Capacity Shortages in Healthcare:

A Simulation Study of the Neonatal Care System

Alexander Dietz
M.Sc. Engineering & Policy Analysis
Delft University of Technology

TUDelft

Erasmus MC
Universitair Medisch Centrum Rotterdam

This page is left intentionally blank

Capacity Shortages in Healthcare:

A Simulation Study of the Neonatal Care System

A thesis submitted to the Delft University of Technology in partial fulfillment of the requirements for the degree of

Master of Science Engineering & Policy Analysis

By
Alexander Dietz
Student Number: 5859549
To be defended publicly on August 29, 2024

Chair	Prof. Dr. Alexander Verbraeck, TU Delft
First Supervisor	Dr. Saba Hinrichs-Krapels, TU Delft
Second Supervisor	Dr. Yilin Huang, TU Delft
External Advisor	Josephine Wagenaar, Erasmus MC

TU Delft

Executive Summary

Healthcare systems worldwide are under increasing strain due to rising demand, limited resources, and rising costs. Neonatal care faces particularly critical challenges, as newborns within the first 28 days of life are highly vulnerable and require intensive care to prevent long-term health complications. In the Netherlands, a severe shortage of operational bed capacity in neonatal care is compounded by significant staffing shortages. In the southwest region, 36% of hospitals have closed neonatal beds due to these staffing shortages. Increasing staffing levels is unlikely in the short term, given the overall shortage of healthcare personnel, the specialized qualifications required for neonatal care, and the high stress levels associated with the job. This situation underscores the urgent need for alternative strategies to prevent further deterioration in neonatal care.

The neonatal care system in the Netherlands is structured into three escalating levels of specialization: neonatal medium care wards, high care wards, and Neonatal Intensive Care Units (NICUs), each addressing varying degrees of medical needs for newborns. This system is structured to deliver the right level of care based on the newborn's condition, but it brings challenges. Patients often need to be transferred between hospitals to get the appropriate care, and if no local beds are available, they may have to be transferred to outside the region. Given these complexities, modeling and simulation is a suitable method for analyzing this interactive and interdependent system. However, the existing literature on this topic is limited, not directly applicable to the Dutch context, and often overlooks the constraints posed by staffing limitations. Hence, the following research question arises:

How can operational bed capacity shortages in neonatal care be reduced within staffing limitations?

A discrete-event simulation model was developed to address the issue of perinatal bed capacity shortages in a regional hospital network. The model was grounded in an analysis of the region's perinatal birth registry data and is capable of simulating patient arrivals, hospital stays, and transfers across various ward levels and hospitals in the region. The model was utilized to evaluate capacity shortages from two key perspectives, each associated with distinct performance indicators.

The first perspective, focused on hospital management, examined the number of beds required for patients within the region and the weekly occupancy rate at the ward level. This view provided critical insights into the impact of capacity shortages on individual hospitals and at the aggregate ward level. The second perspective, from a societal

viewpoint, assessed the capacity transfer rate, specifically the percentage of patients needing to be transferred to hospitals outside the region due to insufficient local capacity. Additionally, it analyzed the weekly capacity transfers, correlating the number of transfers per week with the weekly occupancy rates, and highlighting the implications for the patient population under varying occupancy conditions.

The simulation model facilitated the exploration of various scenarios to answer "what-if" questions. The analysis revealed that under the current capacity constraints, both the NICU and high care wards experience average weekly occupancy rates exceeding 90%, resulting in a capacity transfer rate of over 20%. This means that, on average, one in five patients must be transferred to an out-of-region hospital. Furthermore, ongoing discussions about lowering the minimum gestational age for NICU admissions from 24 to 23 weeks would exacerbate these capacity challenges, making it clear that such a policy change would be unsustainable given the current number of operational beds.

The study identified and assessed several system levers for their potential to mitigate capacity shortages, based on findings from data analysis and literature. Among these levers:

Reducing Length of Stay (LoS): This lever tested the impact of decreasing the LoS across patients at different ward levels. Interestingly, already 10% reduction in LoS for high-care patients significantly alleviated capacity pressures, reducing the number of required beds to align with current availability.

Adjusting Admission Rates: The lever tested modifying admission rates to shift bed demand between different ward levels, aiming to optimize resource utilization. This adjustment introduces a trade-off between ward levels, as improvements in one come at the cost of another.

Changing Patient Pathways: Patients with extended stays experience disproportionately long LoS and, therefore, contribute more to capacity shortages. To address this, the effect of shifting all post-ICU patients from high care to medium care after staying additional days in the NICU was tested. This change resulted in an almost 10-percentage-point decrease in capacity transfers for the high care level.

Using the insights of the system levers and additional information gained through interviews and literature, currently relevant interventions were tested for their impact on capacity shortages.

Phototherapy at Home for Jaundice: While early discharge for jaundiced patients might improve the quality of care, it only reduced the region's bed requirements by 0.6%, with minimal impact on capacity transfer rates and occupancy rates across all wards.

Switching from Intravenous to Oral Antibiotics for Early-Onset Sepsis: Clinical trials suggested that this intervention could reduce LoS. The simulation experiment showed that it led to a 2.3% reduction in the region's bed requirements and a 0.76%-point decrease in the high-care capacity transfer rate, thus, providing valuable impact on the capacity shortages.

Lowering the NICU Gestational Age Threshold: Reducing the NICU threshold to 31 weeks of gestation would bring the required NICU bed count in line with current capacity and lower the capacity transfer rate to just under 15%. However, this would drastically increase pressure on the high care wards, leading to nearly 99% occupancy and a 30% transfer rate.

The analysis concluded that there is no single solution to the current capacity challenges. Trade-offs are inevitable, particularly between different ward levels. To address these challenges, a combined intervention strategy was tested. This strategy integrated phototherapy at home, oral antibiotics for early-onset sepsis, a NICU age threshold of 31 weeks, and a shift of post-IC patients to medium care. The combined approach yielded promising results, reducing the NICU's weekly occupancy rate by 2 percentage points and lowering the high care capacity transfer rate by 0.9 percentage points. While this strategy increased the load on medium care, the ward level was able to accommodate the additional demand, maintaining a manageable weekly occupancy rate of around 75%.

This study highlighted the ongoing challenges of operational bed capacity shortages and provided actionable insights for mitigating these issues within existing staffing limitations. Interventions aimed at redistributing patient loads across different ward levels emerged as particularly promising. Looking forward, the simulation model can serve as a valuable tool for assessing the capacity impact of various interventions, guiding decision-making towards sustainable solutions in this critical area.

Acknowledgements

This quick read was developed over the last half year and marks the end of my master's in Engineering & Policy Analysis at the Delft University of Technology. The work presented here would not have been possible without the support and contributions of many individuals, to whom I owe my deepest gratitude.

First and foremost, I would like to express my sincere thanks to my graduation committee. Josephine, thank you for entrusting this project to a non-medical student. Your willingness to answer every medical question, connect me with stakeholders at the hospitals, and provide detailed feedback on every single draft throughout these past months was invaluable. Saba, I am grateful for your overall guidance, helping me structure my thoughts and writing especially towards the end. Alexander, your feedback was instrumental in refining this work and pointing me in new directions and perspectives. Yilin, thank you for lending an ear to all things related to data analysis and for your essential feedback on the argumentation and technical aspects of the implementation.

I am also deeply appreciative of the interview partners and experts who provided valuable insights and real-life context to this work. My gratitude also extends to my office at Erasmus MC, where I found not only an entertaining work environment but also help with every Dutch or medical question that arose.

A heartfelt thank you goes to Model United Nations and its community, as without them, I might never have ventured into the field of policy analysis. I would also like to thank the mymun team for being an incredibly fun and supportive group to work and travel with, and for consistently pushing the limits of what we achieve together. Additionally, I want to thank my friends, whether from Dresden, Karlsruhe, Den Haag, or beyond— as they have shaped who I am today.

Lastly but most importantly, I thank my parents and family for the unconditional support and most honest feedback along each step. The trust and confidence you have placed in me are something I will cherish forever.

Enjoy reading!

Den Haag, August 2024

Table of Contents

1 Introduction

Healthcare systems worldwide face pressure due to resource constraints and increasing demand and costs (OECD, 2023). Hence, there is an urgent need for innovative solutions across all parts of the system to ensure quality and accessibility. Among the most critical areas in healthcare is neonatal care, as neonates, infants up to 28 days, are some of the most vulnerable in our society and need high-quality care to minimize the increasing risk of long-term health complications (Patel, 2016; Valeri et al., 2015). In 2021, 2.3 million children worldwide died in the first month of their lives, constituting almost half of all under-five-year-old deaths (UNICEF, 2023). While most of these deaths happen in the global south, neonates are also disproportionally at risk in countries in the global north like the Netherlands. Moreover, Although the infant mortality rate is low in the Netherlands, it is relatively higher than in neighboring countries and has stagnated in recent years (College Perinatale Zorg, 2020).

One of the main challenges for neonatal care in the Netherlands are operational bed capacity shortages driven by staffing shortages. For instance, 36% of hospitals in the southwest region of the Netherlands have been forced to close beds due to staffing limitations (Traumacentrum Zuidwest-Nederland, 2023). Given the ongoing capacity constraints, there is the risk of further deterioration in quality and availability of care as capacity strains have been linked with decreasing quality of care and outcomes (Eriksson et al., 2017). Moreover, the emotionally challenging nature of NICU nursing, such as the distress of caring for critically ill newborns and dealing with the grief of families during difficult outcomes, leads to further staff shortages (Braithwaite, 2008; Fiske, 2018). The situation is further exacerbated as given the current situation an increasing number of novice nurses leaving the profession early in their careers (Kox et al., 2020). Establishing a sustainable staffing level requires long-term planning and substantial investment and, hence, is not a realistic option to tackle the current capacity shortages. Thus, interventions outside of staffing that have a direct impact on the ongoing crisis need to be investigated. To do so, one first needs to understand how the neonatal care system works.

1.1 Neonatal Care in the Netherlands

Neonatal care is a subfield of healthcare delivery that has experienced growing attention and investment in the past decades. A neonate is an infant up to the age of 28 days, and neonatal care includes all services provided during this time. A neonate can be admitted due to their gestational age, birth weight, or special need for medical assistance (NVOG, 2007).

Neonatal care organizations can differ across countries based on admission criteria and the level of specialized care provided at each respective level (British Association Of Perinatal Medicine, 2010; Committee on Fetus and Newborn, 2004). In 1975, a regionalized system including defining levels of specialization for hospitals was first introduced in the United States (Ryan, 1975). In the subsequent years and decades, the approach of specialization was adopted in a similar manner across high-income countries, although differences in the specifications for levels of neonatal care remain.

In the Netherlands, neonatal care is categorized into three escalating levels of specialization and intensity: neonatal medium care wards, neonatal high care wards, and NICUs (Planningsbesluit Bijzondere Perinatologische Zorg, 2018). NICUs manage the most critical cases, often involving newborns who are extremely premature and require constant monitoring and assistance with vital functions like breathing and cardiovascular support. High care wards typically cater to infants who, although stable, still need significant medical attention, such as incubation or intravenous therapy due to fragile health. Medium care wards, in contrast, handle cases that are less severe; these infants may need help with feeding or medications post-birth but do not require intensive monitoring. The distribution of specialized neonatal care wards across different hospitals, each offering varying levels of care, necessitates patient transfers to ensure that newborns receive treatment appropriate to their specific medical needs. These transfers introduce additional stress and complexity to the patient's journey (Stark et al., 2023).

Despite the structured approach, the neonatal care system in the Netherlands faces several challenges. As an outcome of capacity shortages, some mothers and neonates have to be transferred between hospitals and regions, raising the risk of long-term adverse effects on the newborn and emotional stress for their families (Gill, 2004). Additionally, neonatal staff planning is complicated "because NICU babies have dynamic medical and surgical needs from admission to discharge" (Feldman & Rohan, 2022). Given these circumstances, there is a knowledge gap in ways to reduce capacity shortages given the existing staffing resource constraints (Hussain et al., 2012).

Current literature on interventions in neonatal care can be categorized into three main areas: technological, hospital management, and clinical interventions. Each of these categories includes various efforts aimed at enhancing patient outcomes and improving cost-effectiveness, as further detailed in chapter 3.1. However, there are still gaps in the literature regarding the inclusion of the impact on capacity shortages when evaluating these interventions. This suggests a need for more comprehensive assessments that consider how interventions affect not only patient care but also the availability of critical resources within neonatal care systems.

This study was focused on the neonatal care region in the southwest of the Netherlands, organized around the Erasmus MC University Hospital in Rotterdam. This network comprises ten hospitals, each offering different levels of care to comprehensively serve the region's needs. The structure includes one NICU, four high care wards, and four medium care wards, ensuring a full spectrum of neonatal services. In theory, each neonatal region is designed to be self-sustaining, with hospitals complementing each other's functions. However, practical scenarios often differ. Hospitals located near other regions sometimes admit patients from those areas if the ZIP code is closer to that hospital. Additionally, the region not only receives neonates from neighboring areas but also occasionally must send them to other regions or even neighboring countries like Belgium to the south. This interdependency indicates that the neonatal care system in one region is influenced by and connected with surrounding systems and requires sophisticated tools for analysis – like as modeling and simulation.

1.2 Modeling and Simulation in Neonatal Care

Modeling and Simulation describes the process of creating a representation of a real-world system and then conduct experiments using computational tools to find out about the system's behavior across various scenarios (Birta & Arbez, 2019). This approach is grounded in systems thinking, a methodology that emphasizes the interconnectedness and interdependencies within a system to gain insights into its overall behavior (Arnold & Wade, 2015). The primary goal of modeling and simulation is to simplify and abstract actual processes and entities to enhance understanding of a real-world system.

On the one hand, simulations provide multiple advantages to decision-makers and research as they can replace a real-world experiment. It provides a cost-efficient way of trying out potential interventions as well as test scenarios that might be too difficult, irreversible, or morally unacceptable to simulate in the real world. For instance, in a healthcare context, simulating the effects of a sudden reduction in staff levels or a rapid increase in patient influx can be extremely challenging to implement without causing disruption or harm. Similarly, experimenting with withholding treatment from a control group to study outcomes would be ethically unacceptable. Moreover, the simulation team has full control over the system and can zoom in on specific subprocesses and input variables to identify the interactions and impact. Simulation models are often also used as a communication tool through animations and the analysis of key performance indicators and the intuitiveness of the approach (Birta & Arbez, 2019; Robinson, 2014).

On the other hand, modeling and simulation might not always be the most suitable choice given its potential disadvantages. The approach is computer resource and time consuming and requires accurate and representative data. Due to the own bias of the project team, the model will always represent a specific angle on a given problem. Thus, it is essential to fully understand the model scope, granularity and goal to evaluate if a model is fit-for-purpose (Birta & Arbez, 2019).

Given its advantages and disadvantages, modeling and simulation has been well established across diverse fields and is seeing rising popularity. Its applications span from supply chain management to military strategy and manufacturing, serving functions such as forecasting, policy evaluation, and risk assessment (Birta & Arbez, 2019). The broad adoption of modeling and simulation underscores its value in providing insights and highlights its potential benefits for enhancing healthcare systems.

Considering these complexities of the neonatal care system, simulation modeling approaches provide a promising chance to gain new insights and evaluate interventions (Cassidy et al., 2019). Simulation techniques are suitable and needed as they can overcome the challenges of variability, uncertainty, and complexity in the described system (Lowery et al., 1994). The neonatal care system is a conglomerate of multiple hospitals and multiple departments inside a hospital, leading to challenges in communication and coordination. Moreover, the individual characteristics of each newborn are primed by uncertainty, highlighting the need for stochastic decision-making through simulation (Pomare et al., 2019). Modeling and simulation techniques have been well-established in healthcare and have improved various fields (Savigny et al., 2017). Furthermore, simulation models serve not only as a direct tool for decision-making but also as a communication tool and enable more stakeholders to become an active part of the discussion and decision process and offer tools to answer *what if* questions that cannot easily be tested in practice (Curry et al., 2006; Robinson, 2014). Hence, it is evident that a systems approach through a simulation model suits the described practice problem.

One of the most common simulation techniques in healthcare is discrete event simulation (DES). Healthcare simulation research using DES often has an objective related to scheduling and patient flow or sizing and planning of beds, rooms, and staffing using stochastic methods for the simulation (Jun et al., 1999; Mielczarek, 2016). DES is suitable as patients follow pathways through the neonatal care system, making it a suitable choice for the described system and problem.

Despite the critical need for modeling and simulation studies on neonatal care systems and their capacity issues, such studies are quite rare, as discussed in chapter 3.2. Previous research focused on modeling and optimizing individual parts of the neonatal care pathway (Fournier & Zaric, 2013). Moreover, studies tend to focus either on human or non-human resources in the system, but not both, and do not investigate interaction effects (Lebcir & Atun, 2021). Therefore, there is a shortcoming in addressing the system holistically (Komashie et al., 2021).

