual level, and there are multiple assessments available that measure health-related QOL. However, in this study it is not feasible to explore this indicator properly since no (randomized) controlled trial was identified in literature that mapped the QOL of patients undergoing CMVS over regular monitoring of these signs. Although direct measurements of QOL were not identified in literature and are hard to establish, statements about QOL can be made via other indicators, such as ICU admission, ICU length of stay, total length of stay and complications. For this, literature will be consulted.

## 3.4 Care pathways

Besides the processes for CVA patients, we are also interested in the distribution of patients over care products that generate the earnings of Slingeland Hospital and to what extend CMVS would cause a shift in this distribution. Therefore, we need to assess the flows of patients the in the care product decision tree, which contains care pathways (Section 2.5.1).

For the selected care products of CVA, there are four nodes in the care product decision tree (Figure 13). Two nodes concern the length of stay of the patients (discussed in the next subsection). The other two represent whether the patient has had an intracerebral or intracranial bleeding or whether neurology and clinical neurophysiology was concerned. The (conditional) probability of an intracerebral or intracranial bleeding is 23.2% and for neurology and clinical neurophysiology 14.1%, readmissions not considered.

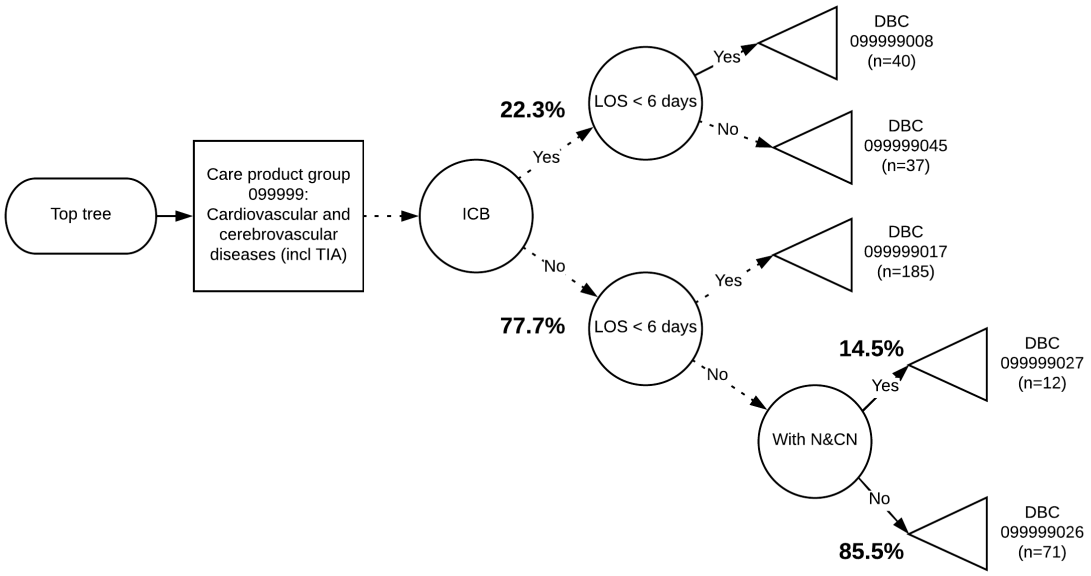



**Figure 13: Branches in CVA care product decision tree with node probabilities (for dotted lines, in reality more nodes are present (mostly non-clinical) that are not needed in this study due to the level of detail of the study). n=345 patients (first admissions only). ICB: Intracerebral or intracranial bleeding; N&CN: Neurology & Clinical Neurophysiology.**

## 3.5 Independent variables

To assess the key indicators for baseline and experimental measurements, the independent variables are of importance. The following sections describe how these indicators will be considered in the study. Also, the scope and level of detail to assess these indicators are discussed. When applicable, a baseline measurement is performed.

### Cost of intervention

The costs of implementation of CMVS are obtained from Fujitsu. Considering a per patient cost, these costs can be implemented in a quantitative model. It is estimated from negotiations that a realistic range for the per patient costs of CMVS in Slingeland Hospital is €200 - €250, -.

### Length of stay

The distribution of the length of stay of patients is different for groups of patients who have different diagnoses and treatments. Therefore, length of stay distributions need to be assessed for care pathways derived from the care product decision tree. In the care product decision tree, there are two nodes that concern a patient's length of stay (Figure 13): one for intracerebral or intracranial bleeding (ICB) patients and one for non-ICB patients. For the following sections, we do not include pneumonia patients (see Section 5.2.2).

Figure 14 shows the empirical distribution for patients who did not have an intracranial or intracerebral bleeding. The distribution shows peaks for a length of stay of two and three days. This corresponds to practise, since there is a screening policy which states that patients normally should go home after 2 or 3 days. Patients who stay longer are severe patients or patients who might have complications.

When leaving a hospital bed is seen as a 'success' in a Bernoulli trial, the length of stay can be approached by a geometric distribution. This is a discrete distribution that gives the number of Bernoulli trials needed to get one success, supported on the set *(1,2,3, ... )*. Its probability mass function is given by Equation 1 where $k \in (1,2,3, \dots)$ represents the number of trials and $0 < p < 1$ is the success probability (parameter of the distribution).

**Equation 1: probability mass function for the geometric distribution**

$$(1-p)^{k-1}p$$

For fitting a geometric distribution to the data, we estimate *p* via the method of moments.

**Equation 2: Parameter estimation of geometric distribution via method of moments**

$$\hat{p} = (\frac{1}{n}\sum_{i=1}^{n} k_i)^{-1} = \frac{n}{\sum_{i=1}^{n} k_i}$$

For the data of Slingeland Hospital, we estimate that the value of p is equal to 0.25. Figure 14 shows the probability mass function of the geometric distribution for this estimator. For this distribution, a length of stay of 1 day is not considered since relatively very little non-ICB patients have a length of stay of 1 day.

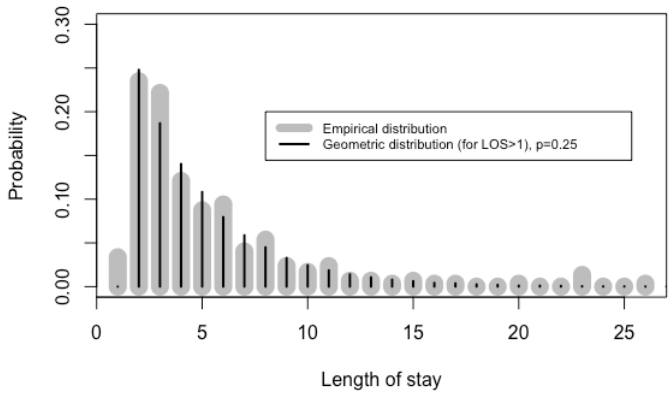



**Figure 14: Empirical and geometric distribution for the length of stay of patients who did not have an intracranial or intracerebral bleeding (n=298)**

For patients who had an intracerebral or intracranial bleeding, the length of stay is distributed according to the empirical distribution as shown in Figure 15. Due to the different prognosis and treatment of these patients, the distribution is different compared to patients who did not have a bleeding. A LOS of one day is mostly caused by the high mortality among these patients. Also, in contrast to patients who had no bleeding, no specific screening policy is maintained by the hospital. In Figure 15, a geometric fit for the length of stay distribution is provided via the same method as described above. Here, p is estimated to be 0.15.

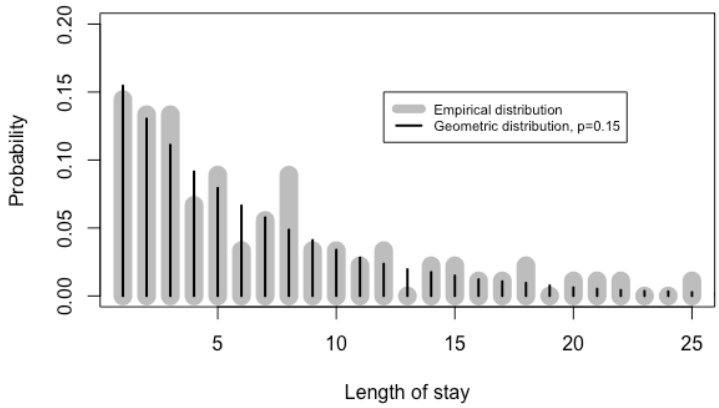



**Figure 15: Empirical and geometric distribution for the length of stay of patients who had an intracranial or intracerebral bleeding (n=90)**

### Time commitment of health professionals

As stated in the introduction, CMVS is expected to make working processes more efficient and therefore reduce time commitment of health professionals. This indicator however will not be quantified due to lack of information available in literature and lack of resources that are needed to obtain cost savings (being the relevant key indicator regarding this supporting indicator) due to a change in personnel workload.

### Diagnostic costs

CMVS will change the way health professionals obtain information of vital signs. This may change their behaviour in requesting diagnostic tests. This indicator will not be considered quantitatively.

### Complications

Figure 16 shows the incidence of complications in CVA patients in Slingeland Hospital. Pneumonia and urinary tract infections are the most frequent complications, followed by deliriums.

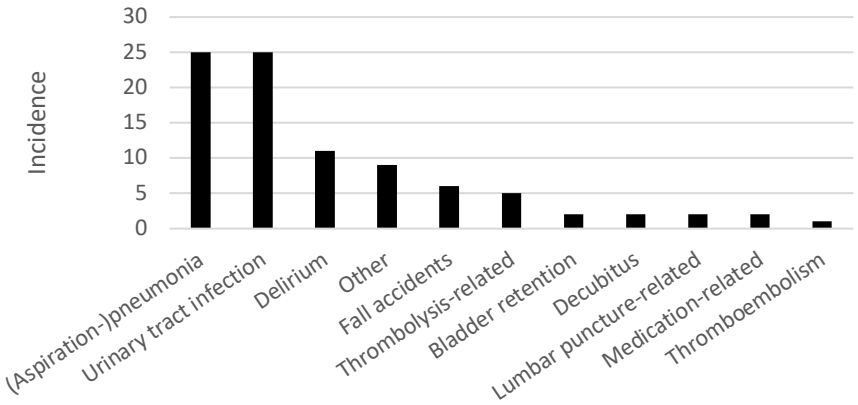



**Figure 16: Complication incidence in Slingeland Hospital**

### RRT interventions

Due to early detection of deterioration, the way RRT interventions are requested will change and therefore maybe the frequency and severity of the interventions. This will not be quantitively taken into account.

### ICU transfers and LOS

Conditional (depending on diagnose and treatment) probabilities of an ICU admission and a patient's ICU LOS must be known to calculate the earnings and costs of an ICU admission.

0.870% of all CVA patients (based on first admissions) are admitted on the ICU. This corresponds to only three patients. Table 3 shows the distribution of ICU admission and the ICU length of stay per DBC.

### Readmissions

The way invoices are sent for care products depend on the elapsed time since a preceding sub-trajectory. Therefore, conditional probabilities of a readmission and the distribution for the elapsed time until a readmission must be known.

On average, 11% of all CVA patients get readmitted. 93% of the readmitted patients are readmitted with the same diagnosis as during the first admission. Therefore, we limit the scope to patients we are readmitted with the same diagnosis. Table 3 shows the fraction of all patients who are readmitted (with the same diagnosis).

Figure 17 shows the empirical cumulative distribution functions for the time to readmission for all the DBC's separately and for all DBC's combined. No appropriate statistical discrete distribution function was identified to fit to these empirical distributions. For the unique DBC's, this is mainly due to lack of fitting data. For the DBC's combined, it was hard to fit an appropriate discrete, long tailed distribution because of the unique shape of the empirical probability distribution and, again, lack of fitting data.

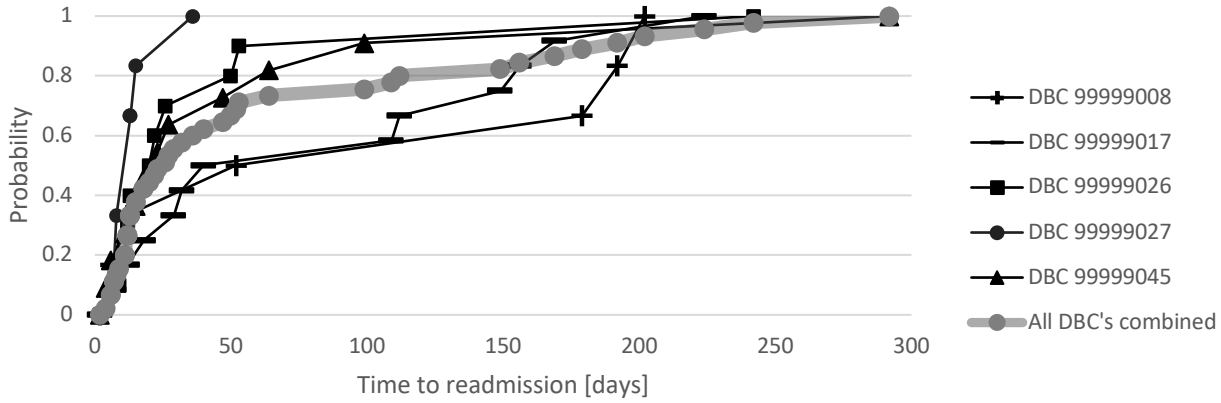



**Figure 17: Cumulative distribution functions for the time to readmission for all CVA DBC's**

**Table 3: Fraction of patients who are readmitted per DBC. * Based on first admissions only. ICB: Intracerebral or intracranial bleeding; N&CN: Neurology & Clinical Neurophysiology**

| DBC | Occurence in data* | Fraction of patients readmitted | Fraction of patients admitted to ICU* | ICU LOS (days) |
|---|---|---|---|---|
| 99999017: Non-ICB, LOS<6 | 186 | 6.45% (n=12) | 0% | - |
| 99999026: Non-ICB, LOS>6 | 73 | 13.7% (n=10) | 0% | - |
| 99999045: ICB, LOS>6 | 39 | 20.5% (n=8) | 2.70% (n=1) | 5 |
| 99999008: ICB, LOS<6 | 43 | 9.30% (n=4) | 2.50% (n=1) | 3 |
| 99999027: Non-ICB, LOS>6, with N&CN | 12 | 33.3% (n=4) | 8.33% (n=1) | 2 |

## 3.6 Conclusion

This chapter discussed a study design for the effects of CMVS. We discussed the dependent and independent variables of the study and performed a baseline measurement for the relevant indicators for the quantitative analysis. Also, we identified the care pathways for CVA patients. It was not possible to perform measurements for the indicators: health, less time commitment of health professionals, diagnostic costs and RRT interventions. These indicators are not considered in this study's scope.

# *Chapter 4*

# Literature

In this chapter, literature will be consulted to obtain input for our model and to find an appropriate modelling technique. In Section 4.1, modelling techniques in comparable studies are identified. In Section 4.2, literature regarding the study's independent variables is reviewed (except for the intervention costs) to obtain levels for adjusting these factors in the final model. Next, in Section 4.3, literature is consulted to discuss avoidable care for CVA patients. The findings are concluded in Section 4.4.

## 4.1 Modelling techniques

In this study, the objective is to scientifically study the behaviour of a system to gain some insight into the relationships among various components and to predict performance under some new conditions being considered. According to *Law (2015)*, there are different ways in which a system might be studied.