1.3 Research Question

Given the current stand in literature, I concluded on the following knowledge gap. There is a limited number of research in simulation modeling specifically for neonatal care systems, raising questions of applicability and generalizability of previous findings, especially as none of the work has been done in a Dutch setting. Moreover, existing simulation models are not used to test interventions for capacity impact and, thus, miss out on linking the model world with the real world. At the same time the medical community is missing out on performing capacity impact assessments for novel interventions in neonatal care which would provide another valuable perspective in medical decision-making processes. As a result, this work investigated the following main research question:

How can operational bed capacity shortages in neonatal care be reduced within staffing limitations?

This thesis aimed to contribute by providing a modeling approach for neonatal care systems and further enhance the understanding of its dynamics and interactions. The thesis used state-of-the-art simulation modeling to answer the evident societal challenge present in the case study of the neonatal care network in the southwest of the Netherlands.

1.4 Thesis Outline

The overall mixed-method research approach is described in Chapter 3. Chapter 4 provides the academic context of the study through two literature reviews that further highlight the knowledge gap and identify first ideas for system levers and interventions. Chapter 4 outlines the system conceptualization that guided the data analysis and model implementation. Chapter 5 elaborates on the performed data analysis of the available perinatal birth registry data, detailing the relevant mechanisms and how they can be modeled. Chapter 6 discusses the model implementation and the verification and validation steps taken to confirm the model's fitness for purpose. Chapter 7 presents the experiments of scenarios, levers, and interventions, along with their results on capacity indicators. Chapter 8 offers a discussion of the study's results considering the theoretical background, provides practical insights for stakeholders, and addresses the limitations encountered during the research. Lastly, Chapter 9 concludes this thesis by summarizing the conclusions drawn from the research and providing an outlook for a possible future research agenda.

1.5 EPA Relevance

This thesis concludes my master's program in Engineering & Policy Analysis. Given the main objectives of the degree, the work combines quantitative aspects—data analysis of perinatal data in the region and a simulation model—with qualitative aspects, such as interviews with stakeholders and a review of the literature. Moreover, it contributes to the grand challenges of healthcare systems, as illustrated by UN Sustainable Development Goal 3 "Good Health and Well-being" (United Nations, 2015). By collaborating closely with the Erasmus MC and other stakeholders in the region, it supports bridging the gap between scientific and societal contributions.

2 Research Design

The overall research design utilized a mixed-method approach, combining quantitative and qualitative techniques aligned with the identified sub-questions. Initially, a literature review was performed to identify known interventions and system levers in neonatal care or simulation and modeling literature that could be promising in overcoming capacity shortages within staffing limitations. Afterwards, information was gathered to conceptualize the neonatal care system based on consultation with experts and a exploratory data analysis. Subsequently, available data from various hospitals in the dataset was analyzed in detail to parametrize the conceptual model and prepare its implementation. The implemented simulation model was used to perform experiments on different scenarios and test system levers for their impact on capacity shortages. Additionally, interviews with practitioners in the region, and the analyzed system levers were used to perform an impact assessment of relevant interventions for the region. Finally, all findings were discussed to provide an overarching answer to the main research question:

How can operational bed capacity shortages in neonatal care be reduced within staffing limitations?

The main question was answered by investigating three sub-questions, each focusing on a specific relevant aspect. These sub-questions also provide the general outline of the research, build upon each other, and represent a specific step in the modeling approach, as seen in Figure 1.

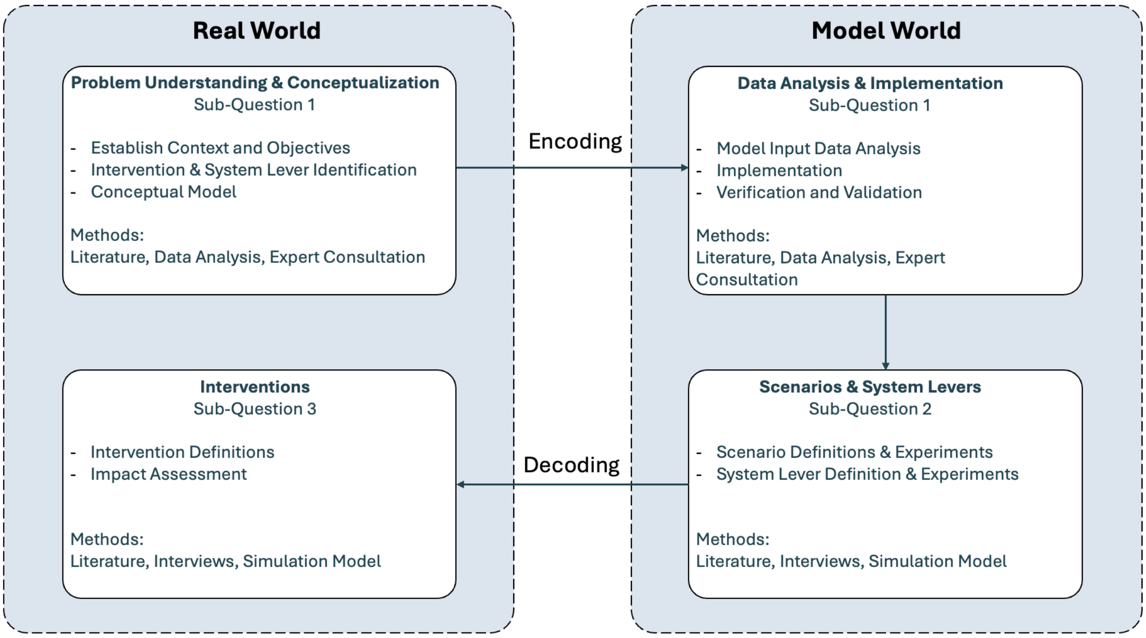


Figure 1 Overview of the research flow

Sub-Question 1: What factors and constraints influence the operational bed capacity shortages in the neonatal care pathway within staffing limitations?

As a first step, a system conceptualization was developed based on knowledge gained through literature and consultations with experts. This conceptualization is supported by an in-depth analysis of the perinatal birth registry dataset. The analysis was conducted using Python and statistical packages like *Pandas* and *NumPy* for data processing, and Seaborn and Matplotlib for visualization. Data cleaning procedures were carried out in the context of subquestion 1. The data was analyzed by categorizing it by hospitals and levels of care to explore the roles individual hospitals play in the network and identify potential bottleneck wards. Additionally, experts were consulted to provide context for the quantitative findings and to confirm assumptions and simplifications of the conceptual model.

Sub-Question 2: Which levers in the neonatal care system have the biggest impact on reducing operational bed capacity shortages within staffing limitations?

The goal of this step was to identify areas within the system that have room for improvement and determine the context in which interventions should be implemented. The selection of levers is based on the findings in literature and results from subquestion 1. All levers need to be in the decision arena of the hospitals or region. This involved implementing the DES model based on the previous conceptualization using *Salabim*, an open-source Python package. Key functionalities and components were verified, and the simulation results were validated against real-life data and expert insights. Each lever was simulated through numerous runs to obtain robust results that could inform policy formulation. By running experiments and analyzing the resulting data with Python packages like *Pandas*, *NumPy*, and *Seaborn*, I identified the levers with the greatest impact on operational bed capacity in the region and potential trade-offs associated with them.

Sub-Question 3: Which interventions in the neonatal care system can address the levers with the biggest impact on reducing operational bed capacity shortages within staffing limitations?

Finally, the goal was to provide recommendations for the most impactful interventions based on the model and further assessments to address the main research question. The interventions tested were derived from conducted interviews and supported by additional literature. A step-wise approach was used for testing: first, the intervention was defined, and the affected mechanisms and/or parameters in the model were identified. Then, the intervention was tested using the model to evaluate its impact on operational bed capacity in the region. Additionally, literature and interviews were used to assess the current implementation level and potential barriers to further implementation across the hospitals in the region. Based on these approaches, I concluded with recommendations for impactful interventions to be implemented at scale to answer the main research question.

These questions must be understood in the context of the research. An operational bed is defined as a physical bed combined with the appropriate personnel to make it functional, as physical limitations are currently not the primary driver of capacity shortages. All questions consider the staffing limitation, aiming to find solutions beyond merely increasing healthcare personnel, given the unlikelihood of a short-term staffing increase. Any proposed intervention must be feasible within the neonatal care system of a region, meaning it must be implementable by individual hospitals or a group of hospitals. Thus, it cannot involve restructuring of the neonatal care system on e.g. the national level.

2.1 The modeling approach: Discrete-Event Simulation

Despite a long history, the application of operations research and systems thinking within the healthcare sector has not kept pace with advancements in other fields. The healthcare system's inherent complexity demands robust modeling and simulation approaches to fully understand and address its multifaceted nature. However, there exists a significant implementation gap where theoretical models often fail to translate into practical applications. One of the critical challenges is the limited involvement of healthcare managers in the modeling and simulation process, which hampers the effective integration of these tools into decision-making practices.

Modeling and simulation has been firmly established across various healthcare domains, providing a valuable framework for analyzing systems characterized by high variability, interconnectedness, and complexity (Robinson, 2014). Healthcare systems, with their intricate interplay of components and wide array of stakeholders, are particularly well-suited for modeling and simulation. These systems are defined by significant uncertainty and interactivity, making traditional linear approaches insufficient for comprehensive analysis and improvement. Therefore, embracing modeling and simulation techniques can enhance our understanding and management of healthcare systems, ultimately leading to more effective and efficient healthcare delivery.

The role of modeling and simulation in healthcare has been well established in literature over the last centuries, especially in aspects such as resource allocation and staff planning (Katsaliaki & Mustafee, 2011). The most used modeling techniques include agent-based modeling (ABM), DES, and system dynamics (SD) (Mielczarek, 2016). All three approaches can be used for ‘what-if’ scenarios in order to investigate policy interventions and to understand the system and its behavior (Lane & Oliva, 1998). This feature becomes especially relevant when real-world experiments are impossible due to ethics, feasibility, or costs, as frequently encountered in healthcare (Stahl, 2008).

The three approaches differ in their scope and functionality. ABMs are useful to model emerging behavior and outcomes based on the interaction of individual agents (e.g., patients and nurses). Due to the stochasticity of ABM models, they are well-suited to model a variety of human behavior (Currie et al., 2020). SD models are mostly applied to model flows of multiple groups by including non-linear relationships between components and feedback loops (Davahli et al., 2020). The goal is to follow the flow of patient groups between various states to identify underlying interactions. Modelers use DES to track individual entities and their interactions with the system over time. Because the model simulates events at discrete points in time, it typically runs more efficiently compared to an ABM approach. Over the past 50 years, DES has become a popular simulation approach for healthcare system questions (Jacobson et al., 2013). DES is suitable for modeling the state change of entities (e.g., patients) with stochastic activities and resource constraints (Forbus & Berleant, 2022). However, it can still track individual patients and their journey through the modelled system and provide the modeler with a high level of flexibility in incorporating diverse events and components in the model.

For the modeling implementation, I chose to use a DES model for several reasons. DES models have been widely used in similar operations research settings and have seen a significant increase in healthcare applications. DES is particularly suitable because it can simulate individual patients while providing an overview of the entire system's performance. Compared to ABMs, DES is preferable in a neonatal care system where patients do not exhibit individual behaviors but follow defined pathways. Additionally, DES offers computational advantages, as only the time steps involving events need to be simulated, reducing the overall run time of a simulation. Further details on the technical implementation are provided in Chapter 5.

2.2 The perinatal Birth Registry: Perined

The main source for the simulation was the national perinatal registry dataset *perined*. The dataset brings together information from midwives, gynecologists, pediatricians, and NICUs across the Netherlands. The data is used by researchers and auditors to improve the quality of perinatal care (Perined, n.d.). The data access was gained through an approval process with Erasmus MC (Number: addendum to application 23.18). For this project, the dataset was filtered to include only the data points related to hospitals in the southwest of the Netherlands that utilize neonatal care. As a result, the dataset encompassed approximately 50,000 births from 2016 to 2022 across eleven hospitals.

Most parts of the implemented model rely on insights based on the perined dataset. Thus, the usefulness of the model highly depends on initial data quality and impacts the replicability of the simulation study (Marsden & Pingry, 2018). To ensure high data quality, I identified issues based on common dimensions: syntactic, semantic, and pragmatic. The syntactic dimension refers to the structure and format, including accuracy and consistency of the data. Various empty values were found in different columns, which I filled with default values for categorical variables. The semantic dimension focuses on the meaning of data, including semantic accuracy and completeness. Since the data is collected manually, it is prone to input errors. Examples include mismatches between admission and release dates that do not align with the length of stay, and multiple records of the same admission. The pragmatic dimension considers the context in which information is used. Since the data was not collected specifically for building a simulation model of the system, there are inherent pragmatic limitations. For instance, the smallest time unit is a day, leading to inconsistencies in when patients are admitted or released. Moreover, only the two most relevant admission criteria were recorded, even though a patient could have more conditions. Additionally, the admission criteria are not clearly defined, leading to individual interpretation by healthcare personnel. As these pragmatic data quality issues could not be addressed through data manipulation, they are addressed in modeling decisions and limitations. All other identified data quality issues were adjusted through python code and consultation with domain experts for validation of data manipulation as well as initial data quality issue identification.

2.3 Expert interviews

In addition to the quantitative analysis and literature reviews, I also conducted expert interviews. These interviews contributed to a deeper understanding of the system, confirmed assumptions made during the modeling process, and initiated the exploration of potential scenarios and interventions that could be simulated with the model. Table 1 shows an overview of the interview partners.

Table 1 Overview of interview partners

Interview ID	Profession of Interviewee	Experience in neonatal care system in years	Hospital Ward Level
1	Neonatologist	> 25	NICU
2	Neonatologist	> 25	NICU
3	Neonatologist	5-10	High Care

The research was approved by the TU Delft Human Research Ethics Committee, as seen in Appendix A. The interviews were conducted either in person or online via MS Teams. With the consent of the interviewees, the interviews were recorded and transcribed using MS Teams. The transcripts were then summarized, and the original recordings and full transcripts were deleted. All data was stored exclusively on TU Delft storage. The interviews were conducted in an open format to adapt to the individual background of each interviewee and allow room for new ideas (Myers, 2013). Based on the recordings and full transcripts, I identified key statements through open coding, which involved systematically breaking down the data into distinct segments, labeling each with descriptive codes, and grouping similar codes together to reveal underlying themes (Strauss & Corbin, 1998). Based on these results, I drafted a summary for each interview, which can be found in Appendix B.

2.4 Reflection on use of AI tools

During the process of this thesis, multiple software tools that use some forms of artificial intelligence were applied. In the writing process, the text was checked with *Grammarly* for grammatical errors and to consider improvements in text flow, such as by converting passive to active sentences. Each suggestion by the software was individually evaluated and accepted or rejected to ensure that the meaning of the text and use of specific words did not get lost.

The interviews were initially transcribed with the transcription feature of *MS Teams*. While this feature provided a good first draft for the transcript; each interview had to be relistened to multiple times to correct transcriptions faults. The software struggled especially with transcribing terms specific to neonatal care or medicine, like NICU or jaundice, as they were often transcribed to the names Nico and Jonas. Moreover, the software was not able to identify how interviewees stressed individual words providing additional meaning to the statements.

For the coding of the model and data analysis, *ChatGPT* was used to discuss ideas for analysis or software architecture and provide initial ideas for the code implementation. For each code snippet, the software was asked to provide explanation on why decisions on parts of each algorithm were done. Moreover, the tool was used to check own code snippets for readability and potential improvements to ensure best practices.

2.5 Limitations

The proposed research design comes with some limitations in various aspects. The limitations can be categorized by data collection and analysis, modeling and simulation, and interpretation of results.

The biggest limitation of this work is already based in the research question and its scope outside of staffing. As motivated the largest constraint to the current capacity shortages are staffing limitations, however, there is no clear path to a change in the near future. Hence, this work focused on identifying other means to tackle capacity shortages. In addition, the study relied on a data-driven approach, making it dependent on the quality and quantity of available data. To address this, a sophisticated data analysis and cleaning process was implemented and expert consultations to ensure a high model-reality fit. Moreover, conducting interviews introduced limitations, as both interviewer and interviewee may be biased by their backgrounds. To mitigate this, I conducted open-format interviews and analyzed the interview data within the context of the interviewee's background. Second, any model represents only a perspective of reality and cannot capture all interactions and complexities. The modeling process involved a trade-off between accuracy and understandability. While the chosen simulation technique, DES, offered various benefits, it also had shortcomings due to its stochastic nature, high data quantity requirements, and potentially long run times. Third, ensuring transparency and comprehension for non-modelers was essential to provide actionable policy recommendations for practitioners. Throughout the research process, maintaining a connection to the practical problem was crucial, as losing this connection is often a barrier to successfully implementing simulation techniques in healthcare(Lowery et al., 1994). By conducting interviews and maintaining frequent exchanges with a practitioner at Erasmus MC a shared understanding and collaborative decision-making in the modeling process were ensured.

3 Literature Review

This research is located at the intersection between a specific healthcare domain — neonatal care — and a methodological approach —modeling and simulation. To gain additional information on the neonatal care system and the status quo of literature on interventions and system levers tackling capacity shortages, two literature reviews were performed. First, the results of a literature review on current developments in neonatal care interventions are presented to identify interventions and levers that the medical community is focusing on. The second section of this chapter elaborates on insights gained from modeling and simulation literature for this study. A scoping literature on simulation modeling in neonatal care was performed to assess previous work in healthcare systems to identify system levers that have been used in similar healthcare contexts to address capacity shortages.

3.1 Current Developments in Neonatal Care

The previous sections have shown the current challenges for neonatal care systems in general and for the specific Dutch case. Therefore, it was of interest to scope the literature for current developments in neonatal care to identify possible interventions that could have an impact on factors relating to capacity shortages and further draw the medical perspective on the current situation.

Given the setting of the case study in a neonatal region in the Netherlands, only interventions that are inside of the decision arena of a hospital or hospital network were considered. I identified technological developments, healthcare workforce, and hospital management as three core topics inside of the applicable decision arena. These topics have also been confirmed through consultation with experts at Erasmus MC and literature (Dickson et al., 2014; Kringos et al., 2010). As a result, the search string included the following terms:

(technolog OR digital* OR guideline OR protocol OR “nurse staffing” OR “staff scheduling”) AND (capacity OR cost OR bed* OR constrain* OR "resource utilization" OR “length of stay” OR admission*) AND ("neonatal care" OR "NICU" OR "neonatal intensive care unit")*

The search was performed on the relevant databases PubMed and Web of Science to cover a wider range of journals. Only articles in English were included and all articles must have been published within the last ten years to ensure that the findings are still relevant to the current situation. The term ‘intervention’ was not used on purpose as it leads to an unmanageable number of papers losing the scoping characteristic of this review. Moreover, I filtered only for neonatal care interventions to ensure a high applicability to the simulation model and due to more prevalent medical conditions in neonates, such as jaundice. The paper selection was done using AS Review Lab to facilitate and accelerate the review process (Van De Schoot et al., 2021).

The search resulted in a sufficient number of interventions and rather also fields of interventions that could be of interest to test for impact on capacity. Moreover, it provided a current stand on the medical perspective on neonatal care. The findings are divided into three major groups: technological, organizational, and clinical interventions. The following sections presents these groups and the aspects of the system that the interventions are trying to improve.

1. Technological Interventions

The field of technology in neonatal care has seen a strong rise in relevance and development in recent years with a focus on increasing the chance of survival or minimizing the length of stay (Taha et al., 2023).

First, there is a rise in monitoring applications, including bedside, that give medical personnel more detailed insights into the medical indicators and enable them to adjust the care program to the individual patient. These monitors include for example pulse oximetry, respiratory function, and near infrared spectroscopy (Taha et al., 2023). These advances are accelerated by current developments in sensing technologies (Variane et al., 2022) and thermal imaging (Topalidou et al., 2019)

Another relevant technological subtopic is the field of telemedicine. Following the promise of providing care at home or less specialized facilities, telemedicine provides opportunities to increase cost-effectiveness and potentially lower capacity burdens (Rasmussen et al., 2020). This becomes especially relevant in a post-IC setting as first studies have shown that an effective use of e.g. video calls, can decrease the amount of additional hospital admissions (Robinson et al., 2016). Additionally, telemedicine application could reduce the need for transport to a NICU after birth and, thus, distribute the bed demand more equally across the different care levels (Sauers-Ford et al., 2019). Overall, these tools are also seen as a way of empowering parents in the care process (Guttmann et al., 2020; Minton et al., 2014; Ranu et al., 2021). Yet, literature also acknowledges the need for additional studies on the impact of telemedicine on clinical outcomes and cost-effectiveness (Sauers-Ford et al., 2019; Tan & Lai, 2012).

In a similar manner, research has focused on finding interventions that can also be performed at home. One of the most prominent examples is phototherapy for jaundice, a common condition in neonates (Pettersson et al., 2021). In this case, parents administer the treatment at home, which leads to a reduction in the number of hospital beds needed. The first implementation trials of this intervention are currently underway in the Netherlands (Westenberg et al., 2022).

2. Hospital Management Interventions

On the level of hospital management, we see an increased exchange of best practices and guidelines to standardize care and ensure quality of care and patient safety. Guidelines are developed for specific medical conditions, like hypothermia (Frazer et al., 2022; Liu et al., 2022; Manani et al., 2013; McCall et al., 2018; Wilson et al., 2018), neurocare monitoring (Bonifacio & Van Meurs, 2019; Variane et al., 2022) or on discharge policies (Quinn et al., 2017).

These guidelines are also driven by an increased usage of available data to make data-informed decisions and recommendations. One essential part of this movement is the development of prediction models. Models aim at predicting length of stay for patients (Singh et al., 2021) or try to determine if a specific level of care, e.g. NICU, is necessary to provide additional information for hospital planners (Shields et al., 2023; Singh et al., 2021)

An increase in data quantity and quality collected over hospitals and time periods also offers new opportunities in data-driven decision making. For instance, prediction models can be used to estimate ward level assignment or length of stay prior birth (Shields et al., 2023). In addition, models can be used to prevent medication errors (Beltempo et al., 2023; Yalçın et al., 2023), identify medical conditions, like sepsis (Gievers et al., 2018; Sullivan et al., 2023), and thus, potentially increase clinical outcomes (McAdams et al., 2022).

In addition, O'Callaghan et al. (2019) searched for current developments in neonatal room design and found that a 'single family room' is the recommend design for neonatal units. This room design showed the highest potential for reduced length of stay and increased infection control. Moreover, adapted room designs also contribute to a more patient focus care idea. One part of this could also be an increased inclusion of parents in family centered care (Segers et al., 2019).

3. Clinical Interventions

As a third theme, I identified multiple clinical interventions that often combine aspects of a technological and organizational intervention. These interventions focus on reducing length of stay by enhancing clinical outcomes. Examples include switching from intravenous to oral antibiotics which also opens up opportunities to include parents at home in the provision of medicine (Keij et al., 2022). Another intervention that aims at transferring patients sooner to home is tube feeding at home(Jie Liu et al., 2015). Here, patients with problems with food intake are fed through a tube but due to the simple set-up it is also possible for parents to take over and have the patient discharged at an earlier stage. In addition, current studies address the impact of thermoregulation (Dixon et al., 2021; Donnellan et al., 2020) and medication errors (Nguyen et al., 2018) on clinical outcomes and LoS.

The three groups of interventions show the variety of current developments in neonatal care interventions at a hospital's scope. Interventions focus on system levers such as the necessity for admission at a level of care, moving care to the patient's home, or lowering the LoS through tackling various underlying drivers. Across the different themes most interventions aim at improving clinical outcomes or be more cost-effective than traditional treatments. Yet, most literature has not assessed the impact of an intervention on capacity related aspects of a hospital. Thus, there is a gap to evaluate the impact of interventions on a hospital's capacity, for instance via modeling and simulation of healthcare systems and respective interventions.

3.2 Modeling and Simulation in Healthcare

A scoping literature review was conducted to understand the current research state better and further narrow the knowledge gap. The goal was to understand neonatal care and the current challenges and open questions in healthcare system modeling in this field. As this research is based in healthcare, the focus was on the two most relevant databases in the field, PubMed and Web of Science. Search categories were neonatal care and healthcare modeling, simulation, and capacity. The search initially included many non-relevant publications, as the term simulation is also used for simulations in educational training for health care professionals and modeling is also used in modeling diseases and the pharmacodynamics of medicines. Hence, articles in these categories were excluded. The combination of all the search terms leads to the following search string:

*("neonatal" OR "neonatal care" OR "neonatal care system" OR "newborn" OR "NICU" OR "neonatal ICU" OR "neonatal intensive care unit") AND ("model*ing" OR "simulation" OR "discrete-event simulation" OR "agent-based model" OR "system dynamics") AND ("capacity" OR "schedul*" OR "resource management") NOT ("education" OR "pharmacodynamics")*

Further constraints were that publications must be in English and published in peer-reviewed journals. This led to 389 articles on PubMed and 170 on Web of Science. By scanning titles and abstracts with the ASReview Lab software, 12 relevant articles were identified for further analysis. Pure optimization studies and studies focused solely on staffing were excluded.

Despite the wide applicability and use of modeling and simulation in various healthcare fields, there is scarce literature on modeling and simulation of neonatal care. The identified literature can be categorized by the used approach and the model's scope as shown Table 2.

Table 2 Overview of analyzed articles on modeling of neonatal care systems

Paper	Approach	Scope
(Lebcir & Atun, 2021)	System Dynamics	Length of stay and resource usage for one neonatal unit in the UK
(Lebcir & Atun, 2020)	System Dynamics	Length of stay for one neonatal unit in the UK
(Kokangul et al., 2017)	Mathematical Modeling (Regression + nonlinear optimization)	NICU nurse capacity for one hospital in the UK
(Kanai & Takagi, 2021)	Mathematical Modeling (Markov Chains)	Patient pathway and length of stay for one hospital in Japan
(Fournier & Zaric, 2013)	Discrete-Event Simulation	Amount of NICU beds and transfer probability for one province in Canada
(DeRienzo et al., 2017)	Discrete-Event Simulation	NICU nurse staffing for one hospital in the US
(Demir et al., 2014)	System Dynamics	Length of stay for one hospital with multiple neonatal wards in the UK

(Asaduzzaman & Chaussalet, 2008)	Mathematical Modeling (Loss Network Model)	Admission refusal probability for a neonatal care network in the UK
(Seaton, Barker, Draper, et al., 2016)	Mathematical Modelling (Cox multistate model)	Length of stay in neonatal care network in the UK
(Manktelow et al., 2010)	Mathematical Modelling (Regression Analysis)	Length of stay in 30 neonatal units in one region of the UK
(Adeyemi & Demir, 2020)	Mathematical Modeling (Linear Modeling)	Length of stay for one hospital with multiple neonatal wards in the UK
(Perera & Calis, 2022)	Mathematical Modelling (Regression Analysis)	Length of stay for one hospital with multiple neonatal wards in the UK

The methods used range from computational, like SD and DES, to mathematical, like queuing theory and regression analysis. Thus, previous research indicates the need for careful selection of the modeling technique based on the system characteristics, the goal of the modeler, and the available data. Moreover, Lebcir & Atun (2021) also touch on the aspect of using a model to facilitate communication with diverse stakeholders, hence, emphasizing the use and need of modeling and simulation beyond optimizing performance indicators.

Most models in the current literature focus only on specific parts, like NICUs (DeRienzo et al., 2017; Fournier & Zaric, 2013; Kokangul et al., 2017), and ignore the surrounding system. Only limited work assesses the complete pathway (Adeyemi & Demir, 2020; Demir et al., 2014; Lebcir & Atun, 2021). Nevertheless, these papers are still limited by modeling only one hospital unit instead of a hospital network, hence omitting valuable dynamics and interactions in the interactions, e.g., transport between hospitals. The authors also acknowledge the knowledge gap for a network-wide modeling approach and call for further work on this aspect (Adeyemi & Demir, 2020; Demir et al., 2014; Lebcir & Atun, 2021).

In addition, all identified literature looked at systems in the United Kingdom, Japan, and North America. However, as described in 2.2., the individual neonatal care systems are differently structured, and it needs to be assessed if the found results can be generalized and applied to the Dutch context. Furthermore, previous research aims to optimize individual parameters, like length of stay or transport probability. Yet, it is unclear if these factors alone are sufficient to explain the present capacity shortages.

The identified studies come with limitations regarding a focus on unidirectional patient flow so not accounting for the situation that a patient could be admitted to the same ward multiple times, hence, not capturing the full complexity of the neonatal care pathway. Moreover, length of stay is often sampled from theoretical distributions that do not account for patient subgroups or medical complexity.

The identified literature describes various ways of modeling neonatal care pathways and systems. However, it does not aim to use these models to test the impact of potential interventions. This is also acknowledged by Adeyemi and Demir (2020) stating that “it would be interesting to know the effects of resource allocation and management policies, change to admission policies, integration of services, and restructuring of neonatal delivery structures on the performance of these systems”. Here, we see a prime example of the inherent gap between simulation and implementation science. On the one hand, simulation studies frequently fail to apply developed models to provide assessments of real-life interventions. On the other hand, medical literature on interventions predominantly focuses on clinical outcomes and does not leverage the potential to assess impacts on a larger scale, such as the capacity of a healthcare system. Consequently, there is a significant need for an integrated approach that combines simulation modeling with practical implementation to evaluate the broader effects of healthcare interventions. Hence, this thesis tackles this gap by assessing system levers and interventions through a modeling and simulation approach on their effect on operational bed capacity in the neonatal care system.

The previous chapter has shown the current stand in literature concerning capacity modeling and simulation in neonatal care concluding that there has been only limited work in the field. While neonatal care systems have some distinct features, e.g. ward levels, kind of medical interventions, it also has similarities to other parts of the healthcare systems, like for instance, regionalization and bed management challenges. As a result, another scoping literature review was conducted to see what learnings can be drawn from modeling and simulation in other comparable healthcare systems. The goal of this search is to identify what system levers have been used in similar settings to later apply them in the simulation model and link them to neonatal care interventions or identify gaps in currently investigated interventions.

The focus was put on ICU settings as it is the closest to the general constraints of neonatal care – being no scheduling, no queue, and specialization across hospitals in a region. Exclusion criteria were added to filter out articles discussing any aspect of a queuing theory or elective medical interventions as those findings are not applicable to a neonatal care setting due to its unplanned and critical nature. Thus, the used search string is:

*("hospital" OR "critical care" OR "intensive care" OR "ICU" OR "intensive care unit") AND ("model*ing" OR "simulation" OR "discrete-event simulation" OR "agent-based model" OR "system dynamics") AND ("capacity" OR "schedul*" OR "resource management") NOT("education" OR "pharmacodynamics" OR "pharmacology" OR "elective" OR "queue*" OR "staffing")*

The search is performed on the relevant databases PubMed and Web of Science to cover a wider range of journals. Only articles in English are included. I used AS Review Lab to facilitate and accelerate the review process (Van De Schoot et al., 2021). Initially, PubMed provided 2575 and Web of Science 2012 results. After scanning for the title and abstract, 76 articles were further analyzed. By scanning the full text, I excluded additional articles that used some queue or scheduling mechanism in their model as this is not applicable to neonatal care.

Simulation models have been used across various healthcare system settings. Given the advantages of simulation models to ask 'what-if' questions, modelers can test out adjusting mechanisms in the model and identify levers in the system. In the following I present the most relevant used levers in literature. Multiple studies try to shift demand between hospitals or care levels. For instance, by applying early discharge strategies (Bai et al., 2018; Mohamed et al., 2017; Qin et al., 2017) or transferring patients to other departments when at running low on available beds (Garnier et al., 2016). Given that the neonatal care system is also assembled through different levels of hospitals, levers that shift demand between hospitals could be applicable. Shahani et al. (2008) tested the impact of alterations in LoS and separation of long stay patients and found that especially patients with a long LoS have disproportionally effect on the capacity shortages. These insights be also applicable to the neonatal care setting, as the LoS for extreme premature patients can easily be multiple months. Other literature focuses rather on the supply side and investigated the impact of increasing the number of beds (Bai et al., 2020; Franck et al., 2020; Gopakumar et al., 2009; Najibi et al., 2022; Shahani et al., 2008). While the literature finds this lever to be impactful, it is not feasible for the scope of this study given the described staffing limitations.

The simulation literature typically addresses capacity shortages in healthcare by focusing on supply or demand solutions. While not all approaches may apply to neonatal care, further exploration of mechanisms that influence admission rates, adjust patient pathways, change LoS, and target high-impact patient groups is warranted. Additionally, the literature emphasizes the importance of modeling healthcare systems by focusing on arrival rates, LoS, and patient pathways within the context of resource constraints, such as operational bed capacity.

4 System Conceptualization

In previous chapters, I have identified the overarching problem concerning capacity shortages in neonatal care and provided additional context for the case study in the south-west of the Netherlands. As the first step of this simulation study, I will develop a conceptual model that provides a deeper problem understanding by combining literature and data analysis, helps to identify scenarios and possible interventions, and guides the following implementation. One of the first and most essential steps of a simulation study is the creation of a conceptual model. There used to be only limited literature on this aspect as conceptual models are often seen more as a creative task – an art – then a science; yet in recent years, more attention has been drawn to the importance of conceptualization (Robinson, 2014). As shown in the research design, the conceptual model follows the initial problem understanding and is an essential preparatory step to develop the model design and, eventually the computer model.

4.1 Model description

To establish a conceptual model, one must define the model objectives, followed by the model content, input, and output. These aspects are supported by the system boundaries, assumptions and simplifications to provide a complete picture (Robinson, 2015). The goal of the model is to simulate the neonatal operational bed occupancy of hospitals in the south-west region of the Netherlands to assess the impact of scenarios and possible interventions. Moreover, another goal is to use the model to identify capacity bottlenecks and leverage points to provide insights into what kind of interventions could be most effective on a system level and on the three ward levels – NICU, high care, medium care.

The model content describes what to model and to what level of detail. To achieve this goal, the model needs to have an arrival process for patients born inside the region and for patients born outside the region. The model should also include hospitals with their ward level, region, and number of operational beds to account for the individual setting of the region. Each patient must be characterized by individual values (gestational age and birth weight), assigned admission criteria, a respective hospital ward level, and treatments used. Based on this information, the patient receives a LoS to reflect the medical complexity of individual patients and improve the accuracy of impact assessment of system levers and interventions tackling individual patient groups or treatments. There needs to be a process to admit patients to a hospital by considering the bed availability of hospitals, the ward level, and the patient's home location. If no bed is available in the region, the patient should be transferred to an outside region hospital. Moreover, it should be possible to readmit inside region patients at a different ward level for additional care. There is no queue for admissions, and a patient must be either admitted or transferred at a respective timestep.