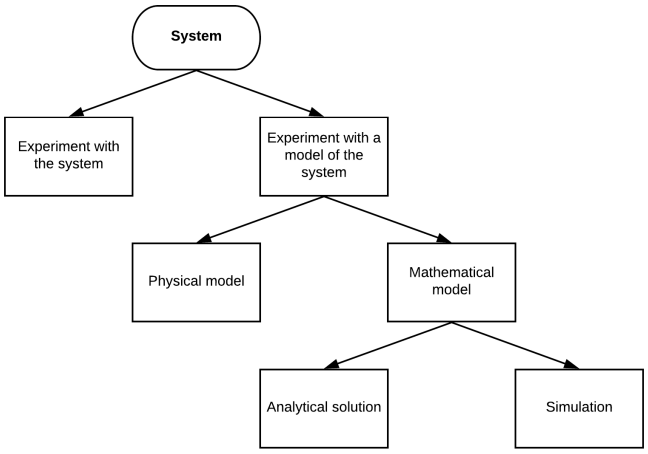



**Figure 18: Ways to study a system *(Law, 2015)***

When it is possible to study a system physically, then is it probably desirable to do so since in this case, there is no question about whether what we study is valid. However, it is rarely feasible to do this. In the case of the Sensing Clinic programme, this also is the case due to high costs and time restrictions. Therefore, we need to experiment with a model of the system. *(Law, 2015)*

When constructing a model, one may consider making a physical model or a mathematical model. Physical models are not typical in in the area of operations research and system analysis. The vast majority of models built for such purposes are mathematical, representing a system in terms of logical and quantitative relationships that are then manipulated and changed to see how the model reacts, and thus how the system would react. *(Law, 2015)*

In mathematical models, if the model is simple enough, it may be possible to work with its relationships and quantities to get an exact, analytical solution. If an analytical solution to a mathematical model is available and is computationally efficient, it is usually desirable to study the model in this way rather than via a simulation. However, many systems are highly complex, so that valid mathematical models of them are themselves complex, precluding any possibility of an analytical solution. *(Law, 2015)* It was concluded from Chapter 2 that the system for the Sensing Clinic programme is highly complex and contains a high number of rationing rules on an individual patient level. Also, the effects of the Sensing Clinic programme affect patients highly conditionally, which makes it very hard to obtain an exact solution compared to using a numerical method. Therefore, for modelling the Sensing Clinic programme, we consider simulation.

### 4.1.1 Simulation

Simulation is one of the most widely used techniques in operations research and management science *(Law, 2015)*. A simulation numerically exercises the model for the inputs in question to see how they affect the output measures of performance. Such simulation models can be classified along three different dimensions: Static vs Dynamic Simulation Models; Deterministic vs. Stochastic Simulation Models; Continuous vs. Discrete Simulation Models. *(Law, 2015)*

A static (or steady-state) model calculates the system in equilibrium, and thus is time-invariant. It is a representation of a system at a particular time or one used to represent a system in which time simply plays no role. A dynamic model accounts for time-dependent changes in the state of the system. *(Law, 2015)*

If a simulation model does not contain any probabilistic components, it is called deterministic. Stochastic models account for some random input components. Therefore, the output is also random, and is therefore only an estimate of the model's true characteristics. *(Law, 2015)*

A discrete model treats objects as discrete, while a continuous model represents the objects in a continuous manner.

### 4.1.2 Simulation modelling techniques in healthcare

Models are increasingly used in medical and economic decision making *(Caro et al., 2012)*. These decision models have the goal to make a comparison in a complex situation in a transparent and consistent matter. The most used models are: decision tree models, state transition (or: Markov) models, discrete-event simulations and dynamic transmission models. *(Zorginstituut Nederland, 2016)*

**Decision tree models**

A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. For relatively simple models or decision problems with special characteristics (e.g., very short time horizons, complex value structures), a decision tree may be appropriate *(Caro et al., 2012)*. For the system we want to model, decision tree modelling is not flexible enough due to the high complexity of the system we want to study.

**State transition models**

State transition models (STMs) conceptualize clinical situations in terms of the conditions that individuals can be in ("states"), how they can move among such states ("transitions"), and how likely such moves are ("transition probabilities") *(Siebert et al., 2012)*. A state transition model should be used, rather than a simpler model if it requires time- dependent parameters (e.g., recurrence probability after cancer treatment), time to an event (e.g., disease-free survival), or repeated events (e.g., second myocardial infarction) *(Ulahannan, 2002)*.

There are two types of state transition models: cohort (or Markov-) models and individual-level state transition models (commonly known as "first-order Monte Carlo" or "microsimulation" models). Whereas cohort models are analysed as single cohorts progressing through the states simultaneously (which does not allow distinguishing one individual from another except by state descriptions), individual-level STMs keep track of each individual's history ("tracker variables"). If the decision problem can be represented with a manageable number of health states that incorporate all characteristics relevant to the decision problem, including the relevant history, a cohort simulation should be chosen because of its transparency, efficiency, ease of debugging, and ability to conduct specific value of information analyses. If, however, a valid representation of any aspect of the decision problem would lead to an unmanageable number of states, then an individual-level state–transition model is recommended. *(Caro et al., 2012)*

In this research, a model of the decision problem would lead to a very high number of states because of the high number of conditions that determine a patient's DBC care product or the costs for this patient. Moreover, studying CMVS requires experimenting with the model on a patient level since the effects of CMVS will be conditional (e.g. a patient with a complication is more likely

to benefit). Therefore, an individual-level STM is a good option for modelling the system in this study.

**Discrete-event simulation**

Discrete-event simulation (DES) is a form of simulation that models a system as it evolves over time by changing its state instantaneously at consecutive points in time *(Law, 2015)*. DES models should be used when the problem which is studied involves constrained or limited resources. DES is also an attractive option in non-constrained models when there are interactions between individuals, populations, and/or their environment; when time to event is best described stochastically rather than with fixed time intervals and time dependencies are important; when individual pathways through the model are influenced by multiple characteristics of the entity; and when recording individual entity experience is desirable. *(Caro et al., 2012)*

The system we want to model in the scope of this research involves no constrictions or a limitation of resources. Also, there is no interaction between individuals, populations, and/or their environment. In this research, it is important to determine the time to event stochastically rather than with fixed time intervals and also, time dependencies are important (e.g. it is important that the time until a readmission is described stochastically and based on a threshold value, this time determines the DBC for the readmission in this study). Also, individual pathways through the model are influenced by multiple characteristics of the entity and recording individual entity experience is desirable (in this system, patient pathways are highly conditional). Concluding, DES is a feasible technique for modelling our system. However, the dynamic state property of DES is not needed when modelling the system of this research because we have no constrained problem or limited resources.

**Dynamic transmission models**

Most dynamic transmission modelling has been performed by using system dynamics, in which transition between compartments is represented by differential equations. With increases in computing power, it has become possible to realize dynamic transmission models by using agent-based approaches in which each member of a population is represented individually. Deterministic compartmental models are useful for modelling the average behaviour of disease epidemics in large populations. When stochastic effects (e.g., extinction of disease in small populations), complex interactions between behaviour and disease, or distinctly non-random mixing patterns (e.g., movement of disease on networks) are important, stochastic agent-based approaches may be preferred. The choice of method may influence the results, and analysts and decision makers should be aware of these effects. *(Pitman et al., 2012)* System dynamics is best suited to problems associated with continuous processes where feedback significantly affects the behaviour of a system, producing dynamic changes in system behaviour *(Sweetser, 1999)*.

The system we are studying contains little continuous processes and feedback only little affects its behaviour. As we already concluded in the section Discrete-event simulation, we do not need to model states dynamically.

## 4.2 Effectiveness of continuous monitoring of vital signs

Section 1.3 already discussed the clinical effectiveness of CMVS. This section further specifies the effects of CMVS to obtain relevant input for our model.

Two systematic reviews were identified that studied the effectiveness of CMVS. A systematic review and narrative synthesis of *Downey et al. (2018)* assessed if continuous monitoring is practical outside of the critical care setting, and whether it confers any clinical benefit to patients. *Cardona-Morrell et al. (2016b)* conducted a systematic review and meta-analysis to identify strategies to improve both intermittent and continuous vital signs monitoring in general wards and their effectiveness in preventing adverse events on general hospital wards.

*Downey et al. (2018)* included 24 studies of which 6 studied outcomes that concern the input variables of this study. *Cardona-Morrell et al. (2016b)* included 9 studies that researched CMVS. All these studies were also included in the review of *Downey et al. (2018)*. Besides the studies that are included in these reviews, no additional studies were identified that considered CMVS. The 6 studies that are obtained from the systematic reviews are listed in Table 4. The studies provide outcomes concerning the length of stay, ICU transfers and ICU length of stay. None of these studies considered the effect of CMVS on readmissions. An additional search was performed in an attempt to obtain more studies that evaluated CMVS, but no extra studies were identified. This search strategy is discussed in Appendix A.

Table 4 shows that the study designs differ compared to the Sensing Clinic study design (Section 1.2): all studies assessed fewer vital signs. Also, different monitoring devices were used on a variety of patient populations. Many of the studies are old, making extrapolation of results less credible. The next sections describe the findings from the included studies regarding the outcomes of interest. Table 5 provides a summary of the findings of the studies.

### 4.2.1 Length of stay

Three studies were identified that considered the relation between CMVS and length of stay.

*Brown et al. (2014)* found that following the intervention, the length of stay was significantly lower in the study unit in the period following the implementation of CMVS compared with the period before the implementation (from 4.0 to 3.6 days; $P = 0.02$).

The study of *Cavallini et al. (2003)* shows a length of stay of 9.2 days for the intervention group and 17.1 days for the control group: a decrease in length of stay of 7.9 days ($P < 0.0001$). However, his large difference should be interpreted carefully. The 15-year-old study assesses the difference

between a stroke care unit and a regular cerebrovascular unit. Nowadays in The Netherlands, a cerebrovascular stroke is always followed by an SCU admission, as was also identified in Section 2.4.

*Tarassenko et al. (2005)* found a decrease in length of stay from 21 days in the control group to 19 days for the intervention group (no statistical significance was obtained). These outcomes should also be interpreted carefully because of the year of execution.

### 4.2.2 ICU transfers

Four studies were identified that considered ICU transfers as outcome measure.

*Brown et al. (2014)* found no significant change in the number of transfers from the intervention unit or the control unit to the ICU when comparing the post-implementation period with the pre-implementation period.

*Ochroch et al. (2006)* found subjects who were transferred to an ICU that were monitored to be sicker and older. Also, there was a trend for the monitored subjects to be transferred to the ICU earlier (day 3 over day 4; P = 0.091). The study however found no significant change in the rate of ICU transfer between intermitted and continuously monitored groups (6,7% of the monitored patients were transferred over 8.5% of the unmonitored group; P = 0.33).

*Taenzer et al. (2010)* found ICU transfers to be declined from 5.6 (95% Confidence Interval (CI): 3.7-7.4) per 1000 patient days to 2.9 (95% CI: 1.4-4.3).

*Watkinson et al. (2006)* found no differences in ICU admissions.

### 4.2.3 ICU length of stay

Two studies were identified that considered ICU length of stay as outcome measure.

*Brown et al. (2014)* found the total number of ICU days of patients transferred from the intervention unit to be significantly decreased (63.44 days/1000 patients postimplementation compared with 120.11/1000 patients pre- and to 85.36/1000 patients for the control concurrent post; P = 0.04).

*Ochroch et al. (2006)* found a significantly shorter ICU length of stay. The median length of stay for the monitored patients was 3 days and for the unmonitored patients 5 days.

## 4.3 Avoidable illness

CMVS facilitates early detection of deterioration and therefore is able to detect medical complications in an earlier stage, or even prevent them (Section 1.3). In this Section, we identify literature from this perspective of preventive care. Here, we do not limit our search to studies that considered CMVS.

**Table 4: Summary of identified studies that evaluated CMVS. None of the studies considered readmissions. LOS: Length of Stay; ICU TRF: ICU transfers; ICU LOS: ICU length of stay.**

| Author, Date, Country | Study design | Continuous monitoring intervention | Vital signs assessed | Control group | Number of participants | Patient population | Outcomes of interest | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | LOS | ICU TRF | ICU LOS |
| Brown et al. (2014), USA | Controlled before-and-after study | EarlySense motion-sensing under-mattress device | HR, RR, movement level | Intermittent vital signs monitoring | Intervention: 2314; Control 5329 | Patients admitted to 2 medical-surgical wards | x | x | x |
| Cavallini et al. (2003), Italy | Non-randomized controlled trial | > 72 h of continuous monitoring | BP, ECG, Pulse oximetry, RR, Temp, EEG | 4 hourly intermittent vital signs monitoring | Intervention: 134; Control 134 | Patients with ischaemic stroke | x | | |
| Ochroch et al. (2006), USA | Randomised controlled trial | OxiNet II continuous pulse oximetry system | Pulse oximetry | Intermittent pulse oximetry monitoring | Intervention: 589; Control: 630 | Patients admitted to one cardiothoracic surgical ward | | x | x |
| Taenzer et al. (2010), USA | Controlled before-and-after study | Patient SafetyNet bedside pulse oximetry monitor | HR, Pulse oximetry | Intermittent vital signs monitoring | Intervention: 6392; Control 7006 | Patients on an orthopaedic ward (intervention) compared with other surgical wards (control) | | x | |
| Tarassenko et al. (2005), UK | Randomised controlled trial | BioSign multi-parameter continuous monitoring device | BP, HR, Pulse oximetry, RR, Temp | Intermittent vital signs monitoring | Intervention: 201; Control: 201 | High-risk patients admitted to general medical and surgical wards | x | | |
| Watkinson et al. (2006), UK | Randomised controlled trial | 72 h of continuous monitoring with Propaq multiparameter portable monitor | BP, ECG, Pulse oximetry, RR, Temp | Intermittent vital signs monitoring | Intervention: 201; Control: 201 | High risk medical and surgical inpatients | | x | |

**Table 5: Summary of outcomes of interest of included studies**

| Study | Participant population | LOS | ICU transfers | ICU LOS |
|---|---|---|---|---|
| Brown et al. (2014), USA | Intervention: 2314; Control 5329 | -10%: 4.0 (before-)to 3.6 (after implementation) days; P = 0.02 | No significant difference | -47%: 120.11 (pre-) to 63.44 (post implementation) days per 1000 patients |
| Cavallini et al. (2003), Italy | Intervention: 134; Control 134 | -46%: 17.1 (control) to 9.2 (intervention) days; (P < 0.0001) | - | - |
| Ochroch et al. (2006), USA | Intervention: 589; Control: 630 | - | No significant difference | -40%: Median LOS from 5 to 3 days |
| Taenzer et al. (2010), USA | Intervention: 6392; Control 7006 | - | -48%: 5.6 to 2.9 per 1000 patient days (95% CI: 1.4-4.3) | - |
| Tarassenko et al. (2005), UK | Intervention: 201; Control: 201 | -9.5%: 21 (control) to 19 (intervention) days | - | - |
| Watkinson et al. (2006), UK | Intervention: 201; Control: 201 | - | No difference | - |

### 4.3.1 CVA complications

Many complications are preventable or, when this is not possible, early recognition and treatment can be effective in ameliorating these events early in their course. For CVA patients, complications are frequent, increasing the length of hospitalisation as well as the costs of care. Most complications develop within the first few weeks of stroke. Also, complications are a major cause of death in the acute and subacute stroke phases. *(Kumar et al., 2010)*

Pre-existing medical conditions, advanced age, and pre-stroke disability can affect an individual's risk for developing these events. Patients with severe, disabling strokes are particularly vulnerable. Complications can hinder functional recovery and after adjusting for stroke severity and age, complications are associated with poorer functional outcome. *(Kumar et al., 2010)*

In Section 3.5 (Complications), we saw that pneumonia and urine tract infections are the most frequent complications for CVA patients in Slingeland Hospital. This corresponds with the findings of the systematic review of *Kumar et al. (2010)*. Here, included studies found pneumonia incidence rates between 4% and 22%. The incidence of urinary tract infections lies between 6,3% and 30.5%. Of these complications, especially pneumonia is expected to be treated more adequately due to CMVS because increased vital-sign abnormalities are associated with a greater probability of pneumonia *(Nolt et al., 2007)*. For urine tract infections, this is more difficult because from a patient's vital signs, only the temperature will be affected due to fever and.