The model consists of one region with respective hospitals. However, it is acknowledged that adjacent regions have transfers coming from and going to a general “outside” region. Moreover, the system is bounded by only including neonatal care. While obstetrics and pediatrics influence neonatal care, both parts of the care system are excluded due to the data availability. Multiple assumptions and simplifications support these boundaries. These requirements can be summarized in the conceptual visualization seen in Figure 2.

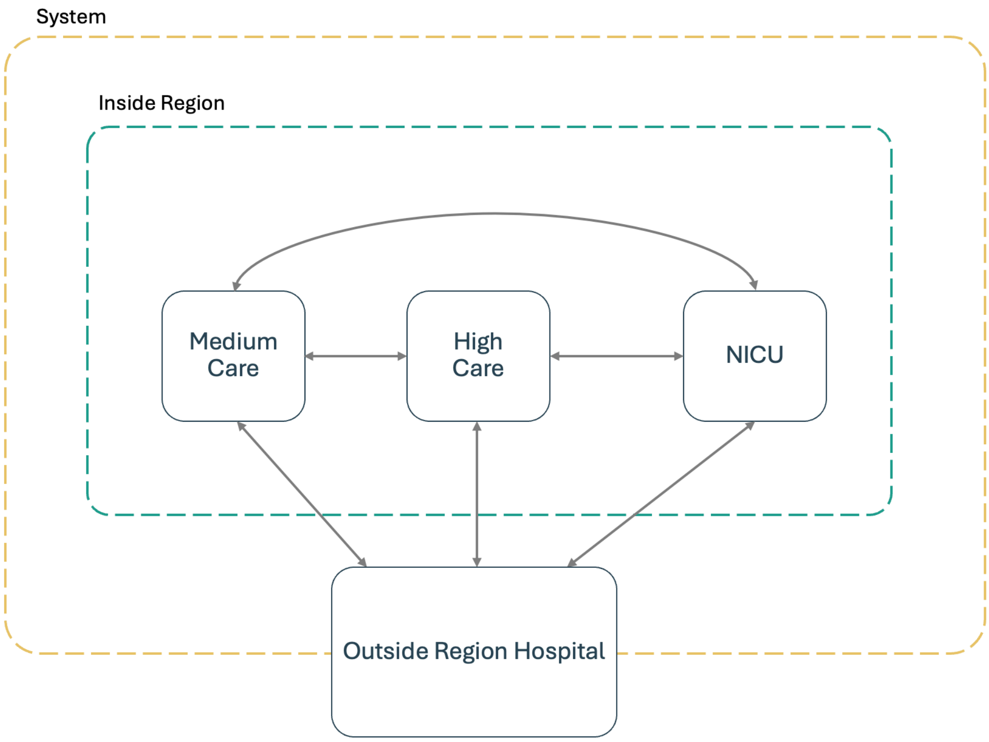


Figure 2 System Boundaries

Each box represents one ward level consisting of multiple hospitals. These hospitals are located inside the region. The arrows represent the potential pathways a patient can take over the period of their total admission. The system boundaries include the complete inside region and touch part of the outside region to incorporate transferring patients outside the region.

To achieve the objectives of the model, several inputs are necessary. Firstly, we need to define the arrival rates for patients from both the internal and external regions. Hospitals should be described in terms of their ward levels and the number of operational beds. Additionally, probabilities for extended stays and transitions between ward levels in the patient pathway must be specified. For an adequate calculation of the LoS, various distributions for relevant medical conditions and treatments must be defined.

4.2 Model Outcomes

To provide tangible answers to the model objectives four outcome measures were defined that can be grouped to two perspectives:

Hospital Management Perspective: This perspective is supported by a weekly moving average occupancy rate per ward level and the required operational bed count for inside region patients. The number of required beds is defined as the number of beds necessary if, in theory, the region only needs to provide care to inside region patients and all patients arrive at the optimal time. This serves as a minimum value for the actual operational bed number. This perspective provides insights into the impact across ward levels for the region and the resulting challenges for the hospitals.

Societal Perspective: This perspective examines the rate of capacity transfers at the ward level, as well as the average number of weekly transfers relative to different weekly occupancy rate groups. It highlights the effects of capacity shortages on patient populations and the broader societal costs associated with these shortages. Additionally, this analysis provides insights into the temporal dynamics of capacity shortages, clarifying that a region operating at full capacity does not necessarily trigger an immediate transfer. Instead, a transfer only occurs when a new patient arrives, and no available beds remain.

By examining both perspectives, the analysis aims to provide a comprehensive understanding of the effects of different scenarios, levers, and interventions on the neonatal care system. This dual approach helps identify practical solutions that balance the needs of hospital management with the societal implications of capacity constraints.

1. Required Beds

The first performance indicator of the system is the number of operational beds required to care for all patients within the region. This indicator is calculated by dividing the sum of the LoS of all patients from the region by 365. This calculation provides a theoretical lower bound on the number of hospital beds needed to adequately serve the regional patient population.

2. Weekly Occupancy Rate

The second indicator is the operational bed occupancy rate, which measures the ratio of used operational beds to available operational beds. This indicator helps in understanding how well the hospital balances sustaining spontaneous increases in admissions while maintaining financial stability. For ICU departments, including the NICU in the region, an optimal occupancy rate guideline is 80-85%. Hospitals need to balance sustaining spontaneous increases in admissions while also maintaining enough patients to ensure financial stability. This also aligns with typically used measures in literature for capacity in healthcare, e.g. as used in Harper et al. (2002).

3. Capacity Transfer Rate

The third indicator is the capacity transfer rate, which is the proportion of inside-region patients who must be transferred to outside-region hospitals due to a lack of available operational beds at the required ward level. This indicator is crucial as it highlights the strain on hospital resources and the potential negative impact on patient care due to transfers.

4. Weekly Capacity Transfers

The fourth indicator combines the concepts of capacity transfers with occupancy rates to provide a more holistic picture. Even though a ward might be at a 100% occupancy it does not automatically mean that there will be capacity transfers as it also requires incoming patients on this day. Thus, this indicator is calculated by summing the number of capacity transfers in the last seven days and linking it to the average occupancy rate of the last seven days for each day and ward level. The resulting information can be used to identify at what weekly occupancy rate the number of capacity transfers increases exponentially.

4.3 Assumptions and Simplifications

Assumptions are modeling decision made based on limited knowledge, while simplifications are decisions made with the goal of creating the simplest model that is fit for purpose (Robinson, 2015). The following assumptions and simplifications have been made:

Assumptions:

- The outside region has unlimited bed capacity and can always accept a patient, acknowledging that the healthcare system will always find a way to provide care even if this requires transport to another region or even country

- Hospitals of a same ward level can provide the same level of care, resulting in no difference in LoS for a hospital, as each hospital has neonatologist that are required to have regular training at the NICU and adhere to the same guidelines (Interview 2, Neonatologie Netwerk Nederland, n.d.)
- Additional stays are always first tried in the closest appropriate hospital to the home location to minimize additional stress and efforts for parents
- The dataset is representative for future patient populations and minimum and maximum values of variables will not change significantly in the next years (e.g. birth weight) (Interview 1,2)

Simplifications:

- A patient stays a minimum of one day in a hospital as this the smallest time unit in the *perined* dataset
- Outside region patients are assigned to a random hospital of appropriate ward level
- Outside region patients cannot have an additional stay inside the region and will be transferred to outside region, if necessary, because their region of origin is responsible to provide care for that patient
- Hospitals have only beds of their respective ward level and do not hold different bed types
- The model does not allow for overbeds, hence, if all beds are occupied any additional patient cannot be admitted to the respective hospital
- Patients can only be readmitted immediately after their first stay; hence, no additional stay possible if patient was dismissed to home at any point
- The number of operational beds does not fluctuate over the simulation period of one year as it was confirmed in personal conversation with a hospital planner that they plan the number of beds each year

4.4 Conceptual Model

For each patient, core characteristics such as birth weight, gestational age, subregion, and admission criteria are sampled to determine the appropriate ward level. Once the ward level is identified, patients are assessed for treatments and estimated LoS. For inside region patients, the system checks if an operational bed is available at the closest hospital with the appropriate ward level. If no bed is available, the adjacent regions of the patient’s home location are checked. If there are still no available beds, the patient is transferred to an outside region hospital. Patients generated from outside regions are admitted to any hospital with available capacity. After the stay of an inside region patient, the system evaluates if an additional stay is necessary, which would trigger the admission process again.

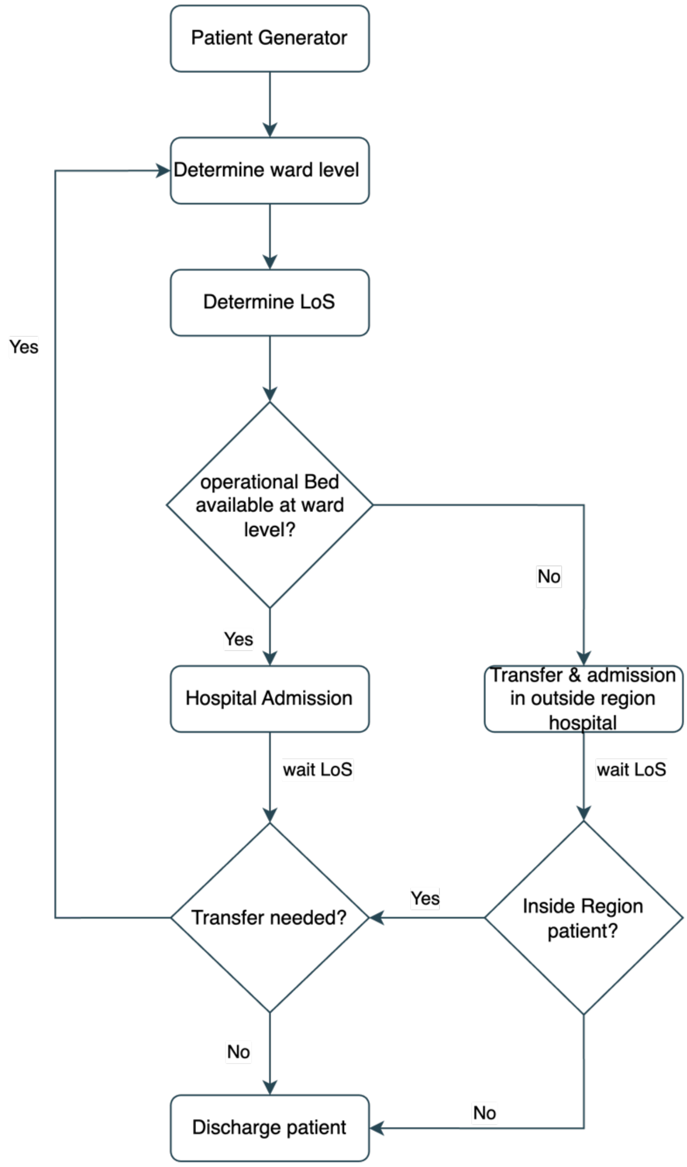


Figure 3 Conceptual Model of patient flow in the neonatal care system

A multi-step process decides the appropriate ward level for a patient. Suppose it is the first admission of the patient. In that case, the model checks the gestational age, birth weight, and congenital abnormalities to see if the patient matches the NICU criteria. If not, it is decided based on the empirical probabilities if the patient is admitted to a high-care or medium-care ward. If the patient requires an additional stay in the system, the following ward level depends on the previous ward level. Previous NICU patients requiring an additional stay are admitted to either high or medium care; all other combinations are decided through empirical probabilities.

After determining the appropriate ward level, the model checks for available operational beds. As highlighted in the data analysis, the objective is to place patients as close as possible to their home location. Therefore, the algorithm first identifies hospitals with the required ward level that are nearest to the patient’s subregion, acknowledging that not every subregion offers every ward level. For example, Zeeland lacks a high-care ward, and the only subregion with a NICU is Rotterdam Noordoever. If the closest hospital does not have an available operational bed, the model then checks the adjacent subregions in succession until it either finds an available bed or decides that the patient must be transferred to an outside region hospital. This ensures an efficient allocation of resources while prioritizing patient proximity to their home location.

5 Data Analysis

I identified various mechanisms and factors necessary to build a suitable simulation model for the neonatal care system in the system conceptualization. Most of these aspects need to be quantized to be implemented and to adjust the general understanding of the conceptualization to the individual setting of the southwest of the Netherlands region. This chapter will analyze the available dataset perined to provide insights into the factors and constraints of the neonatal care system and explain how individual parts of the model can be implemented and parametrized.

5.1 Model Mechanisms

The following chapter describes the functionality that the model offers to serve the model objectives. Based on the available datasets, decisions were made on how to model real-world procedures. Overall, three main processes need to be understood and modeled. First, the admission process for patients was analyzed. Second, the LoS for patients across wards for different medical conditions was modeled. Third, the patient care pathways of a neonate across different hospitals and ward levels were investigated.

5.1.1 Patient Arrival Times

Between 2016 and 2021, around 49,000 patients experienced over 54,000 neonatal admissions in the region. Given that the smallest time unit in the data is one day, the inter-arrival time between patients has limited value for the model. To ensure a comprehensive analysis, the focus was on the number of arrivals per day, aiming to identify a theoretical distribution to describe the patterns. These arrivals include neonates with a home location inside the region and those from outside the region admitted to hospitals within the region. This approach provides a robust understanding of the system's capacity to handle neonatal admissions.

Across the years, 46090 patients with a home location inside the region needed neonatal care. To smoothen outliers and find emerging patterns, I calculated the weekly moving average over the years seen in Figure 4. The weekly moving average is particularly useful in hospital arrival rates to capture consistent patterns and variations, which might be left out by daily or monthly data.

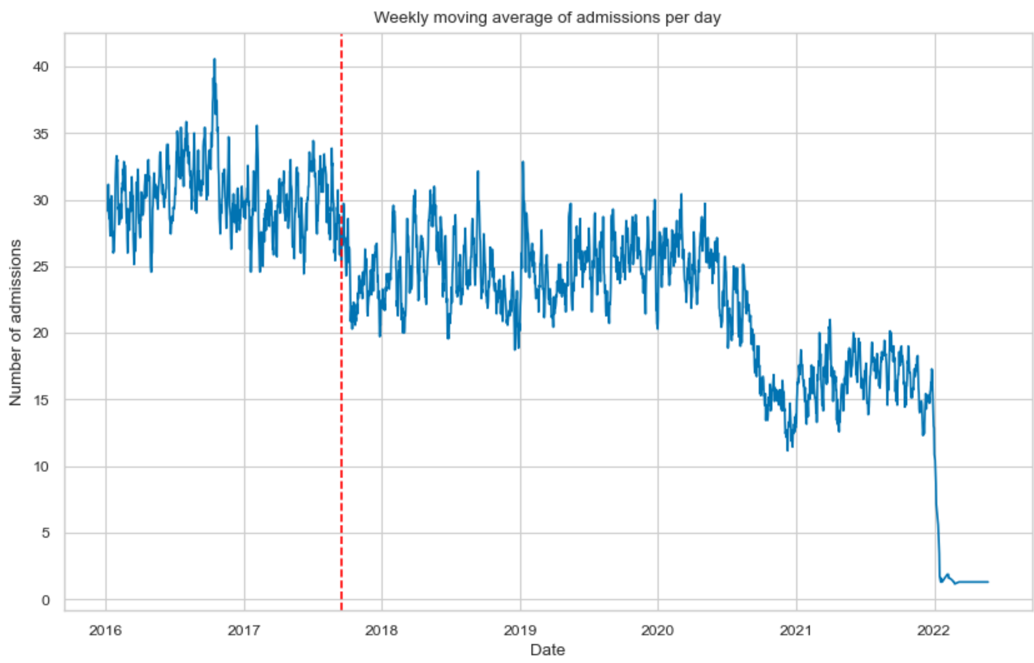


Figure 4 Weekly moving average of admissions per day across all hospitals

We see a consistently decreasing average of daily admissions over the years, indicating lower patient numbers. However, after discussions with practitioners and analysis at the hospital level, it was concluded that this trend is not due to an actual decrease in admissions but rather a decrease in reported admissions to *perined*, as described in 2.2. As a result, only the time range until 01-10-2017 (marked by the red vertical line) is representative and can be used to accurate identify the daily arrival rate as justified in the following two sections.

5.1.1.1 Justification for selected time range

The Erasmus MC (EMC) was the sole hospital mandated to submit all admission data across the entire time range. As the only NICU hospital in the area, the EMC handled all NICU admissions. Analysis showed that the mean daily NICU admissions (either at EMC or outside the region but with a home location inside the region) did not statistically differ across the years. Consequently, it was concluded that the data from 2016 to October 15, 2017, was representative and could be used to adequately model current patient arrivals. As there we no major demographic changes in the previous years, it is assumed that the selected time range was justified for use in modeling other wards and the entire patient population within the region.