The following sections describe literature that helps understand how the independent variables of this study may be affected by CMVS via adequate patient monitoring. Here, we focus on pneumonia in particular because of its frequent occurrence and the room there is for early detection.

### 4.3.2 Length of stay

In-hospital medical complications are associated with longer length of stay. *Ingeman et al. (2011)* found that for pneumonia, the adjusted ratio of LOS was 1.80 (95% CI 1.54-2.11). *Mohamed et al. (2015)* found that congestive heart failure, chronic renal failure, presence of arrhythmias, and development of acute renal failure were associated with greater LOS. *Huang et al. (2013)* found as significant predictive factors for the length of stay: diabetes mellitus, atrial fibrillation, recurrence, and stroke subtype. It is not clear why the studies of *Mohamed et al. (2015)* and *Huang et al. (2013)* did not associate pneumonia with greater LOS.

### 4.3.3 ICU transfers and length of stay

*Alotaibi and Sasi (2016)* showed that it is possible to predict ICU transfers with tree-based ensemble models. This implies that in the future, more complex early warning models can give healthcare professionals the opportunity to perform procedures to avoid an ICU transfer. No further literature was identified that looked at predictors for ICU transfers or ICU length of stay in CVA patients.

### 4.3.4 Avoidable readmissions

*Nahab et al. (2012)* found that for patients discharged with a diagnosis of stroke or other cerebrovascular disease at a university hospital in the USA (n = 2,706), 53% of the 30-day readmissions were avoidable. However, a broad definition of avoidable readmissions was used. Among these preventable readmitted patients, 16% (so 8.5% of the total population) was due to incomplete initial evaluations. CMVS is expected to improve these initial evaluations.

*Lichtman Judith et al. (2013)* identified preventable readmissions according to the AHRQ Prevention Quality Indicators in a large patient population of Medicare fee-for-service beneficiaries aged ≥ 65 years in the USA (n = 307,887). It was found that among 30-day readmitted patients, 12 % (1.7% of the total population) was readmitted with a preventable cause.

*Bhattacharya et al. (2011)* concludes in a study of 265 patients (USA) that the reason for 30—day readmissions are often non-neurological, and sometimes preventable.

## 4.4 Conclusion

In this chapter, we identified the possible modelling techniques to assess the economic impact of the Sensing Clinic programme. Also, findings from literature regarding the expected effectiveness of continuous monitoring of vital signs at Slingeland Hospital were obtained. The conclusions are discussed in the next sections.

### 4.4.1 Modelling techniques

A simulation model is required in this study due to the complex system we want to analyse. In simulation modelling in health care, the most used models are: decision tree models, state transition (or: Markov) models, discrete-event simulations and dynamic transmission models. Decision tree models are not appropriate for this research. State transition models can be divided in cohort (or Markov-) models and individual-level state transition models. Due to the high number of states that is needed to model the system, individual-level STM is an option for modelling the system. DES and System Dynamics are valuable techniques for dynamic systems, but not all properties of these techniques are needed in this study because we want to model a static system. However, the model in this model's research has a limited scope and it is desirable to construct a model that is expandable for future research. Therefore, because of higher flexibility of DES we choose this technique over individual-level STM in this study.

### 4.4.2 Continuous monitoring of vital signs

Many of the studies that evaluated CMVS on our outcomes of interest are old, assessed fewer vital signs or evaluated other target populations than the study design of the Sensing Clinic programme. Therefore, it is unjustified to directly relate these outcomes to the expected effectiveness of the Sensing Clinic programme. However, these outcomes will, among others, be used to make a gross estimate. Table 5 summarizes the outcomes of the identified studies.

When considering complications, we conclude CMVS can provide better treatment for, in particular, a pneumonia. Pneumonia is associated with a longer length of stay with a ratio of 1.80. We conclude that with complex early warning models, it may be possible in the future to prevent ICU transfers. Regarding readmissions, 12-16% of readmissions are preventable for CVA patients.

# *Chapter 5*

# Simulation model

In Chapter 2, we gathered information about the system structure and operational procedures. In Chapter 3, we collected data to specify model parameters and input probabilities, discussed the level of detail of the study and established a simple model structure. In Chapter 4, we studied literature about CMVS and avoidable care and chose an appropriate modelling technique. In this chapter, these outcomes are used to propose a simulation model to evaluate the effect of CMVS on Slingeland Hospitals costs and turnover. Though health is also an outcome of this study, this measure is not assessed quantitively in the simulation model (instead, we assess this via literature) since it was not found feasible to do so in this study (Section 3.3.3).

## 5.1 DES in R

In Chapter 4, we designated DES as a good technique to model the effects of CMVS on Slingeland Hospital's costs and turnover. R is used to construct the model. R is a programming language and software environment for statistical analysis, graphics representation and reporting. To perform DES in R, the package "Simmer" *(Ucar I, 2018)*, version 3.6.5, is used. Simmer is a process-oriented and trajectory-based DES package for R. The model is designed in RStudio, an open-source integrated development environment for R.

## 5.2 Design of the baseline model

In Chapters 2 and 3 we described the system we want to study. Section 2.4 provided the process flowcharts of CVA patients and in Section 3.4, we decided on the most important clinical trajectories according to the DBC care product system for these patients. Section 2.5 provided

system information about financial planning and control. Through this information, a DES model was constructed. Figure 19 provides an overview of the model.

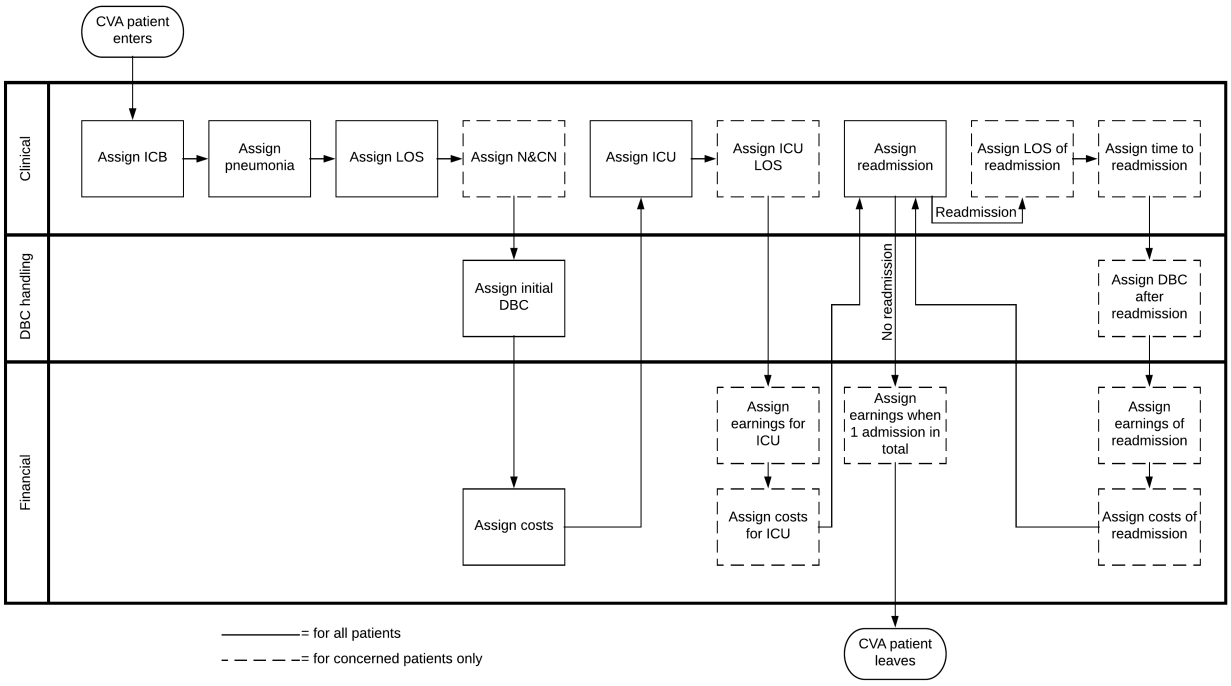



**Figure 19: Overview of the model for CVA patients. ICB: Intracranial or intracerebral bleeding; LOS: Length of Stay; N&CN: Neurology & Clinical Neurophysiology**

In the model, patient trajectories are simulated by setting attributes on a patient level to create unique patient pathways. The model features no dynamic state behaviour because it is incapacitated and a patient that flows through the model does not affect the flow of another patient. I.e., the state of the system is static. For assigning all attributes, the model contains procedures. These are categorized in clinical procedures, procedures for the handling of DBC care products and financial procedures in Figure 19.

When a CVA patient enters the model, first, illness is assigned to a patient: whether there is an ICB and whether there was a pneumonia during the hospital stay. These are the only procedures that are non-conditional. Following, depending on this illness, a length of stay is assigned. Then, for some patients (based on illness and length of stay) we assign whether treatment from neurology and clinical neurophysiology is needed. Now, we can assign an initial DBC to the patient. Also, we assign the costs that are made so far. Next, we determine whether the patient needs an ICU admission and we set the ICU length of stay. Following, for ICU patients, we assign the earnings and costs of the ICU. Then, for all patients, we determine whether the patient is readmitted or not. When a patient is not readmitted, we assign the earnings for the DBC. When a patient is readmitted, we set the length of stay for the readmission. Also, we set the time until the readmission occurs. Depending on this time, we set the DBC after the readmission and the earnings for this DBC. We also update the costs of the patients for this new admission. Then, we check again

whether a new readmission occurs. If so, the readmission procedures are repeated. If not, the patient leaves the simulation.

Many of the procedures are conditional on attributes that are assigned earlier to a patient. Table 6 shows this conditionality for all the procedures. A detailed logic flowchart of the model is included in Appendix B. The following sections describe the model's procedures in more detail.

**Table 6: Conditionality of the model's procedures. ICB: Intracranial or intracerebral bleeding; LOS: Length of Stay; N&CN: Neurology & Clinical Neurophysiology**

| Procedure\depending on: | Initial DBC | DBC of readmission | ICB | N&CN | Pneumonia | ICU | ICU LOS | LOS | LOS of readmission | Earlier costs | Earlier earnings | Readmission | Time to readmission |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Assign ICB | | | | | | | | | | | | | |
| Assign pneumonia | | | | | | | | | | | | | |
| Assign LOS | | | x | | x | | | | | | | | |
| Assign N&CN | | | x | | | | | x | | | | | |
| Assign initial DBC | | | x | x | | | | x | | | | | |
| Assign costs | x | | | | | | | x | | x | | | |
| Assign ICU | x | | | | | | | | | | | | |
| Assign ICU LOS | x | | | | | x | | | | | | | |
| Assign earnings for ICU | | | | | | x | x | | | | x | | |
| Assign costs for ICU | | | | | | x | x | | | x | | | |
| Assign readmission | x | | | | | | | | | | | | |
| Assign earnings when 1 admission in total | x | | | | | | | | | | x | | |
| Assign LOS of readmission | x | | | | | | | | | | | x | |
| Assign time to readmission | | | | | | | | | | | | x | |
| Assign DBC after readmission | | | x | | | | | x | | | | x | x |
| Assign earnings of readmission | x | x | | | | | | | | | x | x | x |
| Assign costs of readmission | | x | | | | | | | x | x | | x | |

### 5.2.1 Care pathways and complications

A patient is assigned to have an ICB or not and assigned to need treatment from the neurology or clinical neurophysiology department or not based on the probabilities that were obtained in Section 3.4. We start the model by distinguishing ICB and non-ICB patients because their care largely differs between each other within CVA patients. Moreover, we follow the DBC tree structure in this way. We only consider neurology and clinical neurophysiology for non-ICB patients with a length of stay fewer than 5 days due to the level of detail we concluded in Section 3.3.2.

In Section 4.4, we concluded CMVS to be in particular of influence for pneumonia among all complications for CVA patients. Therefore, we only consider pneumonia in the model. We derive a probability of 2.79% for having a pneumonia during the hospital admission, based on the data of Slingeland Hospital. Based on a random number, a patient is assigned to have or not have a pneumonia in the model.

### 5.2.2 Length of stay

For assigning a patient's length of stay, three distributions are used. First, for patients who have a pneumonia, a uniform distribution is used. Figure 20 shows the fit of this distribution for the available data. The data includes only 7 patients with a pneumonia.

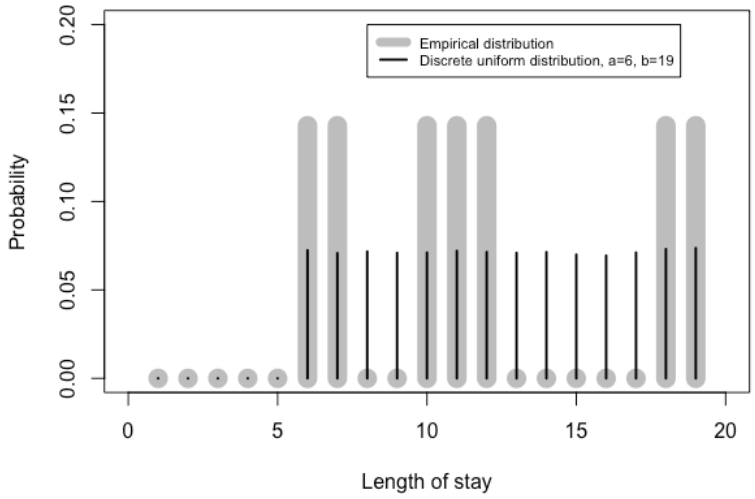



**Figure 20: Empirical and uniform distribution for the length of stay of patients who had a pneumonia (n=7)**

The length of stay for non-ICB and ICB patients are based on the geometric distributions that we found in respectively Figure 14 and Figure 15. For non-ICB patients, we only use the geometric distribution to assign a length of stay larger than 1 day. We first determine whether a patient has a length of stay of 1 day, using the probability of having a length of stay of one day.

### 5.2.3 ICU transfers and LOS

Whether a patient is transferred to an ICU is based on the chance of an ICU admission, given the DBC for that patient (Section 3.5). The ICU length of stay of a patient is based on the mean ICU length of stay for an ICU admission, given the DBC for that patient (Section 3.5). This mean value is rounded to an integer.

### 5.2.4 Readmissions

A patient is readmitted or not based on the conditional probability of a readmission given the DBC for the patient (Section 3.5). Subsetting readmitted non-ICB and ICB patients results in relatively

small populations for distribution fitting (respectively n = 28 and n = 16). Therefore, for the length of stay of readmitted patient, we use distributions that are based on all patients (except pneumonia patients), disregarding the admission. The length of stay distributions for both readmitted ICB and non-ICB patients are included in Appendix C.

The time until readmission is determined by the empirical distribution of the time until readmission for all DBC's combined. This distribution was given in Figure 17. We choose not to let this distribution be conditional for the DBC due to the lack of data for the fits of distributions for the unique DBC's. As stated in Section 3.5, no fit for a statistical distribution could be derived.

### 5.2.5 DBC handling

The initial DBC is set based on whether the patient had an ICB, the length of stay of that patient and whether the patient was treated by the neurology or clinical neurophysiology department.
The DBC after a readmission depends on the time until the readmission according to Section 2.5.1. If this time is larger than 42 days, a new DBC (based on a new length of stay from the relevant distribution) is created. Otherwise, the existing length of stay is updated with the length of stay for the new admission and we check whether this leads to another DBC or not.

### 5.2.6 Costs

Main (non-ICU-) costs of a patient are assigned based on a conditional linear regression model for a given DBC. In this linear regression model, we use length of stay as a predictor. Scatter plots and the linear regression models where costs are plotted against length of stay can be found in Appendix D. For DBC 99999017, one outlier was removed from the data.

When a patient is assigned to go to an ICU, the ICU costs are added based on the unit price of an ICU day and the ICU length of stay.

### 5.2.7 Earnings

A patient gets an attribute for the earnings of the procedures, which is updated according to the finance of the healthcare system.

When a patient is admitted to an ICU, the earnings are updated based on the fare that Slingeland Hospital gets for an ICU day and the length of stay.

The earnings of a DBC depends on whether a patient has had multiple admissions or not. If a patient only had one admission before leaving the system, the fare for the care product is added to the earnings attribute. For patients with readmissions, the logic for updating the earnings depend on whether a patient is readmitted within 42 days. If so, the earnings of only the DBC after readmission (so not the initial DBC), are added. If not, then the earnings of both the initial DBC and the readmission DBC are added.

## 5.3 List of assumptions

The model is subject to assumptions, which are as follows:

- All DBC's agreements are "P * Q", so maximum budget agreements between Slingeland Hospital and insurer are not considered.
- Parallel DBC's (multiple DBC's at the same time) are not considered.
- Readmissions only occur for the same diagnosis as the initial admission.
- The LOS follows the same distribution for first-time admitted and readmitted patients.
- Distribution of the costs of readmitted patients is equal to that of patients admitted for the first time.
- Costs are obtained by a linear regression model where costs are predicted by the length of stay.
- Distribution of length of stay for ICB and non-ICB patients follows geometrical distribution.
- CVA patients only are classified into the DBC care products: 99999008, 99999045, 99999017, 99999027 and 99999026. No other DBC care products within the CVA cluster, or from other specialisms, are considered in the model.
- The reimbursement fraction of the MSB is 13.5%.

## 5.4 Input

The input that is used for the model is given in the list below (for data collection, see Section 3.2).

- Weighted average fare per DBC care product. This was derived via the negotiated prices per care product per insurer with the number of care products per insurer.
- Unit price per care activity (see Section 3.3.1).
- Distributions for conditional length of stay and conditional time until readmission (given a DBC).
- Linear regression models for the costs per length of stay day.
- Illness probabilities (ICB, Pneumonia, need for treatment from Neurology & Clinical Neurophysiology department, ICU admission).
- Average ICU length of stay per care product.

## 5.5 Output

The model delivers the following output:

- Average total costs per year
- Average total and average MSB earnings per year

## 5.6 Uncertainty

From a policy perspective, the value of a model-based analysis lies not simply in its ability to generate a precise point estimate for a specific outcome but also in the systematic examination and responsible reporting of uncertainty surrounding this outcome and the ultimate decision being addressed *(Briggs et al., 2012)*. Different types of uncertainty in decision modelling are described with varying terminology used. In this study, the preferred terms according to *Briggs et al. (2012)* are used.

The first type of uncertainty is stochastic uncertainty (also: first-order uncertainty), describing the random variability in outcomes between identical patients. One can also describe the uncertainty in estimation of a parameter of interest (e.g. the estimation of the success probability in our geometric distribution). This is called parameter uncertainty (also: second-order uncertainty). When the variability between patients that can be attributed to characteristics of those patients is considered, this is called heterogeneity. The last type of uncertainty is structural uncertainty. This term describes the assumptions inherent in the decision model. *(Briggs et al., 2012)*

### 5.6.1 Stochastic uncertainty and number of simulated patients

The model in this study is a stochastic model because it allows for random variation in various inputs. To cope with the stochastic uncertainty, many patients must be simulated to account for the variability between unique patients. Figure 21 shows how the output of the model evolves when a large number of patients is simulated. We can see that the mean yearly costs, mean yearly earnings and the difference between costs and earnings (the margin) converge to a stable level. We can see that after simulating approximately 17,000 patients, the curves converge to a relatively stable level. Simulating this number of patients corresponds to a significance level of $\alpha \approx 1.5\%$ for stochastic uncertainty for the dependent variables mean yearly costs and mean yearly earnings. However, for the margin, we obtain a lower significance level: $\alpha \approx 6.6\%$. To decrease this $\alpha$ to the generally acceptable significance level $\alpha \approx 5\%$, approximately 34,000 patients must be simulated. Calculations of the 95% CI and significance level can be found in Appendix E.

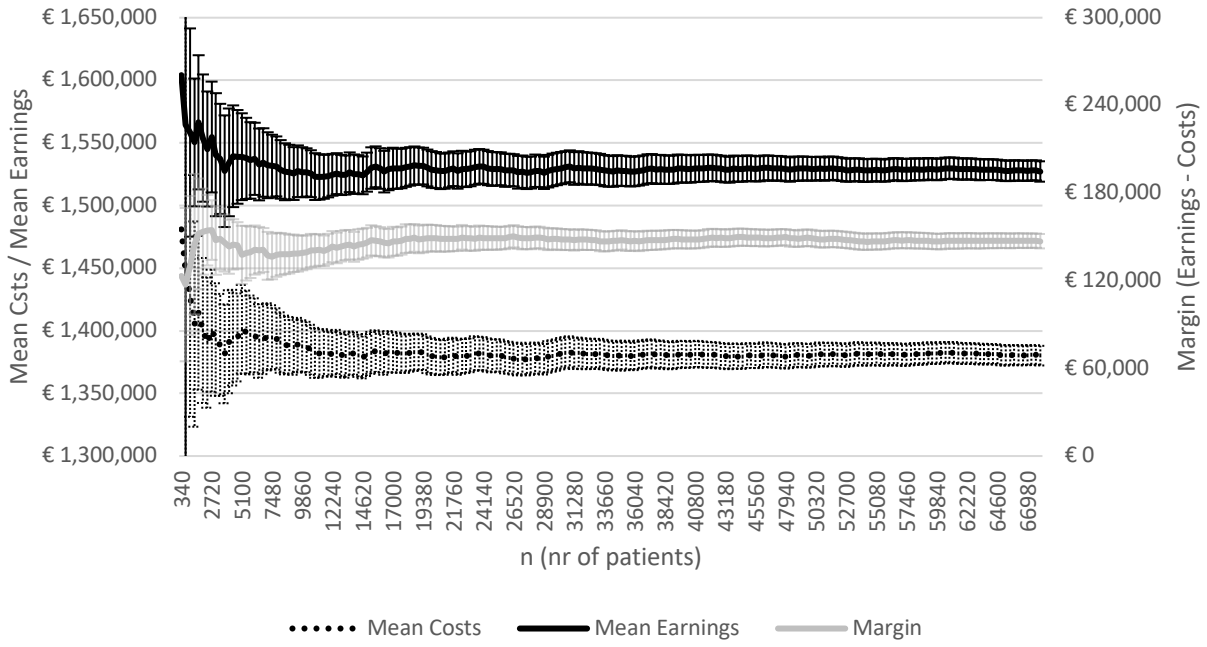



**Figure 21: Mean costs, mean earnings and the margin (Earnings – Costs) and 95% CI's for an increasing number of patients. The CI's for the first runs are not completely visible due to their large range.**

### 5.6.2 Parameter uncertainty

In this study, parameter uncertainty is applicable for all input values listed in Section 5.4. Parameter uncertainty can be represented via deterministic sensitivity analysis (DSA) or via probabilistic sensitivity analysis (PSA). In a DSA, parameter values are varied manually to test the sensitivity of the model's results to specific parameters or sets of parameters. In a PSA, (preferably) all parameters are varied simultaneously, with multiple sets of parameter values being sampled from probability distributions. *(Briggs et al., 2012)* In this study, parameter uncertainty is considered via DSA: univariate sensitivity analysis is performed by the one-factor-at-a-time method (Section 5.9.1). However, not for all input (Section 5.4), (probabilistic) sensitivity analysis was performed due to the scope of this research.

### 5.6.3 Heterogeneity

The relevance of heterogeneity lies in the identification of subgroups for whom separate cost-effectiveness analyses should be undertaken. Despite the model would support subgroup analysis within CVA patients (e.g. by differentiating in the effect of CMVS for ICB and non-ICB patients), this is not considered in this study's quantitative analysis.

### 5.6.4 Structural uncertainty

Structural uncertainty is present in our model by the assumptions that are made. Section 5.3 lists these assumptions. Also, all choices regarding this study's methodology involve structural uncertainty. In the analysis, this uncertainty is not considered.

## 5.7 Verification

To make sure that the model behaves as expected and represents the conceptual model, the model was verified. During programming, the model was constantly debugged by means of modular characteristics of the model. Also, patient level contents were traced during simulation to ensure correct behaviour in specific events.

## 5.8 Validation

Multiple steps have been taken to ensure the model represent reality well enough. The CVA model was discussed continuously with the hospital manager and in-between and final validation meetings have been conducted with the specialist nurse that is concerned with the Sensing Clinic programme via black box validation. Bugs and errors of the model's input and output values were discovered during these meetings, which could be fixed afterwards. Also, the model was validated with the original datasets.

## 5.9 Experimental design

The goal of the simulation model is to quantify the effects of CMVS in Slingeland Hospital on costs and earnings. In Section 3.1, we parameterized these effects and in Chapter 4, we consulted literature regarding the identified parameters. We concluded from this that CMVS is expected to reduce the (ICU-) length of stay, number of ICU transfers, number of readmissions. These factors can directly be manipulated in the model. Also, pneumonia can be treated better via CMVS. Despite that it is not the case that we either completely prevent a pneumonia or not (i.e. a starting pneumonia can also be treated better via early detection, though it was not prevented), we assume for the experimental design that CMVS only prevents a fraction of the pneumonia.

It is important to know how the uncertainty in the output can be apportioned to different sources of uncertainty in its inputs. This is called sensitivity analysis. One of the simplest and most common approaches for sensitivity analysis is that of changing one-factor-at-a-time (OFAT), often described as univariate sensitivity analysis in a health economic or statistical context. To model the combined effects of CMVS, we perform a scenario analysis (also: multivariate sensitivity

analysis). The configurations for performing these experiments are given in the following sections. First, the way the model is altered from the baseline model is discussed.

### 5.9.1 Sensitivity analysis

For the OFAT configurations we choose levels over a large range for the factors of interest such that the sensitivity of the system can be analysed properly. Table 7 shows these ranges. For the length of stay, we vary the decrease between 6% and 30% with 5 steps of 6%. For the other factors, a range between -10% and -50% with 5 steps of 10% is used. As step size, we use 5, meaning that we need 5*5+1=26 runs to perform this OFAT simulation.

**Table 7: OFAT experimental configuration**

| Factor | Range of level | Step size |
|---|---|---|
| LOS | -6% till -30% | 6% |
| ICU transfers | -10% till -50% | 5% |
| ICU LOS | -10% till -50% | 5% |
| Readmissions | -10% till -50% | 5% |
| Pneumonia incidence | -10% till -50% | 5% |

As we identified in Section 5.6.1 that after simulating approximately 17,000 patients, the mean costs and mean earnings converge to a constant level with a low significance level for these factors, we simulate this number of patients here. So, we do not consider the extra patients that are needed to account for the uncertainty in the margin between earnings and costs. This is because the large number of runs needed in the OFAT design will create high running time and therefore we accept lower uncertainty in the OFAT results regarding the margin between earnings and costs. In sensitivity analysis, it is important to use the method of common random numbers to control the randomness in the simulation. Otherwise the effect of changing one factor may be confounded with other changes. *(Law, 2015)* Therefore, in the model, each experiment uses the same random number stream to reduce such variances.

To perform the experiments, adjustments are made to the baseline model to allow changes in the factors of interest. For the length of stay, we need to change the parameter for the geometric distribution when we want to model a change in the length of stay. Equation 3 shows the formula that relates a change in the mean of a geometric distribution to the distribution parameter $p$. In the model, we change $p$ according to this formula to establish the decrease in length of stay.

**Equation 3: Changing the mean of a geometric distribution**

$$\Delta p = \frac{1}{\Delta \bar{X}}$$

By implementing a change in length of stay via the geometric distribution, we do not account for a length of stay of 1 day for non-ICB patients. For the ICU transfers, the probability of an ICU transfer is multiplicated by a fraction depending on the percent change. The same principle is used for the probability of a readmission and pneumonia. For the ICU length of stay, the average ICU

length of stay that is obtained from data is multiplicated by a factor (before rounding the value to an integer).

### 5.9.2 Scenario analysis

Scenario analysis is a process of analysing possible future events by considering alternative possible outcomes. This is suitable in the context of the Sensing Clinic programme, since we have no exact picture of the future and therefore want to model several alternative future developments. We choose to model three scenarios, covering our expectations of the effects of CMVS: a cautious, standard and optimistic scenario. The levels of the factors can be found in Table 8 and are based on findings in literature and expert opinions.

Regarding the length of stay, in the studies we identified in literature, we found a typical decrease in length of stay of 10%. For choosing a decrease in length of stay, we need to consider that this factor does not include a decrease in length of stay due to better pneumonia treatment (which may have been measured in the identified studies). We choose a 10% decrease in length of stay to be the standard scenario for this indicator. Because the Sensing Clinic programme assesses more vital signs than these studies, we choose an optimistic scenario where the LOS decreases by 20%. In the cautious scenario, the LOS drops with 5%.

For ICU transfers and ICU length of stay, we choose a decrease of respectively 15% and 15% for the standard scenario, corresponding with literature findings. Since there are little ICU admissions for CVA patients, we choose a 40% decrease in length of stay for the optimistic scenario (preventing a few patients already makes a big relative difference). For the ICU LOS, we choose a decrease of 25%. In the standard scenario, we assume 5% decrease in ICU transfers and no difference in ICU LOS.

For the readmissions, we base our scenarios on the findings in literature that 12-16% of readmissions are preventable for CVA patients when considering aspects that are related to CMVS. Therefore, in the standard scenario, we model a decrease of -10%, in the optimistic scenario a decrease of -25% and in the cautious case a decrease of 5%.