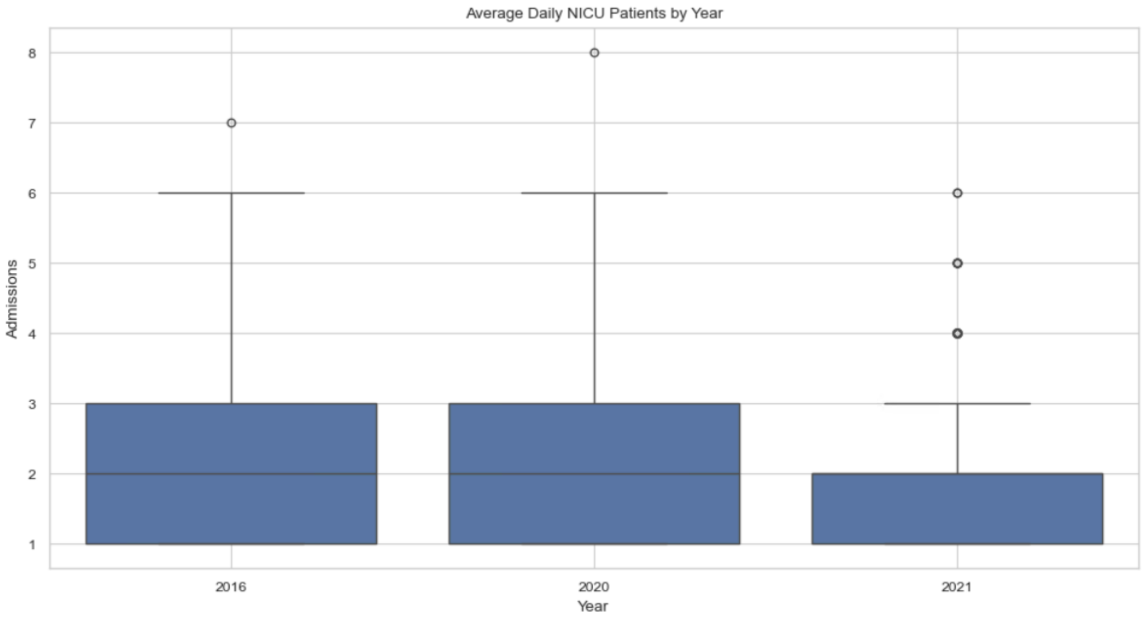


Figure 5 Comparison of average daily NICU patients between 2016, 2020, and 2021

Figure 5 shows that there were only minor differences in the average daily admission rates for the NICU between the first and the two last years. Moreover, minimum and maximum values are in the same range as seen in Table 3.

Table 3 Statistical overview of average daily NICU admissions for first and last two years of the dataset

Year	Mean
2016	2.06
2020	2.04
2021	1.95

Thus, it was assumed that the 2016 arrival rate is still representative of the current years. To confirm this assumption, a Kruskal-Wallis test was performed. The Kruskal-Wallis test is a non-parametric statistical test used to determine if there are significant differences between the medians of three or more independent groups. If the test indicates significant differences, it suggests that at least one group median is different from the others, but it does not specify which groups are different. The following hypotheses were used:

H_0: The daily NICU admissions in the region have the same distribution between the years.

H_1: The daily NICU admissions in the region have not the same distribution between the years.

The Kruskal-Wallis test resulted in a p-value of 0.67, leading to the conclusion that the null hypothesis cannot be rejected at a 5% confidence level. Hence, there is not enough evidence to reject the notion of the same mean of daily arrivals for NICU patients over the years. Based on this finding, it is justified to follow the same assumption for the full patient population and identify one distribution that describes the overall arrival process.

5.1.1.2 Theoretical Distribution of daily patient arrivals

As a second step, the goal was to find a theoretical distribution that could capture the daily arrivals for the region. To achieve this, the daily arrivals were visualized in a histogram, as shown in in Figure 6. Based on visual inspection, a bounded normal distribution appeared to be a good fit. This assumption was further confirmed using a QQ-plot and the Kolmogorov-Smirnov test.

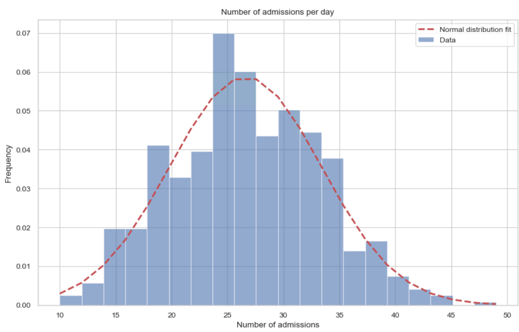


Figure 6 Relative frequency for daily patient arrival numbers for the region

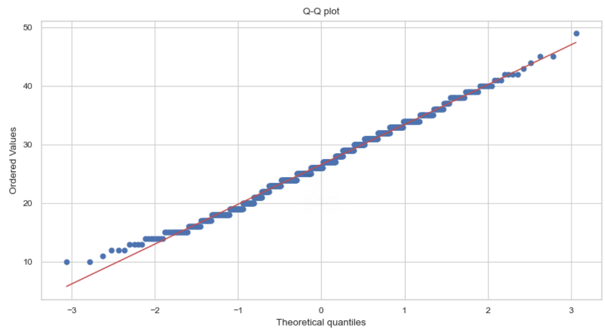


Figure 7 QQ-plot comparing normal distribution against the observed distribution of daily patient arrivals

In the QQ-Plot in Figure 7, we see a good fit of the observed daily arrivals against the bounded normal distribution with small deviations in the left tail.

To confirm the results of the visual inspection, a Kolmogorov-Smirnov (KS) test was performed to determine if there is enough statistical evidence against the assumption of a normally distributed arrival rate. The KS test compares the empirical distribution of the data with the cumulative distribution function of the reference distribution, in this case, the bounded normal distribution. The test used the following hypotheses:

H_0: The distribution of daily patient arrivals in the region follows a normal distribution.

H_1: The distribution of daily patient arrivals in the region does not follow a normal distribution.

With a p-value of 0.15, the null hypothesis cannot be rejected at a 5% confidence level, indicating there is not enough statistical evidence to reject the notion that the data follow a normal distribution. Therefore, a bounded normal distribution with a mean of 29.5 and a standard deviation of 7.5 will be assumed in the model. Since integer values are required, the sampled numbers will be rounded to the nearest integer. Additionally, the sampling will be bounded by a minimum of 10 and a maximum of 53 arrivals per day – the observed extreme values in the dataset.

5.1.1.3 Seasonality Checks for daily patient arrivals in the region

As a third step, the goal was to determine if there is seasonality in the arrivals. Hospital arrivals can exhibit various forms of seasonality, such as an increase in admissions during the winter flu season. Therefore, the investigation focused on whether there is seasonality in neonatal admissions in the region.

First, I analyzed seasonality based on the four seasons – winter, spring, summer, autumn. As seen in Figure 8, there are visually only small deviations between the respective seasons. For visualization, a letter-value plot – an advancement of a normal boxplot – is used as it is especially suitable for larger datasets (Hofmann et al., 2017). Each box in a letter-value plot represents a progressively smaller portion of the data, providing a more granular view of the data distribution. For instance, the inner-most box contains the middle 50% of the data.

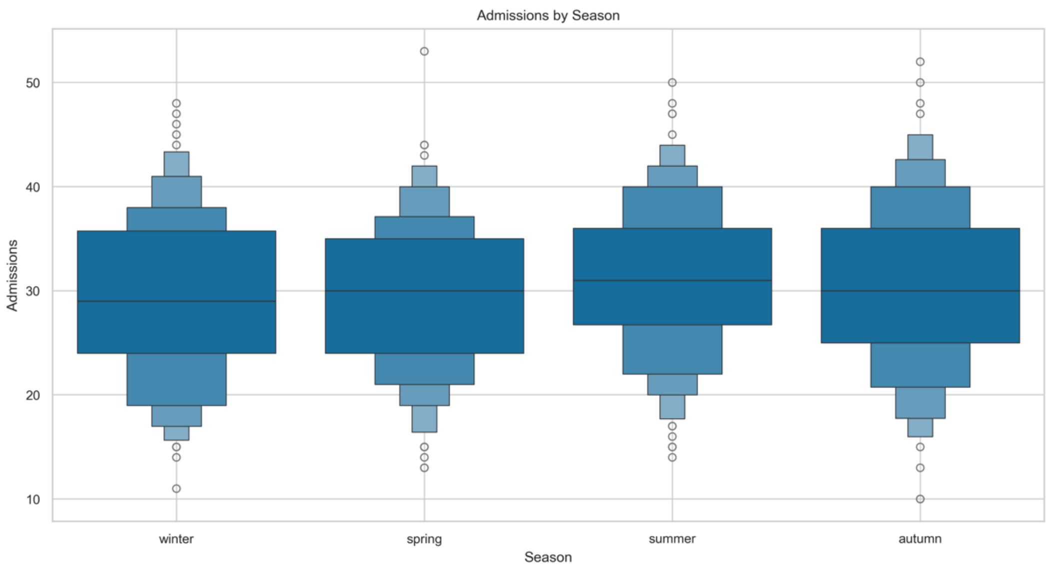


Figure 8 Comparison of average daily admissions across the yearly seasons

Each season hovers around the yearly mean and has similar extreme values. Summer tends to be a bit higher, prompting an investigation to determine if these differences are statistically significant. To confirm this assumption, a Kruskal-Wallis test was performed with the following hypotheses:

H_0: The median number of admissions is the same for all four seasons. H_1: At least one season has a median number of admissions that is significantly different from the others.

With a p-value of 0.13, the null hypothesis cannot be rejected at a 5% confidence level. Hence, there is not enough evidence to suggest significant seasonality in the daily arrivals for the neonatal care system. The lack of significant seasonality based on the seasons was also supported in a personal conversation with a hospital planner. However, it would be advisable to further confirm this by using a larger dataset or comparing it to other regions.

Additionally, I investigated if there is a monthly temporal seasonality. As seen in Figure 9, there is a slight increase in the summer months of July and August, while the lowest mean occurs in February. However, since all months fall within similar ranges, I conducted a test to determine if any of the differences are statistically significant.

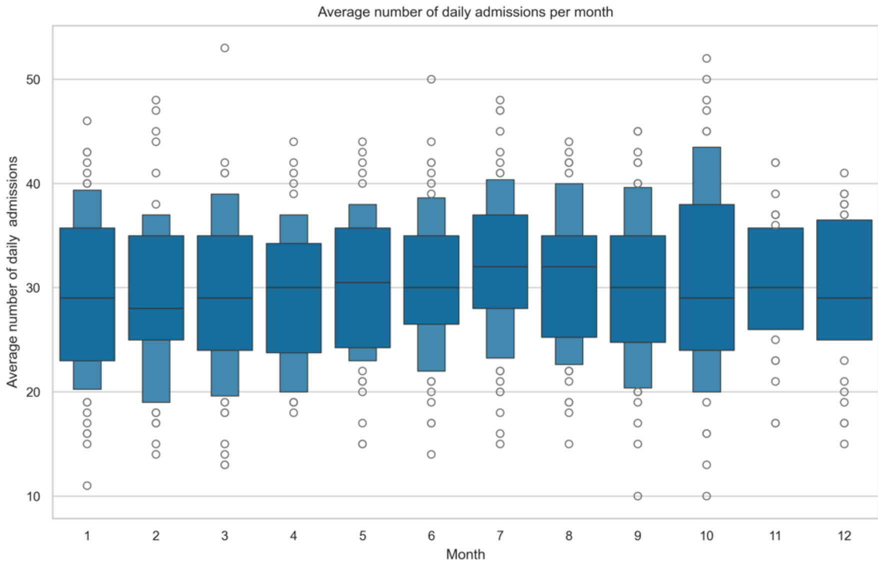


Figure 9 Average daily admissions by month

Thus, a Kruskal-Wallis test was performed on the twelve months with the following hypotheses:

H_0: The mean of daily admissions is the same for all twelve months. H_1: At least one month has a mean of daily admissions that is significantly different from the others.

With a p-value of 0.70, the null hypothesis cannot be rejected, indicating there is not enough statistical evidence to assume different means of daily admissions across the twelve months.

5.1.1.4 Conclusion for Patient Arrival Rate

This section showed that the arrival process is best described through the daily admissions across hospitals. The 2016 daily arrivals are statistically not different for the NICU compared to 2020 and 2021; hence, it can be assumed that they are still representative for today. The daily arrivals across the region can be described through a bounded normal distribution. No statistical evidence for temporal seasonality was found in the data; thus, the model will use a constant patient arrival process based on the identified distribution.

5.1.2 Length of Stay

Having analyzed the arrival rates, the second essential part of the system is the service time, represented by the LoS of patients in neonatal care. The LoS can depend on various factors given the complexity, individuality, and uncertainty of each patient. However, given the goal and scope of the model, multiple assumptions and hypotheses were necessary to determine what impacts the LoS. This is further facilitated by the fact that the time unit of the available data, and therefore the model, is a day, which increases the likelihood of aggregating factors that only differ in smaller time steps. Thus, the underlying processes were described with a regression analysis, providing a high level of interpretability while keeping the modeling parameterized.

The perined dataset provides a wide range of admission criteria and treatment variables that can be used to abstract the medical condition of the patient. Moreover, literature shows a clear link between gestational age and LoS, as well as other factors such as birth weight and sex (Seaton, Barker, Jenkins, et al., 2016). The three ward levels offer different types of care to various patient groups, resulting in different LoS patterns and influential factors, as seen in Figure 10. From here on, gestational age in the text will be used in the format weeks + days, such as 38+5, indicating 38 weeks and 5 days of gestation.

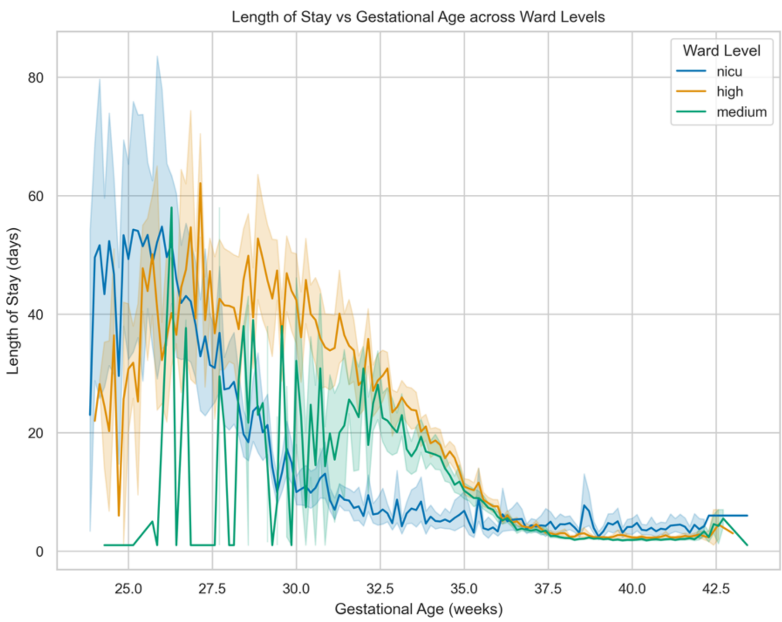


Figure 10 Length of stay per ward level across gestational age

We see that the LoS drastically increases with decreasing gestational age in a nonlinear fashion for all three ward levels. NICU patients have the longest average LoS while medium ward level patients the lowest. Moreover, across all wards the patterns change between 31+0 and 32+0 weeks of gestational age, the cut-off for mandatory NICU admission. Hence, I decided to split the dataset into the three ward levels and identify the influential factors beyond gestational age for each ward.

Table 4 Statistical comparison of LoS for each ward level

Ward	Count	Mean	Standard Deviation	Min	50%	Max
NICU	4243	12.50	20.00	1	5	175
High Care	21981	5.68	10.59	1	2	162
Medium Care	21129	3.2	5.1	1	2	68

Table 4 shows the wide range of LoS, from patients admitted for only one day to those staying for almost half a year due to their conditions. The selected dataset also includes patients who did not survive. For extreme preterm births around 25+0 weeks of gestation, the mortality rate increases to more than 50%. Consequently, there is a wide variance in LoS for this age group at the NICU.

The goal was to express the LoS for each ward through regression equations, as regression models are a common choice and provide advantages in terms of interpretability and adaptability. However, to ensure the model is not overfitted to the available dataset and thus only provides limited knowledge beyond it, precautions were necessary. Additionally, strong multicollinearity was found across various impactful factors, as seen in Figure 11. With multicollinearity, the estimated coefficients can become sensitive to small changes in the data leading to an increase in variance and, hence, unreliable predictions.