No numbers were identified in literature regarding a possible decrease in pneumonia incidence, but it is known that CMVS can provide better treatment for this illness. In the standard scenario, we choose a decline of 25%. For the optimistic case, this is 40% and in the cautious case 5%. This is based on expert opinions.

**Table 8: Scenario analysis design**

| Factor | Cautious | Standard case | Optimistic |
|---|---|---|---|
| LOS | -5% | -10% | -20% |
| ICU transfers | -5% | -15% | -40% |
| ICU LOS | -0% | -10% | -25% |
| Readmissions | -5% | -10% | -25% |
| Pneumonia incidence | -5% | -25% | -40% |

For these 3 scenarios, we choose to simulate 34,000 patients to obtain an acceptable significance level for the margin between earnings and costs (Section 5.6.1). As in the OFAT simulations, we use the method of common random numbers. The changes of the factors are established by the methods as discussed in Section 5.9.1.

## 5.10 Conclusion

In this chapter, we proposed a stochastic simulation model for evaluating the economic impact of continuous monitoring of vital signs. A DES model was constructed using the package Simmer in R. The model is incapacitated. Also, patients that flow through the model do not influence the states of other patients. Procedures are used to determine a patient's care pathway, conditional on prior events or characteristics such as having a pneumonia or a patient's length of stay. The model is capable of assessing mean yearly costs and earnings for both the MSB and Slingeland Hospital. First order uncertainty is represented in the model and by simulating approximately 17,000 patients, the model's output converges. An experimental design is proposed consisting of OFAT experiments and scenario analysis.

# *Chapter 6*

# Results

This chapter shows the results that are obtained from the simulation model with the experimental design that was described in Chapter 5. First, the OFAT results are discussed in Section 6.1, showing the effect on each factor on the model. Then, the results of the scenarios are given in Section 6.2. Section 6.3 states the conclusions of this chapter.

## 6.1 Results OFAT simulation

In this section, we state the results of the one-factor-at-a-time simulations. As specified in the experimental design, the OFAT simulation consisted of 5*5+1=26 simulation runs. For each run, 17,000 patients were simulated.

### 6.1.1 Length of stay

Figure 22 shows the effect of a decreasing length of stay on costs and earnings. There is an almost linear relationship between the length of stay and both cost and earnings of Slingeland Hospital.

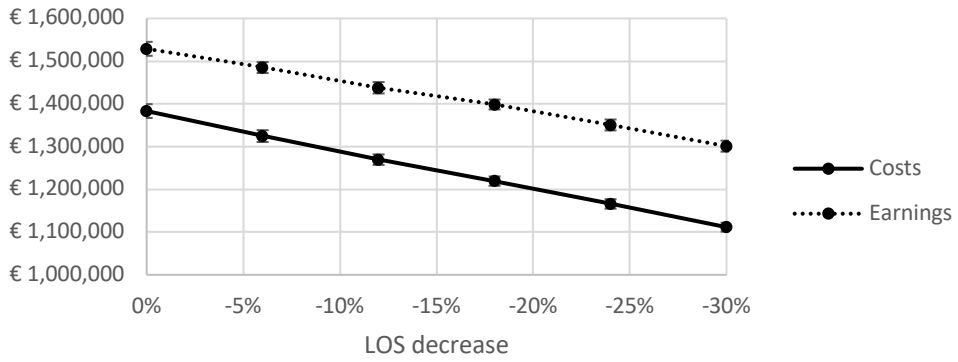



**Figure 22: Costs and earnings for a decrease in length of stay (LOS). Error bars: 95% CI for first order uncertainty (barely visible in this figure).**

When the length of stay decreases, costs drop more quickly than earnings. This can be seen better in Figure 27, where the margin between costs and earnings is plotted for a decreasing length of stay. This figure also reveals that the relationships between costs and earnings and the length of stay is not completely linear since the curve is slightly bended compared to a linear line (plotted as a grey line in the figure).

### 6.1.2 ICU Transfers and LOS

Figure 23 and Figure 24 show respectively the costs and earnings for a decreasing ICU transfer rate and a decreasing ICU length of stay. The changes in costs and earnings are relatively small. This can be identified by the small range of costs and earnings on this graph's axis. The confidence intervals are larger compared to the other factors due to the low ICU incidence among stroke patients. However, it must be noted that due to the scaling in this figure, these interval bars are also enlarged.

In contrast to the length of stay, for ICU transfers and LOS, the difference between costs and earnings does not change for a decreasing ICU transfer rate. We can see in the figures that the effect on costs and earnings directly correlate for these factors due to the fixed costs and earnings for an ICU day. Therefore, the margin between costs and earnings for ICU related changes is not displayed in Figure 27.

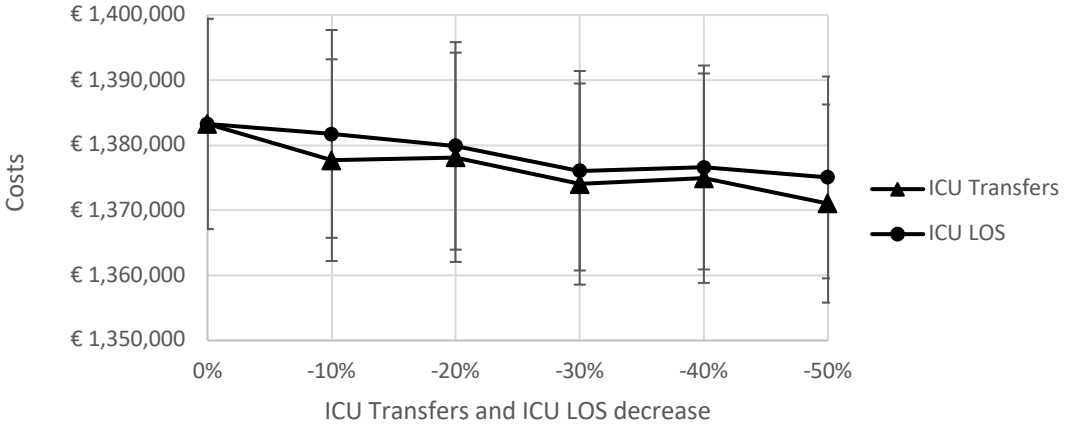



**Figure 23: Costs for decreasing ICU Transfer rate and ICU length of stay. Error bars: 95% CI for first order uncertainty. Note the relatively small range of the Costs axis due to the subtitle changes.**

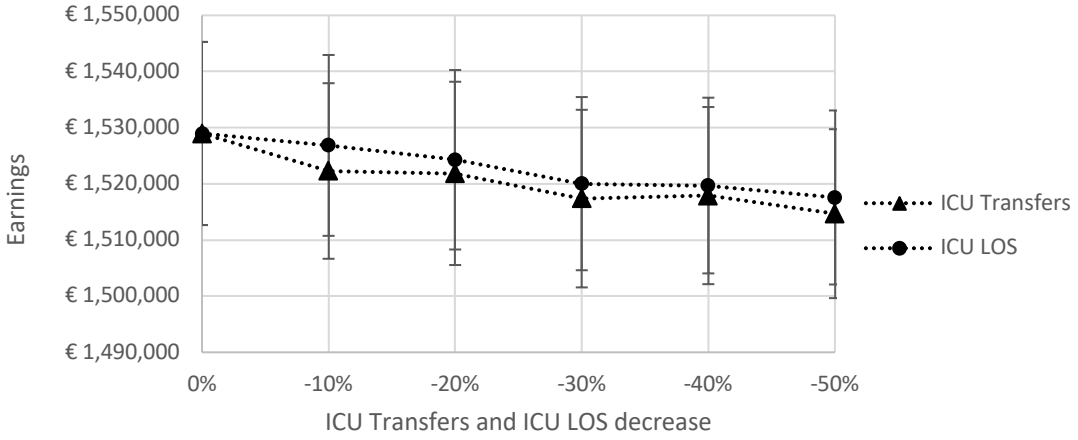



**Figure 24: Earnings for decreasing ICU Transfer rate and ICU length of stay. Error bars: 95% CI for first order uncertainty. Note the relatively small range of the Earnings axis due to the very subtitle changes.**

### 6.1.3 Readmissions

Figure 25 shows the decreasing costs and earnings for a decreasing number of readmissions.

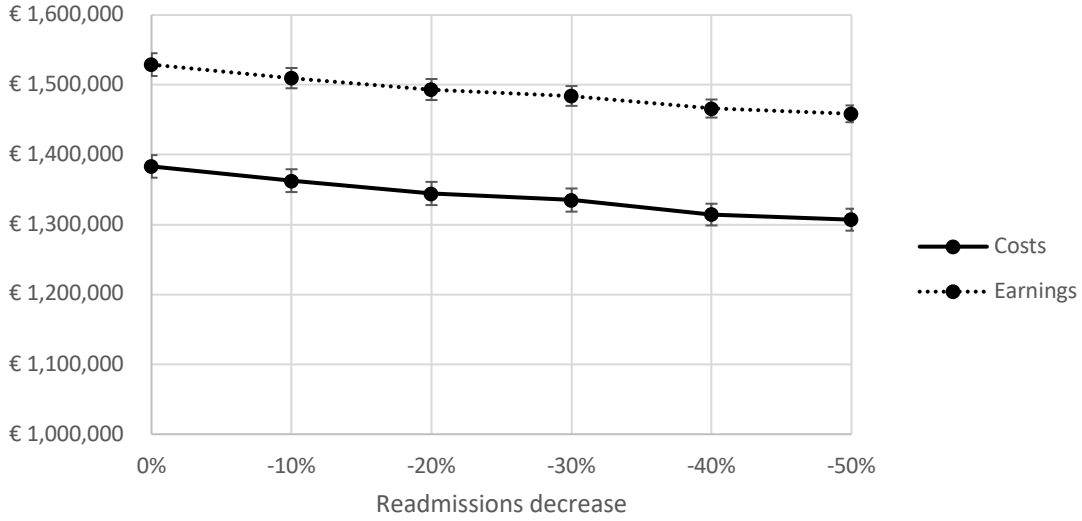



**Figure 25: Costs and earnings for decreasing number of readmissions. Error bars: 95% CI for first order uncertainty.**

Although there is a high first order uncertainty, a decreasing number of readmissions results in a larger decline of costs than earnings. This observed change in the margin between costs and earnings however is low compared to the change that a length of stay drop causes. Figure 27 shows this relationship.

### 6.1.4 Pneumonia incidence

Figure 26 shows the costs and earnings for a decreasing pneumonia incidence. Though costs and earnings are both decreasing, the effects for in particular smaller decreases in pneumonia incidence are very limited.

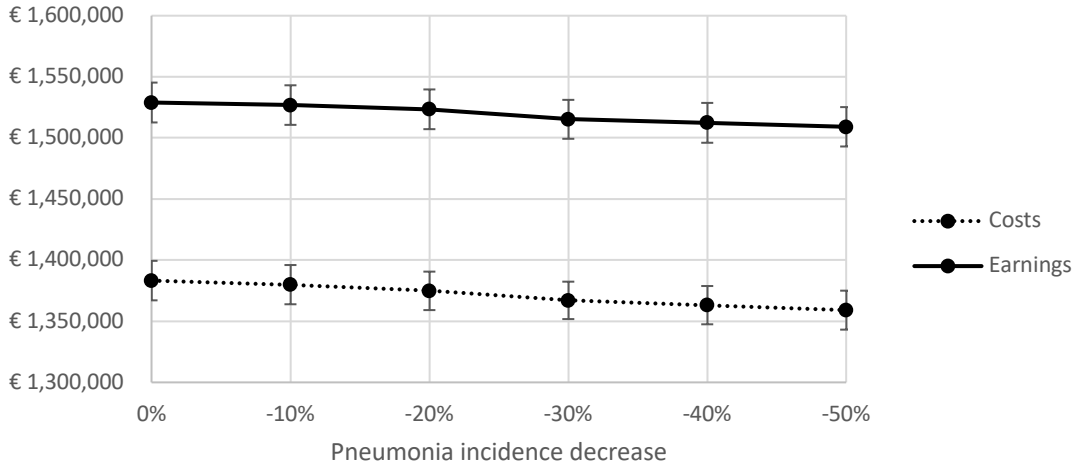



**Figure 26 Costs and earnings for decreasing pneumonia incidence. Error bars: 95% CI for first order uncertainty.**

There is only a limited change in the margin between costs and earnings for a decreasing pneumonia incidence (Figure 27).

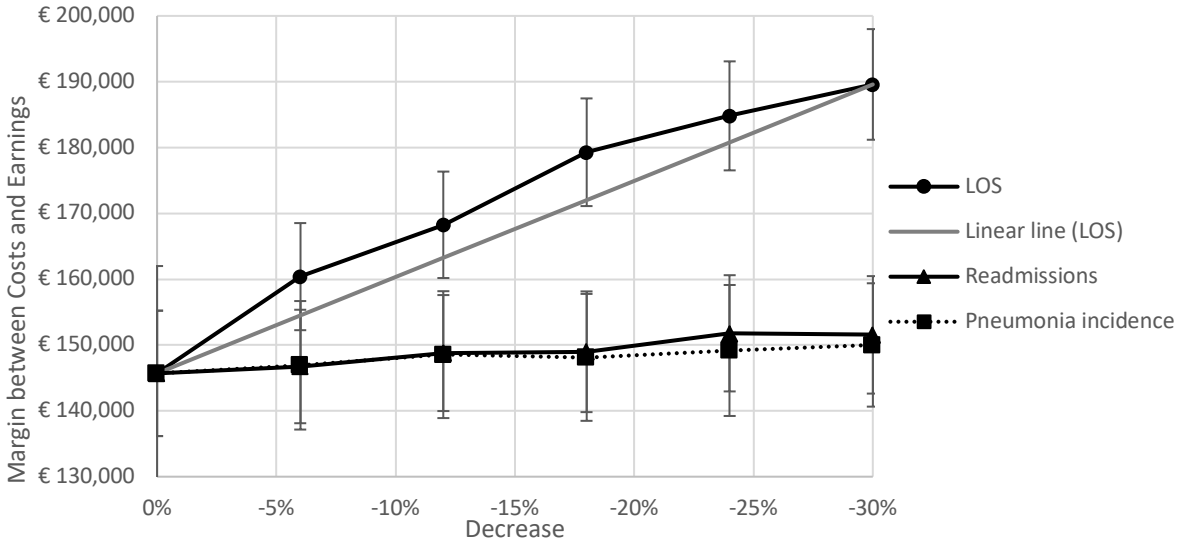



**Figure 27: Change in the margin between Costs and Earnings for a decrease in LOS, readmissions and pneumonia incidence. Error bars: 95% CI for first order uncertainty**

## 6.2 Scenarios

In this section, we state the results of the scenario analysis (Section 5.9.2). For the scenario analysis, 4 runs are needed. In contrast to the OFAT experiments, here, we chose to simulate 34,000 patients per run to take better account of uncertainty in the margin between earnings and costs (Section 5.9.2).

Figure 28 shows the mean costs and earnings of these runs (a 95% CI is negligible small, so this is not displayed) for the baseline measurement and the cautious, standard and optimistic

scenarios. Table 9 shows the 95% CI for the percent change of costs and earnings for the scenarios compared to the baseline measurement.