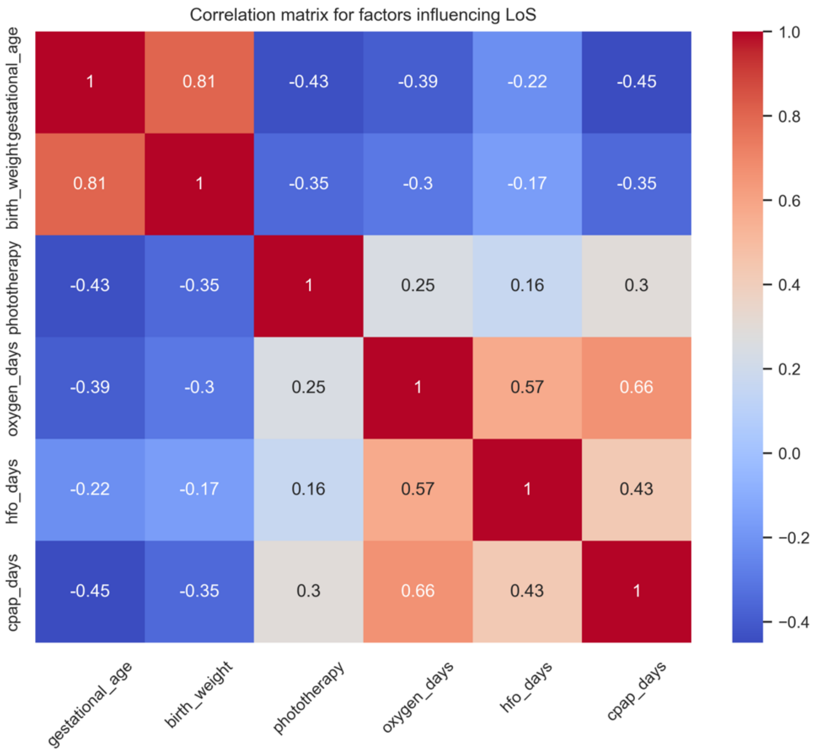


Figure 11 Correlation Matrix for selected factors that impact LoS

As a result, Ridge regression models were applied. Ridge regression aims to minimize the sum of squared residuals while adding a penalty proportional to the square of the magnitude of the coefficients. This approach helps in reducing the coefficients, controlling the complexity of the model without eliminating the variables entirely, thus preserving all variables in the model. The general formulation can be seen in Equation 1.

Equation 1 Ridge Regression for Length of Stay

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \epsilon_i$$

with:

$$\min_{\beta} \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right\}$$

By controlling for multicollinearity among the predictors, Ridge regression ensures that the model remains stable and interpretable, enhancing its predictive performance on new, unseen data. This way, the Ridge regression model not only captures the underlying patterns in the data more effectively but also provides robust predictions for new datasets (McDonald, 2009). The following present the developed regression models and conclusions for each ward level.

5.1.2.1 Length of Stay for NICU

The Perined dataset provides information on circa 4250 NICU admissions with a mean stay of 12.50 days.

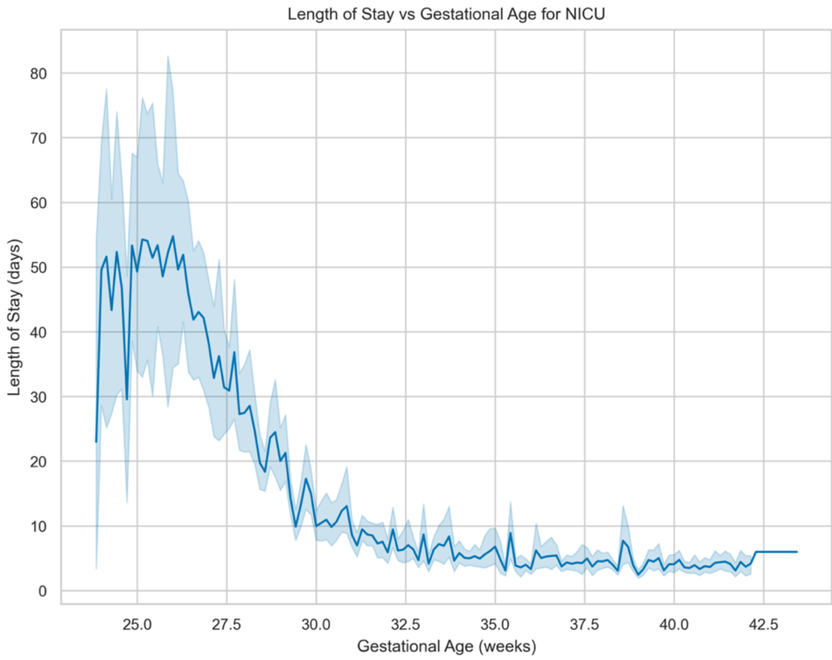


Figure 12 LoS for NICU patients across gestational age in weeks

As expected, the LoS drastically increases for extreme premature neonates below approximately 32+0 weeks of gestation. With decreasing gestational age, there is also an increase in LoS variance. Two factors likely contribute to this phenomenon. First, the number of observations decreases with decreasing gestational age, leading to more influence from individual admissions. Second, uncertainty and medical complexity, including higher mortality rates, increase for extremely premature newborns, resulting in various treatment options and different LoS. As a result, NICU LoS will be modeled separately for those below and including 32+0 weeks and those above 32+0 weeks of gestation.

As a first step, factors beyond gestational age that influence LoS for NICU neonates were identified. The correlation between various factors and LoS was analyzed for the two subgroups (below and including 32+0 weeks and above 32+0 weeks). These insights were then used to develop respective Ridge regression models.

5.1.2.1.1 Length of Stay for NICU below and including 32+0 weeks of gestation

For the extreme premature group, several factors show strong correlations with LoS, including O2 support, CPAP, anemia treatment, birth weight, and conventional or HFO ventilation. Additionally, thrombocytopenia treatment and phototherapy have a weak correlation with LoS and will also be included in the regression analysis.

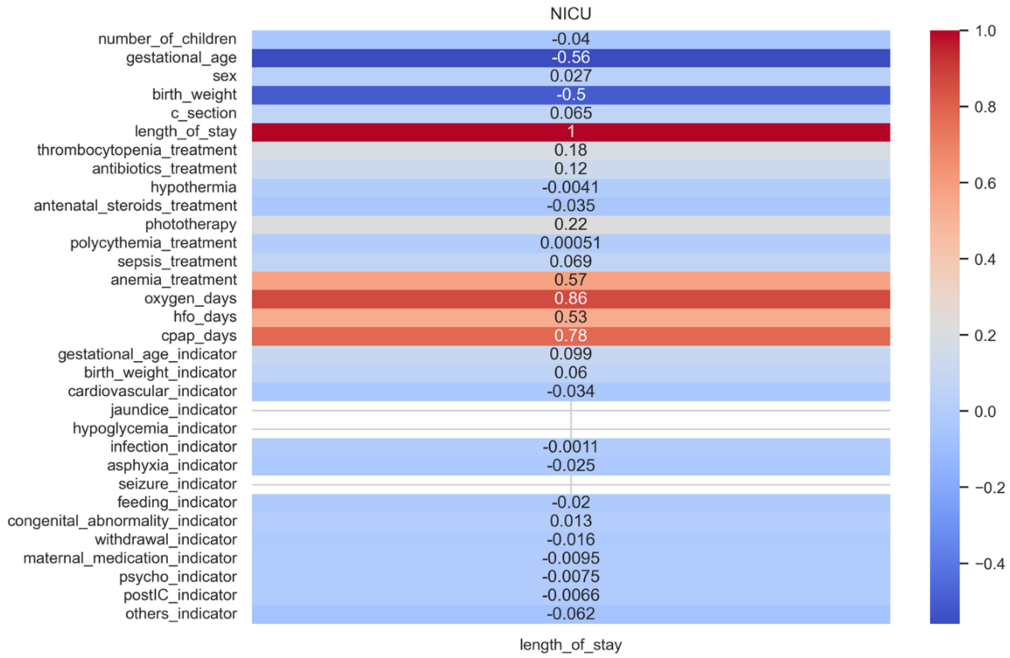


Figure 13 Correlation Matrix for LoS at NICU below and including 32+0 gestational age weeks

Interestingly, all admission criteria show no significant correlation with LoS. This highlights an inherent structural weakness in the dataset, which requires selecting the two most important indicators for each patient. This selection process does not capture the full complexity of medical conditions, leading to a lack of correlation across these indicators. This finding underscores the challenges in modeling and predicting LoS for extremely premature neonates, as the medical conditions and treatment protocols can be highly variable and multifaceted.

When applying Ridge regression on the dataset with the correlated variables, we obtained the following results:

Variable	Coefficient
Intercept	5.20
Gestational age	-0.0023

Birth weight	-0.0010
Phototherapy	0.43
Anemia treatment	1.55
CPAP days	0.75
O2 days	0.39
HFO days	0.63
Thrombocytopenia treatment	0.03
Antibiotics treatment	-1.13
Adjusted R^2	0.43

The strongest factors, beyond gestational age and birth weight, in the regression are anemia treatment and days of respiratory treatments, like CPAP and HFO. Moreover, the use of antibiotics has a relatively strong negative effect on LoS. Overall, the model explains a decent 0.43 of the variance in the data. It struggles to capture the full variance of LoS for the highly complex patient group of extremely premature NICU patients. However, when comparing the actual and predicted values for the entire group, it is evident that the model can adequately represent the population, as seen in Table 5.

Table 5 Statistical comparison between actual and predicted LoS for NICU patients below and including 32+0 weeks gestational age

	Actual	Predicted
Mean	22.72	24.74
Standard Deviation	26.47	25.47
Min	1	5
50%	12	13
Max	175	171

Most importantly, the regression stays in the bound of the observed data and, hence, offers the chance to adequate sample the stay duration for NICU patients in the selected age group.

5.1.2.1.2 Length of Stay for NICU above 32+0 weeks of gestation

Most of the patients admitted to the NICU with more than 32+0 weeks of gestational age had a previous stay at another ward level and are admitted for medical conditions that require the expertise of a NICU hospital. Thus, the impact of gestational age on LoS decreased compared to the below 32+0 weeks group. The strongest correlation can still be found for days of O2 support, CPAP, conventional/HFO ventilation. Additionally, treatment for anemia shows a weak positive correlation.

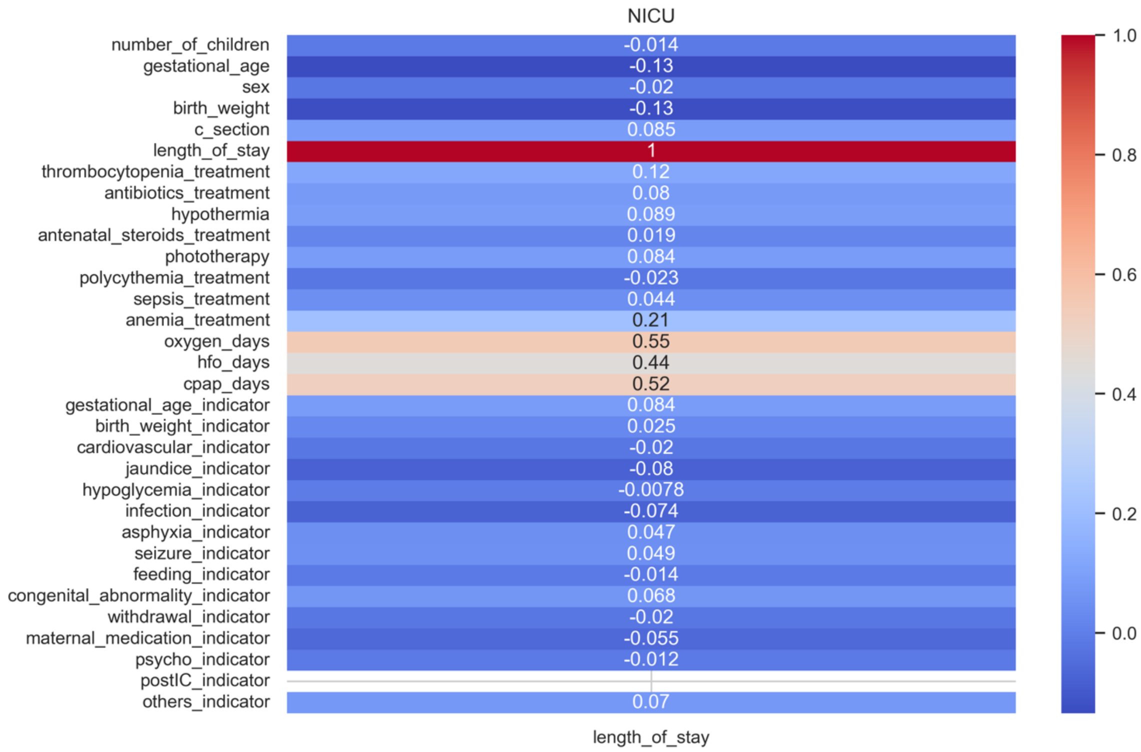


Figure 14 Correlation Matrix for LoS at NICU above 32+0 weeks gestational age

Again, the admission indicators are not correlated with LoS. This leads to the same selection of regression variables as for the other NICU age group. Based on the correlated factors, another Ridge regression was performed, leading to the results shown in Table 6.

Table 6 Ridge regressions results for NICU patients above 32+0 weeks of gestation

Variable	Coefficient
Intercept	21.60
Gestational Age	-0.06
Birth Weight	-0.0013
Anemia Treatment	3.45
CPAP days	0.51
O2 days	0.66
HFO days	0.10
Adjusted R^2	0.84

The results of the Ridge regression for NICU patients with more than 32+0 weeks of gestational age reveal several key insights. The model shows an adjusted R^2 value of 0.84, indicating that 84% of the variance in LoS is explained by the included variables, demonstrating a strong fit to the data. Gestational age and birth weight both have slight negative correlations with LoS, suggesting that higher gestational age and birth weight are associated with marginally shorter hospital stays.

Table 7 Comparison between actual and predicted LoS for NICU patients beyond 32+0 weeks of gestation

	Actual LoS	Predicted LoS
Mean	5.12	4.74
Standard Deviation	6.76	4.60
Min	1	1
50%	3	4
Max	100	107

Overall, the model provides a reasonable approximation of the LoS, capturing the central tendency and the range of the data. While there is a slight underestimation of the mean and variability, the model does not have major outliers and adequately represents the population. This suggests that the Ridge regression model is effective in predicting LoS for NICU patients with more than 32+0 weeks of gestational age, although there is room for improvement in capturing the full variance of the data.

5.1.2.1.3 Comparison to actual LoS for NICU patients

When applying the developed regression equations to the existing Perined dataset, the approximation is close to the actual values for most gestational ages.

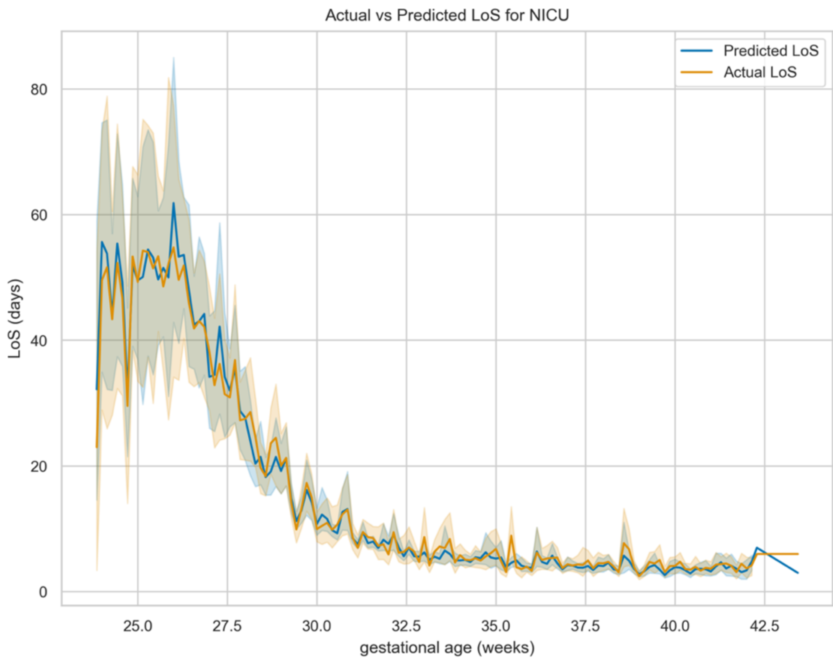


Figure 15 Comparison between actual and predicted LoS for NICU patients

Especially for low gestational age, both the actual and predicted LoS show increased variance displaying the medical complexity and variety of patients. By only using the available information from perined, it is not possible to fully capture all influential factors to the fullest. Yet, when looking at statistical description for all patients the regression models can provide useful estimations for the LoS of NICU patients.

Table 8 Comparison LoS in days between observed and predicted values for NICU patients

	Actual LoS	Predicted LoS
Mean	12.50	12.29
Standard Deviation	20.01	18.76
Min	1	1
50%	5	6
Max	175	171

Despite the inherent limitations of using only the available information from the Perined dataset, the models demonstrate their utility by providing close approximations of actual LoS across a range of gestational ages. The slight differences between actual and predicted means, as well as standard deviations, indicate that while the model may not capture every nuance, it is robust enough to offer valuable estimations. Hence, the model is not only suitable to be used in the simulation model but also provides valuable insights for practitioners in hospital planning.

5.1.2.2 Length of Stay for High Care Ward

As the next step, the LoS for high care patients was analyzed. The Perined dataset provides information on 21,981 high care admissions with a mean stay of 5.6 days. Similar to NICU patients, the LoS drastically increases for extremely premature neonates below approximately 32+0 weeks of gestational age.