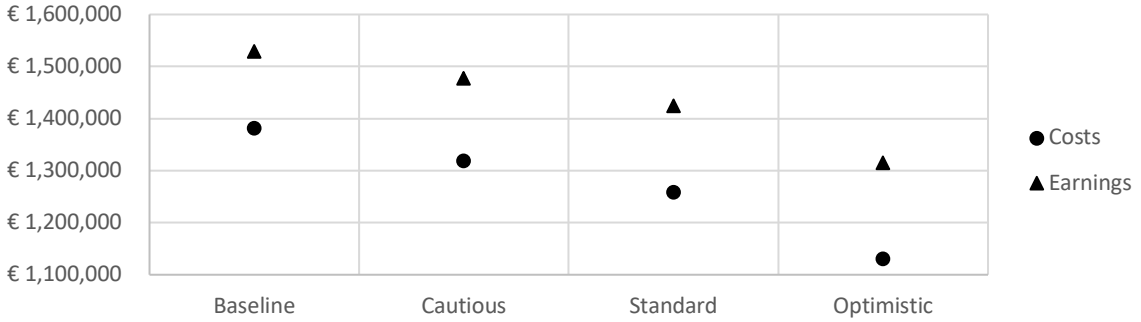



**Figure 28: Costs and earnings for baseline, cautious, standard and optimistic scenario. Error bars: 95% CI for first order uncertainty.**

**Table 9: 95% CI for absolute and percent change of costs and earnings for the scenarios compared to baseline.**

| | Cautious | Standard | Optimistic |
|---|---|---|---|
| Change in costs | -€62,414 ± €15,286<br>-4.66% ± 0.77% | -€123,145 ± €8,926<br>-9.05% ± 0.75% | -€251,311 ± €13,858<br>-18.31% ± 0.61% |
| Change in earnings | -€54,729 ± €15,875<br>-3.57% ± 0.69% | -€104,530 ± €11,081<br>-7.08% ± 0.68% | -€213,806 ± €14,851<br>-14.20% ± 0.65% |
| Change in MSB earnings | €7,388 ± €2,143<br>-0.48% ± 0.09% | €14,112 ± € 1,496<br>-0.96% ± 0.09% | €28,864 ± €2,005<br>-1.9% ± 0.09% |

There is a greater decrease in costs than in earnings for all the scenarios. This difference between costs and earnings increase as the scenarios become more optimistic. This can be observed better in Figure 29, which shows the change in the margin between costs and earnings for the scenarios. Table 10 shows the absolute change of the margin (in total and per patient) between costs and earnings for the scenarios. The costs for implementing the Sensing Clinic programme will lie between €200 and €250 per patient. Therefore, it is estimated that the costs of implementing CMVS on the CVA ward will lie between €68,000 per year and €85,000 per year. So, although the model predicts an increased positive margin between costs and earnings when implementing CMVS, the costs for implementing will be higher than what the cost savings will make up for in all scenarios.


**Figure 29: Change in the margin between costs and earnings for baseline, cautious, standard and optimistic scenario. Error bars: 95% CI for first order uncertainty.**

**Table 10: 95% CI for change of the margin between costs and earnings**

| | Cautious | Standard | Optimistic |
|---|---|---|---|
| Change in margin between total earnings and costs | +€11,617 ± €9,327 | +€18,615 ± €7,546 | +€37,505 ± €8,202 |
| Change in margin between per patient earnings and costs | +€34 ± €27 | +€55 ± €22 | €110 ± €24 |

## 6.3 Conclusion

In this chapter, the results of the OFAT method and the scenario analysis were given. Regarding the sensitivity analysis with the OFAT method, we conclude that in particular length of stay is a factor that largely influences costs and earnings. This factor also creates the largest change in behaviour in the difference between costs and earnings. For ICU transfers and ICU length of stay, we see a high uncertainty in the results and the model shows identical behaviour for costs and earnings. The decrease in costs and earnings is subtle. For the readmissions, we see decreasing costs and earnings with low first order uncertainty. With high first order uncertainty, the decrease in costs is larger than the decrease in earnings when there are fewer readmissions. The system is not sensitive for a decreasing pneumonia incidence.

The scenario analysis shows a larger decrease in costs than in earnings for all scenarios compared to baseline. The absolute and relative decreases in earnings and costs for the scenarios are given in Table 9. The increased margin between earnings and costs is given in Table 10. In all scenario's, this increased margin due to the clinical effects of CMVS does not compensate for the costs of the intervention.

# *Chapter 7*

# Discussion

In this study, the health economic impact of CMVS for CVA patients in Slingeland Hospital was evaluated. This was done by means of literature research regarding the impact of CMVS on patient health via clinical outcomes and a discrete event simulation model to evaluate the economic impact. In this chapter, first, we evaluate and discuss the conclusions of the study in Section 7.1. Then the study's limitations are considered in Section 7.2. Section 0 proposes future directions for research and Section 7.4 completes the chapter with this study's recommendations.

## 7.1 Conclusions

Based on literature findings, we conclude that CMVS in greater or lesser extent is likely to decrease (ICU-) length of stay, the number of ICU admissions and readmissions. However, significant and recent evidence to support this is limited. Key target populations include patients with ischaemic heart disease and CVA, vascular and orthopaedic patients.

We constructed a DES model that evaluated the economic impact of the intervention for CVA patients by considering costs via a grosscosting method and earnings by simulating the complex reimbursement system between insurers and hospitals in healthcare. The DES model shows that costs decrease more than earnings for all the scenarios that are used to analyse the possible effects of CMVS for CVA patients. In all scenario's, the increased margin between earnings and costs due to the clinical effects of CMVS does not compensate for the costs of the intervention.

Univariate sensitivity analysis reveals that a decreasing length of stay has the largest influence on both costs and earnings. Also, fewer readmissions affect costs and earnings significantly. For both LOS and readmissions, costs are more affected than earnings. The pneumonia incidence was found too low to make a difference in terms of the outcomes of the study. Decreasing ICU transfers

and length of stay showed slightly decreasing costs and earnings, but due to the low ICU admission rate, this coincided with high uncertainty.

## 7.2 Limitations

Multiple limitations are present in this study. First, it should be noted that the scope in our approach in evaluating the health economic impact is clinical care in the hospital. To optimize the health economic impact of this intervention, it would be better to consider its effect on the whole healthcare chain. However, this would require more complex system analysis and modelling and additional data.

In our study design, we identified some effects of CMVS that were not considered in the model: health, less time commitment of health professionals, diagnostic costs and RRT interventions Reduction in time commitment of health professionals results in more efficient care. This is not quantified in the model in terms of the resulting cost savings. This however may have a large impact because personnel is the largest expense in hospitals. Therefore, the model may give too conservative results. Also, we did not investigate in literature whether CMVS would lead to more or less demand for diagnostics to eventually model this. It is possible that CMVS results in either a decrease or increase in demand for diagnostic and therefore either increases or decreases costs. The same reasoning also applies to the RRT interventions.

We performed no validation on the hospital's earnings via yearly insurer reimbursement data for clinical CVA patients. Therefore, despite thorough verification, there is uncertainty about whether the absolute earnings as estimated with the model are valid. Here, the assumption that all reimbursement of DBC care products takes place via P*Q agreements may be of significant influence since in practice, for most of the care products, there are maximum budgets. Also, this assumption means that the changes in earnings that our model estimates are not directly established in reality. Also, we performed no validation regarding the cost allocation in care units via the distribution keys (Section 2.5.3).

Regarding cost prices, the gross costing method used in cost allocation provides relatively low granularity in the allocation of costs. Both direct and indirect costs are used in the linear regression model while CMVS is expected to only affect the direct costs. Moreover, even if only direct costs were considered, a decrease of costs in the model only estimates cost savings in reality.

Although first order uncertainties are considered, some were not included due to simplification or lack of fitting data. One first order uncertainty that is not considered is the variation of costs within one nursing day for a DBC care product (via the linear regression model). This can be seen via some moderate adjusted $R^2$ and mean absolute error scores for the fittings in Appendix D. Though we are in particular interested in averages concerning costs, it would be better to consider this uncertainty. Also, there was a lack of fitting data for estimating a distribution of the ICU length

of stay and to distinguish between various care products for the time to readmission. Regarding the parameter uncertainty, we performed no PSA and no DSA regarding all the input parameters of the model. Therefore, the quantified uncertainty of the model's output in relation to its input is limited. All choices in the study contributed to structural uncertainty. E.g. we preferred modelling a patient group based on diagnoses rather than, for example, based on ward admission since this makes simulating care pathways more feasible. Also, two DBC care products were not considered in the model and we fitted geometric distributions for the LOS.

Limited data quality presented other challenges. The pneumonia incidence obtained from data is suspected to not represent reality due to registration insufficiencies and because of the large difference with incidence values obtained from literature. Therefore, the model's output may undervalue the effect of CMVS on complication prevention. Other data may also deviate from reality. E.g., we assume that all DBC care products are assigned in the right way, but errors may be present. There is an underestimation of the number of readmissions since we have a starting and end date in our data. Therefore, we probably labelled some patients as first time admitted while they were already admitted before the start of our dataset. The same applies to patients who are readmitted after the end of the dataset. We also assumed that the length of stay of readmitted patients does not differ from first-time admitted patients, while Appendix C shows that this can be the case for in particular non-ICB patients. Also, only data from patients diagnosed with CVA is considered. Therefore, one patient may have had more treatment related to the CVA diagnose on another ward which was not visible in our analysis. The data is also limited for assessing the length of stay with a higher resolution than one day. In reality, it matters for the costs whether a patient leaves the hospital earlier or later on a day. Also, during the data processing, we excluded data due to various reasons. A flowchart is shown in Appendix F.

In this study, the effectiveness of CMVS was based on limited evidence from literature. Larger clinical trials (such as a large randomized controlled trial) are required to further ensure the effects of CMVS so more confident (i.e. experiment with smaller ranges for the study's factors) sensitivity analyses can be performed.

## 7.3 Future directions

In conducting this study, we identified new challenges that provide starting points for new directions in studying the health economic evaluation of CMVS.

First, further validation can be performed, in particular regarding the model's output for the hospital's earnings.

The constructed discrete event simulation model is flexible and robust and therefore provides leads for extensions. Now, the model is incapacitated and does not account for all the expected effects of CMVS (Section 3.1). Adding these other effects in the model would give a better picture of in particular the change in costs. Adding constrained or limited resources can help identifying whether a reduction in beds or personnel can be realized. Also, the model's scope can be extended by also considering the effects of CMVS on care outside the hospital. The model does also not consider quality of life or mortality of patients. Therefore, no cost-effectiveness study could be performed to obtain an incremental cost-effectiveness ratio (ICER: statistic used to summarise the cost-effectiveness of a health care intervention). To do so, first data must be obtained regarding the change in QOL and/or mortality of patients who perceive CMVS.

We designated multiple key target populations for CMVS. It would be relevant to model the economic impact of these populations by means of this study's simulation framework. This could provide relevant information for decision making in choosing cost-effective key target populations for CMVS.

The model's output generated first order uncertainty, which was in particular significant for the OFAT experiments. To minimize this uncertainty, more patients can be simulated. Running time can be reduced by choosing a less extensive experimental design for the OFAT experiments. To cope with the $2^{nd}$ order uncertainty that is present in the model we DSA on some input variables. However, in general PSA quantifies $2^{nd}$ order uncertainty in a better way when probability distributions of parameter values are identified. To do this, a method such as bootstrapping can be used.

For modelling the costs, we used cost prices for care activities that included both direct and indirect costs. The cost price model of the hospital (LOGEX) provides the possibility to aggregate costs in more dedicated cost prices. For example, personnel costs can be allocated separately. This would allow the model to account for the expected effects of CMVS on specific costs instead of general costs.

Data limitations were present so regarding the concerning input for the model (e.g. pneumonia incidence), better data collection can be performed to obtain a more valid model.

Little alterations to the model need to be made to account for heterogeneity via subgroup analysis. For example, in the case of CVA patients, one can distinguish between implementing CMVS for ICB and non-ICB.

## 7.4 Recommendations

Based on this study, we state the following recommendations for Slingeland Hospital.

- Evaluate other key target populations using this study's approach and model to map the different effects of CMVS for multiple target populations.
- Extended the model by implementing the effect of CMVS on time commitment of health professionals, diagnostic costs and RRT interventions and perform literature research on the expected effects on these effects.
- Improve data quality, in particular regarding complication incidence, and perform further validation, in particular regarding the hospital's earnings.
- Obtain data on the effectiveness of the intervention regarding QOL of patients such that a cost-effectiveness or cost-utility study can be performed using this study's simulation model.
- Update the model's scenario analysis when future research in the academic field provides better evidence.
- Based on this study, the decision maker should decide whether spending between approximately €90 (low intervention costs, optimistic scenario) and €215 (high intervention costs, cautious scenario) per patient per admission is worth implementing CMVS, depending on the future scenario and intervention costs. Here, the positive results on clinical outcomes for the patient, the innovative character and large opportunities to further study and improve CMVS should be considered. Moreover, the model's uncertainty and the complex health economic system that is described in this study should be taken into account.

# References


Alotaibi, N., & Sasi, S. (2016). Tree-based ensemble models for predicting the ICU transfer of stroke in-patients. 1-6.

Appelboom, G., Camacho, E., Abraham, M. E., Bruce, S. S., Dumont, E. L. P., Zacharia, B. E., . . . Connolly, E. S. (2014). Smart wearable body sensors for patient self-assessment and monitoring. *Archives of Public Health, 72*(1), 28.

Banks, J., McArthur, J., & Gordon, G. (2000). Flexible monitoring in the management of patient care processes: a pilot study. *Lippincott's case management : managing the process of patient care, 5*(3), 94-103; quiz 104-106.

Beckett, D., Gordon, C., Paterson, R., Chalkley, S., Macleod, D., & Bell, D. (2009). *Assessment of clinical risk in the out of hours hospital prior to the introduction of Hospital at Night* (Vol. 8).

Bennett, S., Quick, J. D., & Velásquiz, G. (1997). Public-private roles in the pharmaceutical sector: Implications for equitable access and rational drug use: World Health Organization (WHO).

Berwick, D. M., Nolan, T. W., & Whittington, J. (2008). The Triple Aim: Care, Health, And Cost. *Health Affairs, 27*(3), 759-769.

Bhattacharya, P., Khanal, D., Madhavan, R., & Chaturvedi, S. (2011). Why do ischemic stroke and transient ischemic attack patients get readmitted? *Journal of the Neurological Sciences, 307*(1), 50-54.

Briggs, A. H., Weinstein, M. C., Fenwick, E. A. L., Karnon, J., Sculpher, M. J., & Paltiel, A. D. (2012). Model Parameter Estimation and Uncertainty Analysis: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force Working Group–6. *Medical Decision Making, 32*(5), 722-732.

Brown, H., Terrence, J., Vasquez, P., Bates, D. W., & Zimlichman, E. (2014). Continuous Monitoring in an Inpatient Medical-Surgical Unit: A Controlled Clinical Trial. *The American Journal of Medicine, 127*(3), 226-232.

Cardona-Morrell, M., Prgomet, M., Lake, R., Nicholson, M., Harrison, R., Long, J., . . . Hillman, K. (2016a). Vital signs monitoring and nurse–patient interaction: A qualitative observational study of hospital practice. *International Journal of Nursing Studies, 56*, 9-16.

Cardona-Morrell, M., Prgomet, M., Turner, R. M., Nicholson, M., & Hillman, K. (2016b). Effectiveness of continuous or intermittent vital signs monitoring in preventing adverse events on general wards: a systematic review and meta-analysis. *Int J Clin Pract, 70*(10), 806-824.

Caro, J. J., Briggs, A. H., Siebert, U., & Kuntz, K. M. (2012). Modeling Good Research Practices—Overview: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force–1. *Medical Decision Making, 32*(5), 667-677.

Cavallini, A., Micieli, G., Marcheselli, S., & Quaglini, S. (2003). Role of monitoring in management of acute ischemic stroke patients. *Stroke, 34*(11), 2599-2603.

Churpek, M. (2016). Moving beyond Single-Parameter Early Warning Scores for Rapid Response System Activation. *Critical Care Medicine, 44*(12), 2283-2285.

Churpek, M. M., Adhikari, R., & Edelson, D. P. (2016). The value of vital sign trends for detecting clinical deterioration on the wards. *Resuscitation, 102*, 1-5.
Downey, C. L., Chapman, S., Randell, R., Brown, J. M., & Jayne, D. G. (2018). The impact of continuous versus intermittent vital signs monitoring in hospitals: A systematic review and narrative synthesis. *Int J Nurs Stud, 84*, 19-27.
Downey, C. L., Tahir, W., Randell, R., Brown, J. M., & Jayne, D. G. (2017). Strengths and limitations of early warning scores: A systematic review and narrative synthesis. *International Journal of Nursing Studies, 76*, 106-119.
Eijkelkamp, W. (2017). *Continue monitoring van vitale functies van vitaal bedreigde patiënten - Een interventie om de dreigende disbalans in zorgvraag en –capaciteit en de patiëntenzorg binnen het Slingeland Ziekenhuis positief te beïnvloeden.* (MBA), Businesschool Nederland.
Eurostat. (2018). Amenable and preventable deaths statistics. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Amenable_and_preventable_deaths_statistics
Gross, B., Dahl, D., & Nielsen, L. (2011). Physiologic Monitoring Alarm Load on Medical/Surgical Floors of a Community Hospital. *Biomedical Instrumentation & Technology, 45*(s1), 29-36.
Hans, E. W., van Houdenhoven, M., & Hulshof, P. J. H. (2011). *A framework for health care planning and control*. Enschede: Department of Applied Mathematics, University of Twente.
Hofmann, B., & Welch, H. G. (2017). New diagnostic tests: more harm than good. *BMJ, 358*.
Hravnak, M., Devita, M. A., Clontz, A., Edwards, L., Valenta, C., & Pinsky, M. R. (2011). Cardiorespiratory instability before and after implementing an integrated monitoring system. *Crit Care Med, 39*(1), 65-72.
Huang, Y.-C., Hu, C.-J., Lee, T.-H., Yang, J.-T., Weng, H.-H., Lin, L. C., & Lai, S.-L. (2013). The Impact Factors on the Cost and Length of Stay among Acute Ischemic Stroke. *Journal of Stroke and Cerebrovascular Diseases, 22*(7), e152-e158.
Ingeman, A., Andersen, G., Hundborg Heidi, H., Svendsen Marie, L., & Johnsen Søren, P. (2011). In-Hospital Medical Complications, Length of Stay, and Mortality Among Stroke Unit Patients. *Stroke, 42*(11), 3214-3218.
Kisner, D., Wilhelm, M. J., Messerli, M. S., Zünd, G., & Genoni, M. (2009). Reduced incidence of atrial fibrillation after cardiac surgery by continuous wireless monitoring of oxygen saturation on the normal ward and resultant oxygen therapy for hypoxia. *European Journal of Cardio-Thoracic Surgery, 35*(1), 111-115.
Kumar, S., Selim, M. H., & Caplan, L. R. (2010). Medical complications after stroke. *The Lancet Neurology, 9*(1), 105-118.
Langhorne, P., Stott, D., Knight, A., Bernhardt, J., Barer, D., & Watkins, C. (2010). Very Early Rehabilitation or Intensive Telemetry after Stroke: A Pilot Randomised Trial. *Cerebrovascular Diseases, 29*(4), 352-360.
Law, A. M. (2015). *Simulation Modeling and Analysis* (5th ed.).
Lichtman Judith, H., Leifheit-Limson Erica, C., Jones Sara, B., Wang, Y., & Goldstein Larry, B. (2013). Preventable Readmissions Within 30 Days of Ischemic Stroke Among Medicare Beneficiaries. *Stroke, 44*(12), 3429-3435.
Ludikhuize, J., Smorenburg, S. M., de Rooij, S. E., & de Jonge, E. (2012). Identification of deteriorating patients on general wards; measurement of vital parameters and potential

effectiveness of the Modified Early Warning Score. *Journal of Critical Care, 27*(4), 424.e427-424.e413.

Mohamed, W., Bhattacharya, P., Shankar, L., Chaturvedi, S., & Madhavan, R. (2015). *Which Comorbidities and Complications Predict Ischemic Stroke Recovery and Length of Stay?* (Vol. 20).

Morgan J.A., M. S. P., Blike G. (2010). Cost Effectiveness of Patient Surveillance Systems. *Anesth Analg 110(35):S-249*.

Nahab, F., Takesaka, J., Mailyan, E., Judd, L., Culler, S., Webb, A., . . . Helmers, S. (2012). Avoidable 30-day readmissions among patients with stroke and other cerebrovascular disease. *The Neurohospitalist, 2*(1), 7-11.

Nolt, B. R., Gonzales, R., Maselli, J., Aagaard, E., Camargo, C. A., & Metlay, J. P. (2007). Vital-sign abnormalities as predictors of pneumonia in adults with acute cough illness. *The American Journal of Emergency Medicine, 25*(6), 631-636.

Ochroch, E. A., Russell, M. W., Hanson, W. C., 3rd, Devine, G. A., Cucchiara, A. J., Weiner, M. G., & Schwartz, S. J. (2006). The impact of continuous pulse oximetry monitoring on intensive care unit admissions from a postsurgical care floor. *Anesth Analg, 102*(3), 868-875.

OECD, & European Observatory on Health System and Policies. (2017). State of Health in the EU - Netherlands (Country Health Profile 2017).

Parimi, N., Hu, P. F., Mackenzie, C. F., Yang, S., Bartlett, S. T., Scalea, T. M., & Stein, D. M. (2016). Automated continuous vital signs predict use of uncrossed matched blood and massive transfusion following trauma. *Journal of Trauma and Acute Care Surgery, 80*(6), 897-906.

Pitman, R., Fisman, D., Zaric, G. S., Postma, M., Kretzschmar, M., Edmunds, J., & Brisson, M. (2012). Dynamic Transmission Modeling: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force Working Group–5. *Medical Decision Making, 32*(5), 712-721.

Rijksinstituut voor Volksgezondheid en Milieu (RIVM). (2017). Volksgezondheidenzorg.info, Kosten van ziekten. Bilthoven.

Siebert, U., Alagoz, O., Bayoumi, A. M., Jahn, B., Owens, D. K., Cohen, D. J., & Kuntz, K. M. (2012). State-Transition Modeling: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force-3. *Value in Health, 15*(6), 812-820.

Slight, S. P., Franz, C., Olugbile, M., Brown, H. V., Bates, D. W., & Zimlichman, E. (2014). The return on investment of implementing a continuous monitoring system in general medical-surgical units. *Crit Care Med, 42*(8), 1862-1868.

Slingeland Ziekenhuis. (2016). Jaardocument Slingeland Ziekenhuis 2016.

Smith, G. B., Prytherch, D. R., Schmidt, P. E., & Featherstone, P. I. (2008). Review and performance evaluation of aggregate weighted 'track and trigger' systems. *Resuscitation, 77*(2), 170-179.

Sulter, G., Elting, J. W., Langedijk, M., Maurits, N. M., & De Keyser, J. (2002). Admitting Acute Ischemic Stroke Patients to a Stroke Care Monitoring Unit Versus a Conventional Stroke Unit: A Randomized Pilot Study. *Stroke, 34*(1), 101-104.

Sweetser, A. (1999). *A Comparison of System Dynamics (SD) and Discrete Event Simulation (DES)*.

Taenzer, M. D. F. A. A. P. Andreas H., Pyke, B. E. Joshua B., McGrath, P. D. Susan P., & Blike, M. D. George T. (2010). Impact of Pulse Oximetry Surveillance on Rescue Events and Intensive Care Unit TransfersA Before-and-After Concurrence Study. *Anesthesiology, 112*(2), 282-287.

Tarassenko, L., Hann, A., Patterson, A., Braithwaite, E., Davidson, K., Barber, V., & Young, D. (2005, 3-4 Nov. 2005). *BIOSIGN: multi-parameter monitoring for early warning of patient deterioration.* Paper presented at the The 3rd IEE International Seminar on Medical Applications of Signal Processing 2005 (Ref. No. 2005-1119).

Ucar I, S. B., Azcorra A. (2018). Discrete-Event Simulation for R. *Journal of Statistical Software*.

Ulahannan, T. J. (2002). Decision Making in Health and Medicine: Integrating Evidence and Values. *Journal of the Royal Society of Medicine, 95*(2), 108-109.

Varela, M., Ruiz-Esteban, R., Martinez-Nicolas, A., Cuervo-Arango, J. A., Barros, C., & Delgado, E. G. (2011). 'Catching the spike and tracking the flow': Holter-temperature monitoring in patients admitted in a general internal medicine ward. *International Journal of Clinical Practice, 65*(12), 1283-1288.

Watkinson, P. J., Barber, V. S., Price, J. D., Hann, A., Tarassenko, L., & Young, J. D. (2006). A randomised controlled trial of the effect of continuous electronic physiological monitoring on the adverse event rate in high risk medical and surgical patients. *Anaesthesia, 61*(11), 1031-1039.

Weenk, M., van Goor, H., Frietman, B., Engelen, L. J., van Laarhoven, C. J., Smit, J., . . . van de Belt, T. H. (2017). Continuous Monitoring of Vital Signs Using Wearable Devices on the General Ward: Pilot Study. *JMIR Mhealth Uhealth, 5*(7), e91.

Wong, M. W., Tsui, H. F., Yung, S. H., Chan, K. M., & Cheng, J. C. (2004). Continuous pulse oximeter monitoring for inapparent hypoxemia after long bone fractures. *J Trauma, 56*(2), 356-362.

Yong, M., & Kaste, M. (2008). Association of characteristics of blood pressure profiles and stroke outcomes in the ECASS-II trial. *Stroke, 39*(2), 366-372.

Zorginstituut Nederland. (2016). Richtlijn voor het uitvoeren van economische evaluaties in de gezondheidszorg.

# *Appendix A*

# Search strategy

Here, the search strategies are given by which we included studies regarding CMVS in in Sections 1.4, 2.2.2 (Populations in comparable research) and 4.2 (Effectiveness of continuous monitoring of vital signs).

First, a search was performed to obtain systematic reviews regarding CMVS. The search query “("Review") AND ("monitoring") AND ("Vital Signs")” was used to search was used in the databases Scopus and Pubmed (settings: article title). After reading the titles of the identified records, two systematic reviews were included that concerned CMVS. These reviews were used to include records for the Sections mentioned above. This is displayed in Figure 30.

After obtaining these studies, an additional search was performed in an afford to obtain more studies regarding continuous monitoring of vital signs via the search query “"Continuous" AND "Monitoring" AND "Vital signs") in the database Scopus (settings: article title). No new records were identified. For health economic evaluation in specific, the query “("Cost-effectiveness" OR "Cost effectiveness") AND ("monitoring") AND ("Vital Signs")” was used in Scopus (settings: abstract). No new records were identified.

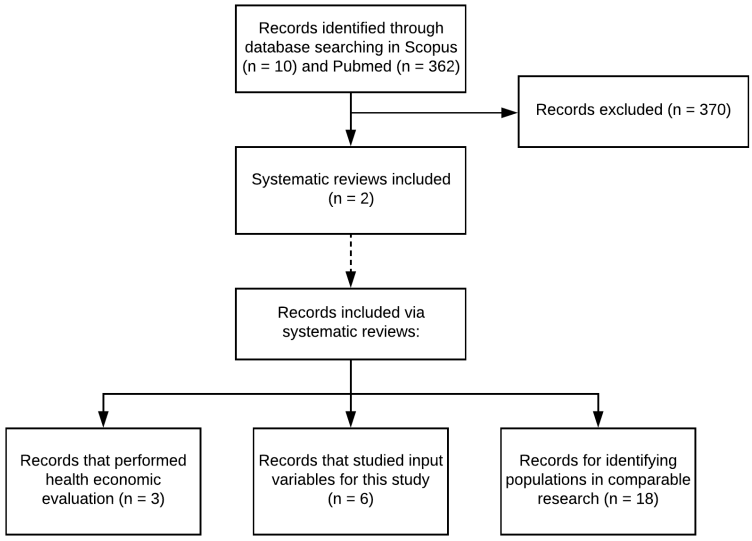
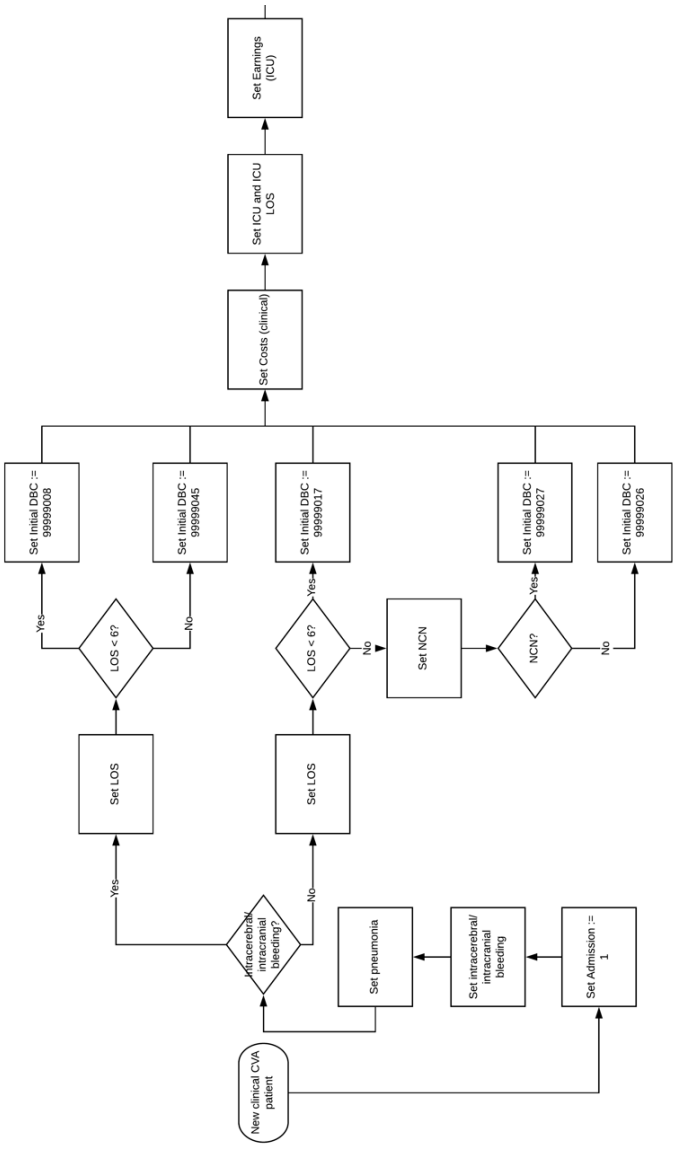