However, an interesting trend was observed where the LoS seems to decrease again for extreme premature patients born before approximately 28+0 weeks of gestation. One potential explanation for this could be that these patients, initially born at a high care hospital, require the specialized services of a NICU and are therefore transferred as soon as possible. This rapid transfer could lead to shorter recorded stays at the high care level for these extreme preterm infants.

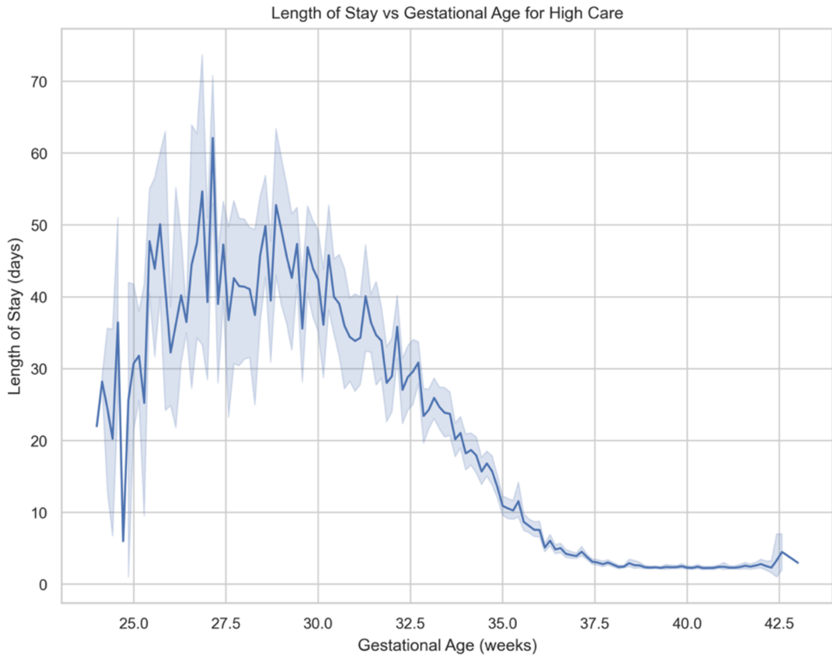


Figure 16 LoS over gestational age for high care patients

Based on this analysis, the dataset was split by gestational age into three groups: below and including 28+0 weeks, between 28+0 and including 37+0 weeks, and above 37+0 weeks of gestational age. As a first step, factors beyond gestational age that influence LoS for high care neonates were identified. Correlations between various factors and LoS were analyzed for the respective subgroups. Based on these results, a regression formula was developed to express LoS through the available factors. The goal was to use as few factors as possible to avoid overfitting and multicollinearity while maintaining interpretability. By following this approach, the models aimed to provide accurate predictions of LoS for high care neonates across different gestational age groups, while being easy to understand and apply in clinical settings.

5.1.2.2.1 Length of Stay for High Care below and including 28+0 weeks of gestation

Patients with a gestational age below and including 28+0 weeks at a high care hospital show a wide range of factors and, thus, not many have a clear correlation with LoS as seen in Figure 17. Weak correlation can still be seen with CPAP days, O2 support days, anemia treatment, phototherapy, and antibiotics treatment. Compared to other age groups wand ward levels, gestational age has a lower correlation with LoS.

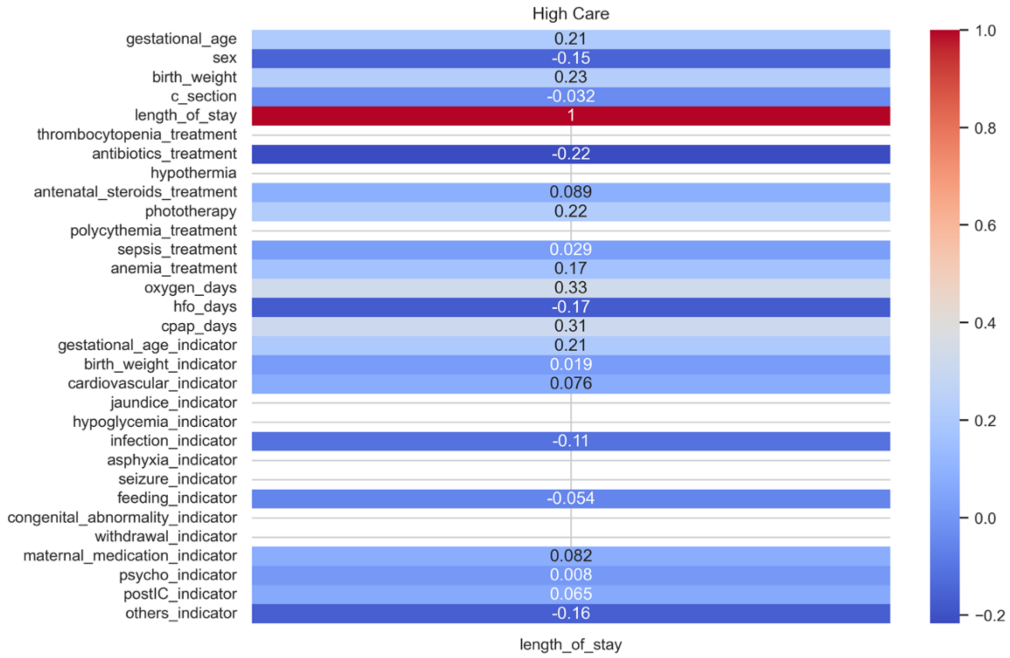


Figure 17 Correlation on LoS for high care patients below and including 28+0 weeks gestational age

Based on the factors with a noticeable correlation, I developed a ridge regression model yielding the following coefficients seen in Table 9.

Table 9 Ridge Regression Outcome LoS High Care below and including 28+0 weeks of gestational age

Variable	Coefficient
Intercept	-62.93
Gestational age	0.54
Phototherapy	19.28
Anemia	3.30
CPAP days	0.40
O2 days	0.47
Antibiotics	-22.80
Adjusted R^2	0.37

The model explains 37% of the variance when tested against the dataset. The strongest coefficients can be found for the use of phototherapy and antibiotics, highlighting the importance of these treatment options. When aggregating the LoS on population level, we see that the function can achieve similar results, as seen in Table 10.

Table 10 Statistical comparison between actual and predicted LoS for high care patients below 28+0 weeks gestational age

	Actual LoS	Predicted LoS
Mean	40.40	40.53
Standard Deviation	21.59	13.07
Min	1	6
50%	43	40
Max	117	86

The difference in maximum values suggests that the model struggles to account for extreme values, likely due to Ridge regression's robustness against outliers. Additionally, the model cannot fully capture short-time admissions followed by a transfer to a NICU, indicating potential areas for further refinement.

5.1.2.2.2 Length of Stay for High Care between 28+0 and 37+0-weeks of gestation

The group between 28+0 and 37+0 weeks of gestational age in high care is a mix of previous NICU patients and patients born at the high care. Thus, there are large deviations in their respective LoS and influential factors. We see a strong correlation of gestational age. In addition, birth weight, CPAP, post IC and premature birth admission indicator, phototherapy treatment, oxygen support days, and anemia treatment are correlated.

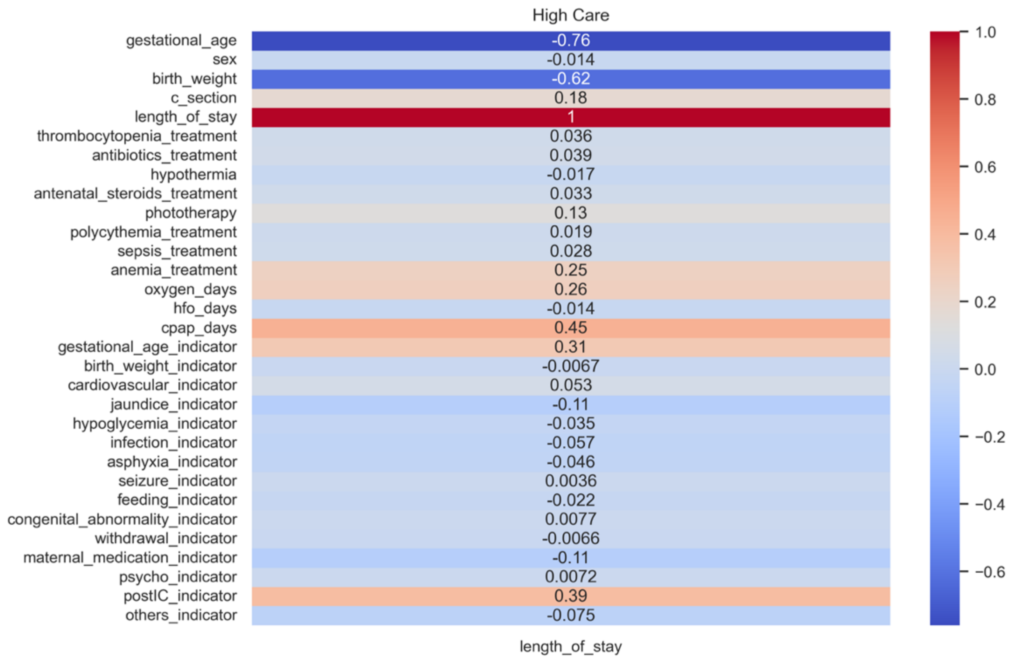


Figure 18 Correlation on LoS for high care patients between 28+0 and 37+0 weeks gestational age

For the regression model, the premature birth admission indicator was excluded as its effect is better capture through gestational age and it did not significantly improve the model results. Using these factors the Ridge regression yield the following coefficients see in Table 11.

Table 11 regression results for high care patients between 28+0 and 37+0 weeks of gestation

Variable	Coefficient
Intercept	158.35
Gestational age	-0.5631
Birth Weight	-0.0036
Phototherapy	2.99
Anemia	2.13
CPAP days	0.49
O2 days	0.39
Post IC	2.19
Adjusted R^2	0.63

The model explains 63% of the variance when tested against the dataset with strongest positive coefficients being phototherapy, anemia treatment, and post-IC indicator. When aggregating the LoS on population level, we see that the function can achieve similar results as seen in Table 12.

Table 12 Statistical comparison between actual and predicted LoS for high care patients between 32+0 and 37+0 weeks gestational age

	Actual LoS	Predicted LoS
Mean	14.98	15.01
Standard Deviation	15.15	12.76
Min	1	1
50%	8	11
Max	142	84

The difference in maximum values suggests that the model struggles to account for extreme values, likely due to Ridge regression's robustness against outliers. Thus, further refinements could be made by including additional factors that influence a post-IC admission or have a separate regression for this group of patients.

5.1.2.2.3 Length of Stay for High Care above 37+0 weeks of gestation

For High Care above 37+0 weeks gestational age, we see a strong negative correlation with gestational age and birth weight. Moreover, the admission indicator post-IC, anemia treatment, phototherapy, and use of oxygen support and CPAP, and the others indicator, show correlation and become potentially relevant factors in predicting LoS. In addition, treatment for sepsis become relevant for this age group as the risk for sepsis increases for higher gestational age groups. The admission indicator for gestational age is also correlated but again excluded as its effect is already better included through the gestational age in days.

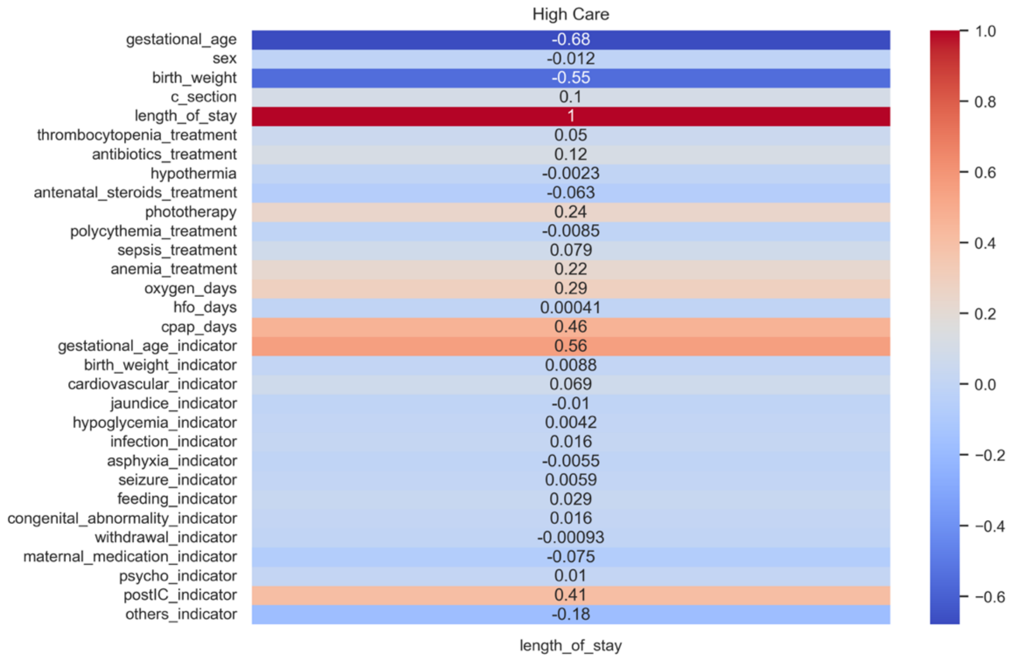


Figure 19 Correlation on LoS for high care patients above 37+0 weeks gestational age

The selection of correlated factors shows the diversity in medical conditions and treatments for this patient group. While CPAP days stay strongly correlated, the correlation for oxygen support treatment decreased in comparison to other age groups. Using these factors the Ridge regression yield the following coefficients seen in Table 13.

Table 13 Ridge regression coefficients for high care patients above 37+0 weeks gestational age

Variable	Coefficient
Intercept	7.94
Gestational age	-0.0157
Birth Weight	-0.0004
Phototherapy treatment	1.52
Anemia treatment	2.54
Sepsis treatment	2.25
CPAP days	0.93
Oxygen support days	0.86
Others admission indicator	-0.14
Post IC admission indicator	4.73
Adjusted R^2	0.15

The model only captures 15% of the variance in the data, further, underlying the challenges to predict LoS for this age group. The strongest positive effect is seen for anemia and sepsis treatment and post-IC admission indicator.

As a next step, the model was applied to the empirical dataset to gain a comparison on a population level as seen in Table 14.

Table 14 Statistical Comparison between actual and predicted LoS of high care patients above 37+0 weeks gestational age

	Actual LoS	Predicted LoS
Mean	2.55	2.55
Standard Deviation	3.62	1.40
Min	1	1
50%	2	2
Max	137	52

The comparison shows that the model captures the overall average well but struggles to include extremely high values. These results indicate that there are additional complexities in the LoS, especially for the long post-IC admissions, that cannot be fully expressed with the available variables in the dataset and the chosen regression approach.

5.1.2.2.4 Comparison predicted to actual LoS for High Care Ward

Bringing all three regression models together, we see that the model can capture the core characteristics of LoS in High Care as seen in Figure 20. The predicted values follow the observed pattern and tend to be in the same range for each gestational age.

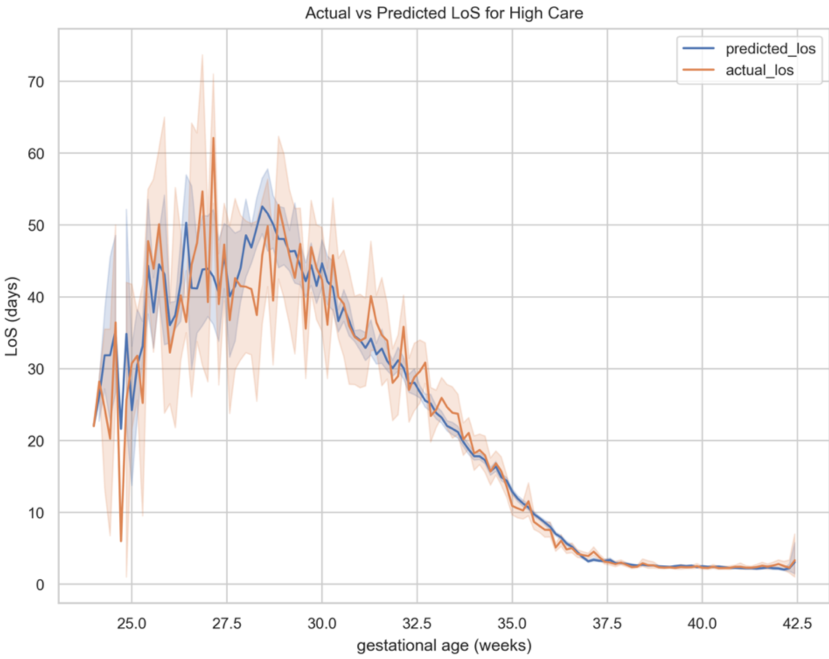


Figure 20 Comparison between actual and predicted LoS for high care patients

Comparing core statistics, we see again the pattern that predictions tend to be more conservative than the empirical data. This highlights the medical complexity of patients and the impact of random nature and other factors outside of the dataset.