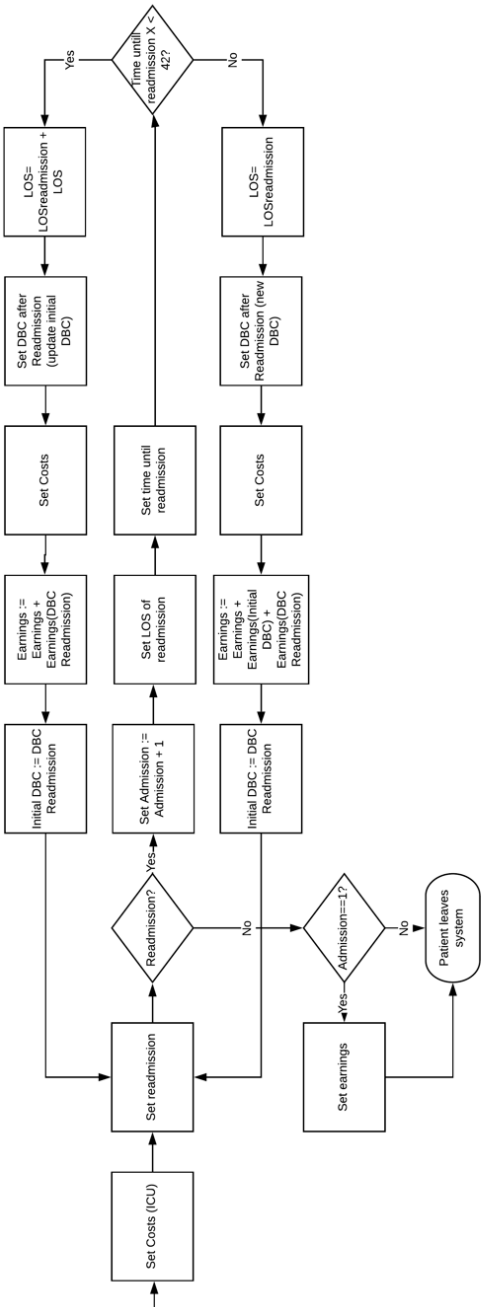

**Figure 30: Search strategy**

# *Appendix B*

# Logic flowchart

Below, an extensive logic flowchart is given for the simulation model. The flowchart continues on the next page.




Set Costs (ICU)
Set readmission
Readmission?
Yes
No
Initial DBC := DBC Readmission
Earnings := Earnings + Earnings(DBC Readmission)
Set Costs
Set DBC after Readmission (update initial DBC)
LOS= LOSreadmission + LOS
Time until readmission X < 42?
Yes
No
Set Admission := Admission + 1
Set LOS of readmission
Set time until readmission
Initial DBC := DBC Readmission
Earnings := Earnings + Earnings(Initial DBC) + Earnings(DBC Readmission)
Set Costs
Set DBC after Readmission (new DBC)
LOS= LOSreadmission
Admission==1?
Yes
No
Set earnings
Patient leaves system

# *Appendix C*

# Length of stay of readmitted patients

Figure 31 and Figure 32 gives the empirical distribution for the length of stay of respectively non-ICB and ICB patients.

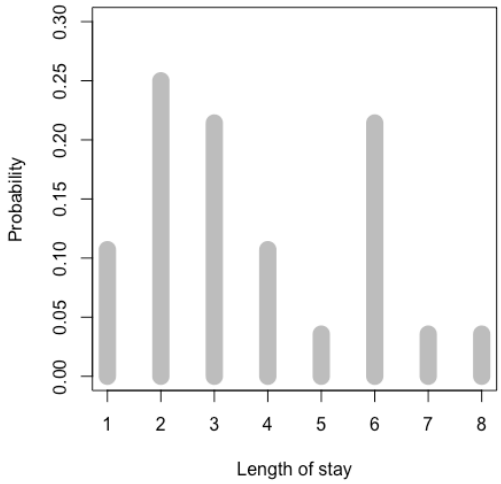



**Figure 31: Length of stay for readmitted non-ICB patients (n=28)**

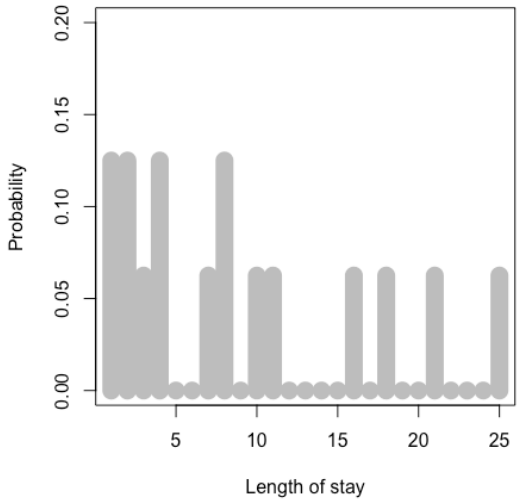



**Figure 32: Length of stay for readmitted ICB patients (n=16)**

# *Appendix D*

# Linear regression models for cost prediction

Below, the linear regression models that are used to estimate costs via the length of stay are given. All figures contain the intersect and slope value, together with the test statistics mean absolute error and adjusted $R^2$.

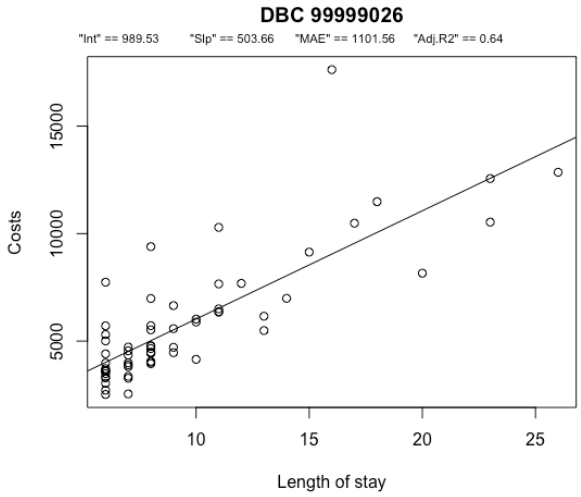



**Figure 33: Scatter plot and linear regression model for cost prediction of DBC 99999026. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$**

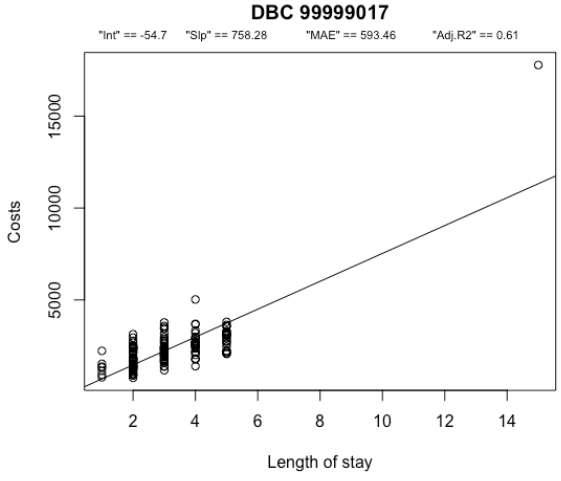



**Figure 34: Scatter plot and linear regression model for cost prediction of DBC 99999017. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$**

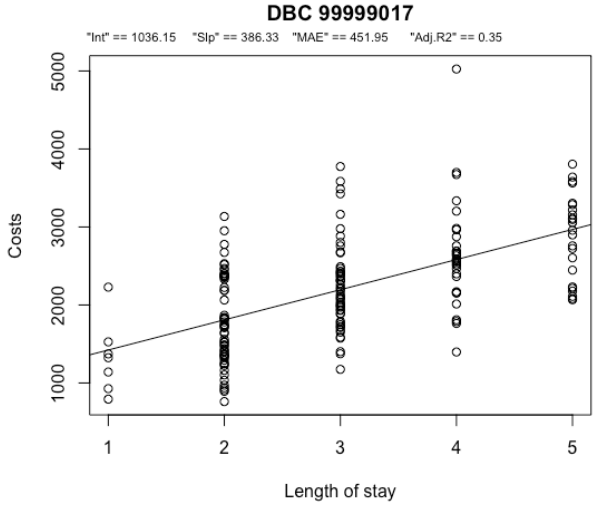



**Figure 35: Scatter plot and linear regression model for cost prediction of DBC 99999017 with removed outlier. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted R2**

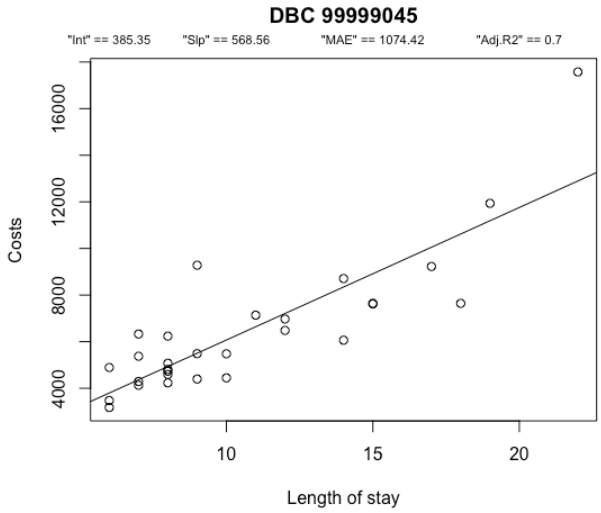



**Figure 36: Scatter plot and linear regression model for cost prediction of DBC 99999045. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$**

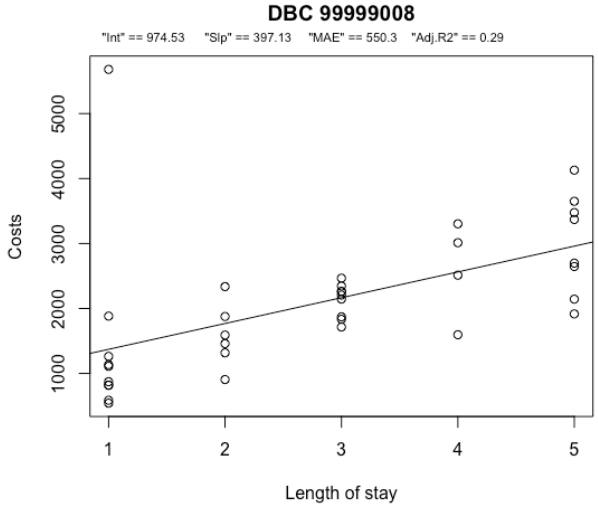



**Figure 37: Scatter plot and linear regression model for cost prediction of DBC 99999008. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$**

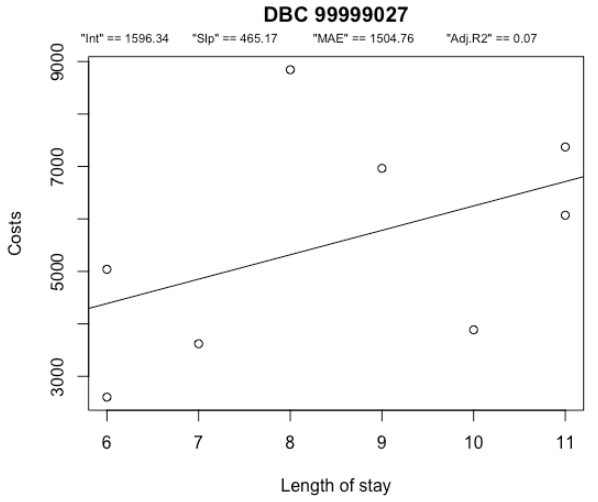



**Figure 38: Scatter plot and linear regression model for cost prediction of DBC 99999027. Int: intersect, Slp: Slope, MAE: Mean Absolute Error, Adj.R2: Adjusted $R^2$**

# *Appendix E*

# Establishment of confidence intervals

All confidence interval half-widths in this study are achieved by treating the output of the model as independent and identically distributed (IID) random variables. In this case, a random variable existed of mean costs and earnings for 340 patients (equivalent to 1 year). According to the central limit theorem (probability distribution of the average of IID variables with finite variance approaches a normal distribution), we can estimate the mean of the whole sample by taking the average of all samples. Following, a confidence interval half width (left side of Equation 4) for the mean of this sample can be obtained. For the confidence interval a significance level of 95% (i.e. α = 0.05) is used. This value is often used in simulation studies.

For estimating the significance level of the number of patients (Section 5.6.1), use the following method:

**Equation 4: Confidence interval half width compared to mean smaller than relative error**

$$\frac{t_{n-1,1-\alpha/2}\sqrt{\frac{S^2(n)}{n}}}{\bar{X}} < \gamma'$$

When we want this interval to be sufficiently small, we must obtain the relative error. Usually, we estimate the relative error by Equation 5.

**Equation 5: Estimation of relative error**

$$\gamma = \frac{|\bar{X} - \mu|}{\bar{X}}$$

However, since we estimate |μ| by $\bar{X}$, we must use the corrected target value (Equation 6).

**Equation 6: Corrected target value**

$$\gamma' = \gamma/(1+\gamma)$$

To obtain the level of significance for the obtained number of patients in Section 5.6, we calculate the relative error from Equation 4 and Equation 6. From the relative error, we calculate α. *(Law, 2015)*

# *Appendix F*

# Exclusion of data

To obtain data for the input of the simulation model, data from the original dataset was excluded. Figure 39 shows how much data was excluded and for which reason.

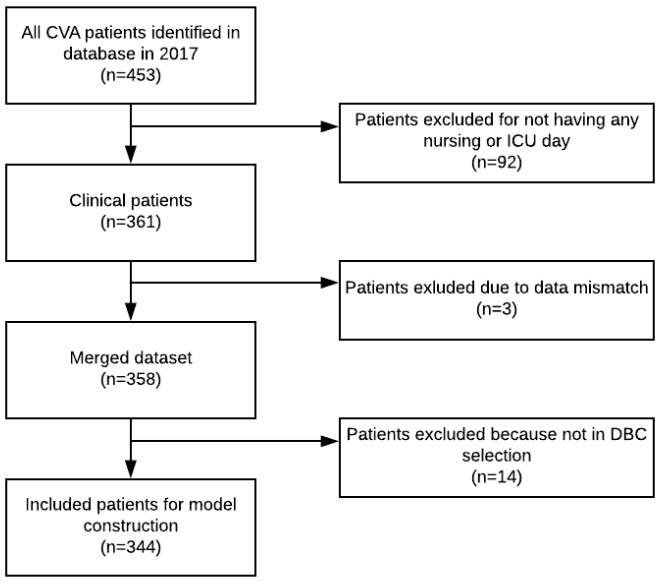



**Figure 39: Exclusion of data**