Table 15 Statistical Comparison between actual and predicted LoS for High Care

	Actual LoS	Predicted LoS
Mean	5.66	5.66
Standard Deviation	10.53	8.83
Min	1	1
50%	2	2
Max	142	86

This concludes the analysis of LoS for high care ward patients. Regression models were developed for three different age groups, identifying relevant patient characteristics and treatments. These regressions were used in the subsequent model implementation to adequately simulate LoS for this patient population.

5.1.2.3 Length of Stay for Medium Care Ward

The perined dataset provides information on 21129 medium care admissions with a mean stay of 3.21 days. As expected, the LoS drastically increases for premature neonates below circa 37 weeks of gestational age. In addition, we see high variance below the 32+0 weeks of gestation.

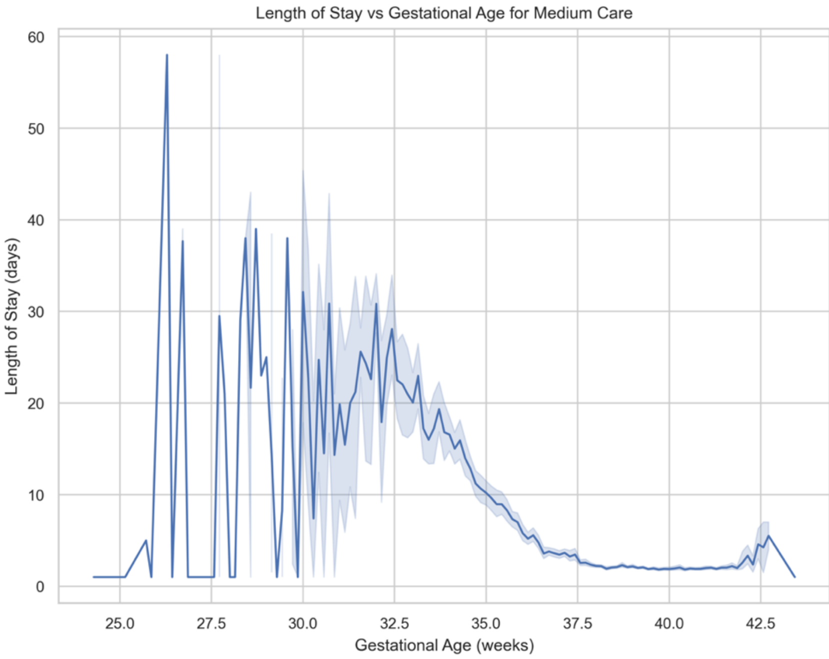


Figure 21 LoS across gestational age for medium care patients

This high variance is since these patients are either born at the medium care level but are directly transferred to the NICU because of their prematurity, or they are former NICU patients having a post-IC admission, leading to long LoS. Based on these observations, the dataset was split into three subgroups: 1) below 31+0 weeks, 2) 31+0 to 38+0 weeks, and 3) above 38+0 weeks gestational age. The following sections,

5.1.2.3.1 Length of Stay for Medium Care below and including 31+0 weeks of gestation

For this group of medium care patients, the most correlated factors, besides gestational age, were asphyxia indicator, post IC and others admission criteria, and phototherapy, CPAP, and O2 support treatment, as seen in Figure 22.

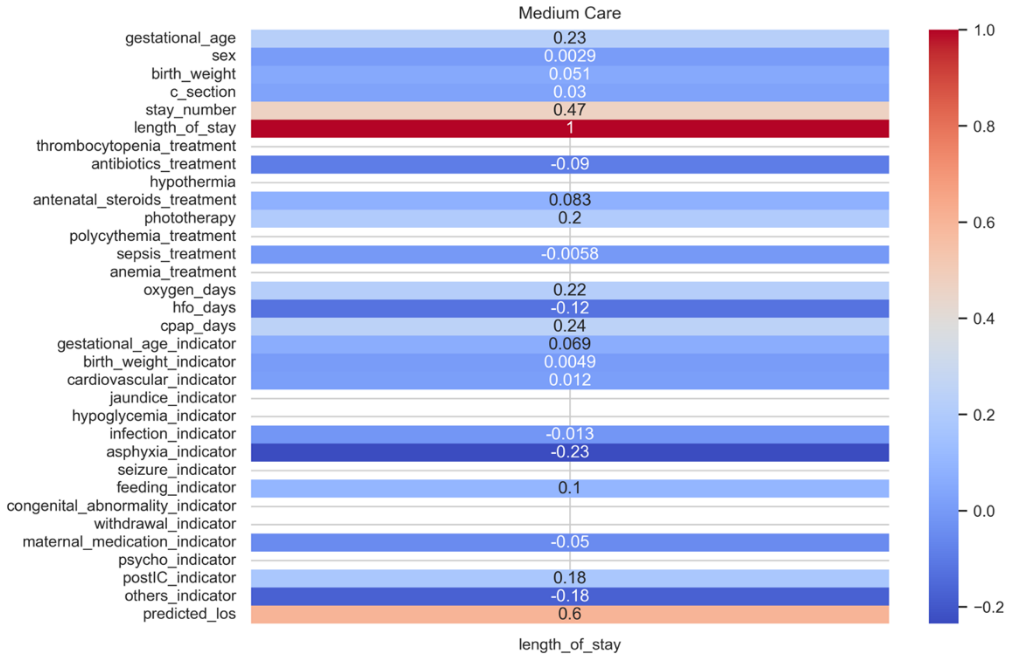


Figure 22 Correlation on LoS for medium care below and including 31+0 weeks gestational age

Moreover, the correlation matrix shows that various admission criteria or treatments are not present in this group demonstrating the lower level of care and less severe medical conditions. Using the correlated factors the Ridge regression model yields the following coefficients as seen in Table 16.

Table 16 Ridge regression results for medium care patients below 31+0 weeks gestational age

Variable	Coefficient
Intercept	-34.05
Gestational age	0.1613
Phototherapy treatment	13.93
O2 days	0.08
CPAP days	0.53
Stay number	12.03
‘others’ admission criteria	-1.22
Post IC admission criteria	11.11
Adjusted R^2	0.43

The model can explain 43% of the observed variance. The use of phototherapy or a post-IC stay can extend the expected LoS by more than 10 days. Using this regression model and applying it on the selected patient group I get the following statistical description as seen in Table 17.

Table 17 Statistical comparison between actual and predicted LoS for Medium Care patients below 31+0 weeks gestational age

	Actual LoS	Predicted LoS
Mean	18.97	18.97
Standard Deviation	18.72	12.24
Min	1	1
50%	14	13
Max	62	65

The regression model provides an adequate level of accuracy over the patient population by having a similar mean and extreme values. The standard deviation is lower than in the actual data indicating less variance in predictions. Thus, it is reasonable to apply it for this patient group in the simulation model implementation.

5.1.2.3.2 Length of Stay for Medium Care above 31+0 below 38+0 weeks of gestation

For Medium care patients between 31+0- and 38+0-weeks gestational age, the most correlated factors with LoS are gestational age, birth weight, and the indicator for prematurity. Weak correlation can be seen with use of phototherapy treatment, c-section, and oxygen support days.

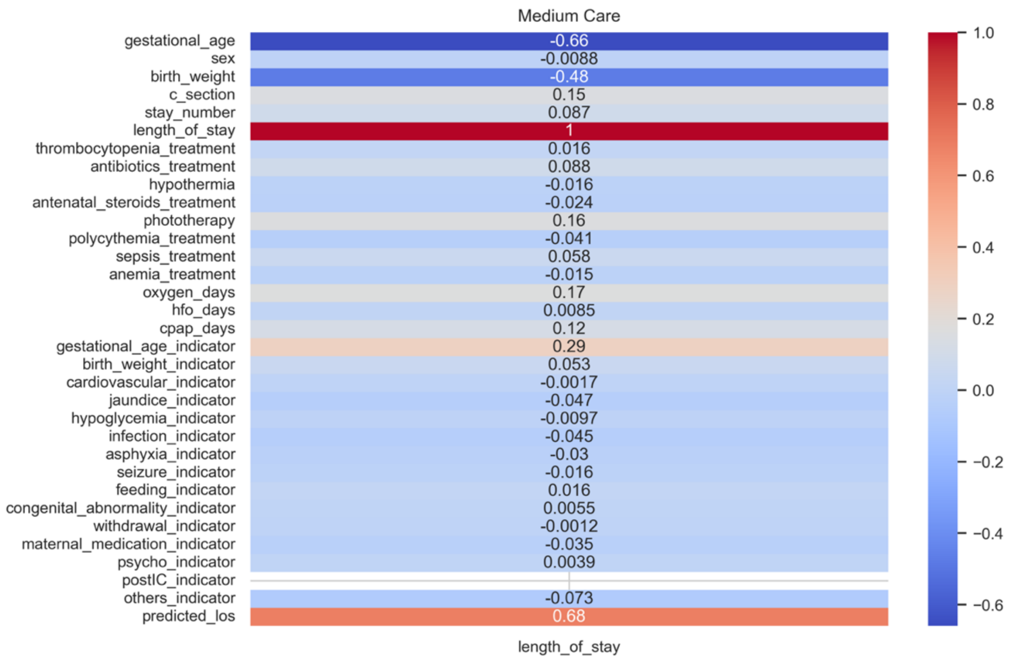


Figure 23 Correlation on Los for medium care patients above 31+0 and below 38+0 weeks gestational age

Using these factors the Ridge regression yield the following coefficients seen in Table 18. The model explains almost half of the variance.

Table 18 Ridge regression coefficients for medium care patients above 31+0 below 38+0 weeks gestational age

Variable	Coefficient
Intercept	120.12
Gestational age	-0.4312
Birth Weight	-0.0017
Phototherapy	2.12
C-Section	1.57
O2 days	0.85
Adjusted R^2	0.49

Applying the presented regression model on the patient group in perined we see that a statistical description between actual and predicted LoS is close enough to be used in a simulation model, as seen in Table 19.

Table 19 Statistical comparison between actual and predicted LoS for medium care above 31+0 below 38+0 weeks gestational age

	Actual LoS	Predicted LoS
Mean	6.50	6.54
Standard Deviation	7.87	5.43
Min	1	1
50%	3	5
Max	66	45

The prediction tends to be more conservative due to the inherent character of ridge regression models to be robust against outliers leading to more weight to values around the mean. Still, the overall average is similar enough to the observed data and the range of predicted values inside of the actual range.

5.1.2.3.3 Length of Stay for Medium Care above 38+0 weeks of gestation

For medium care patients above 38+0 weeks of gestational age the correlated factors are clinical sepsis, cesarean section, phototherapy, days of O2 support, and days of CPAP, as seen in Figure 24.

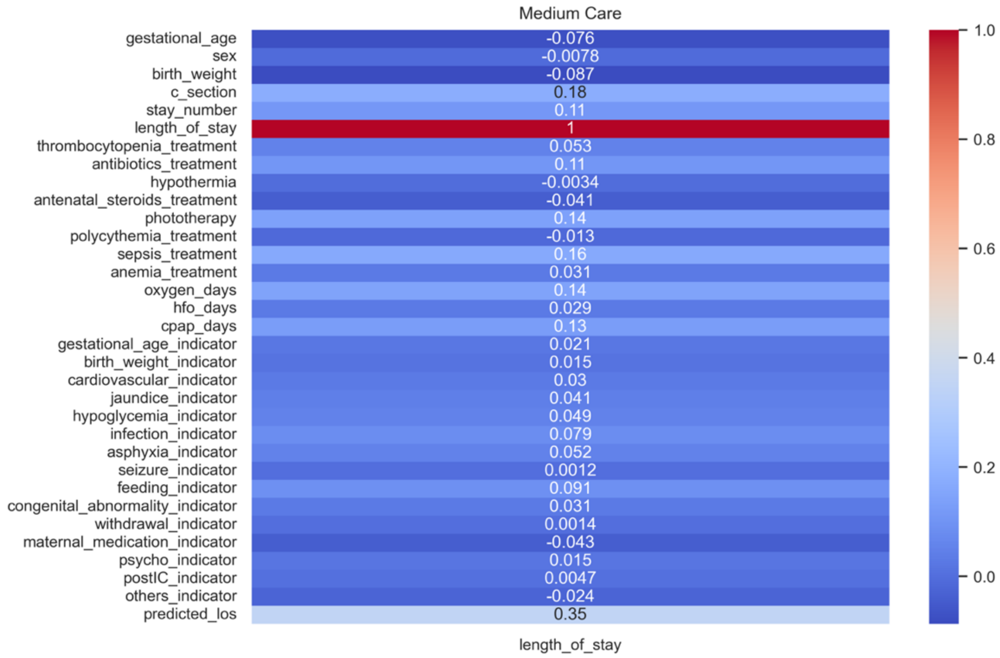


Figure 24 Correlation on LoS for medium care above 38+0 weeks gestational age

Gestational age and birth weight are not correlated with LoS for this group and overall all correlations are weak which highlights the diversity in conditions for this patient group. Using the selected correlated factors the Ridge regression yield the following coefficients see in Table 20.

Table 20 Ridge regression coefficients for medium care patients above 38+0 weeks gestational age

Variable	Coefficient
Intercept	1.60
Phototherapy Treatment	2.64
C-Section	0.90
CPAP days	0.36
O2 days	0.91
Clinical Early-onset sepsis Treatment	2.95
Adjusted R^2	0.12

The model only explains 12% of the variance which resonates with the previous findings of only weakly correlated variables in the dataset. Applying the presented regression model on the patient group in perined we see that a statistical description between actual and predicted LoS is close enough to be used in a simulation model, as seen in Table 21.

Table 21 Statistical comparison between actual and predicted LoS for medium care patients above 38+0 weeks gestational age

	Actual LoS	Predicted LoS
Mean	2.00	2.00
Standard Deviation	2.27	0.77
Min	1	1
50%	1	2
Max	68	17

Due to the characteristics of Ridge regression models to penalize major outliers, the predicted values remain below the actual values and there are most likely additional factors necessary to explain the LoS more accurately.

5.1.2.3.4 Comparison predicted to actual LoS for Medium Care Ward

When applying the regression models on their respective patient groups, we can compare the overall performance of the estimation method for all medium care ward patients as seen in Figure 25.

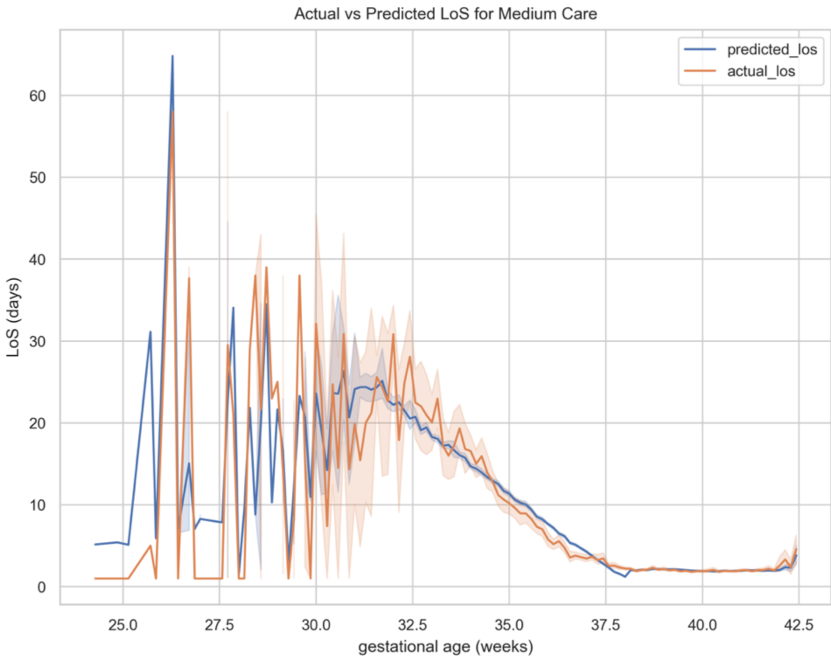


Figure 25 Comparison between actual and predicted LoS for medium care patients across gestational age

We see that the regression model captures the overall LoS pattern across the different gestational age groups well. Smaller deviations are visible at points between two regressions, e.g. at 38+0 weeks. Comparing the statistical description between actual and predicted LoS, as seen in Table 22, it is evident that the model predicts a quite accurate mean, min, and max for the dataset. The standard deviation is smaller which is likely linked to the characteristic of ridge regressions to limit the impact of outliers.

Table 22 Statistical comparison between actual and predicted LoS for Medium Care Patients

	Actual LoS	Predicted LoS
Mean	3.20	3.23
Standard Deviation	5.09	3.68
Min	1	1
50%	2	2
Max	68	62

The three presented ridge regression models explain the LoS patterns for medium care patients well enough and furthermore, provide valuable insights into the driving factors for LoS for each gestational age group.

5.1.2.4 Conclusion Length of Stay for Medium Care Ward

In this section, I analyzed LoS for neonates across ward levels and gestational age groups. I used ridge regression models based on the perined dataset with correlated variables. For the implementation in the model, I additionally incorporated specific checks to refine the predictions: if the rounded predicted LoS was zero, I adjusted it to one day– the minimum LoS. Additionally, if the predicted LoS was less than the days of CPAP, oxygen support, or HFO therapy, I set it to the minimum duration among these treatments. Moreover, NICU patients born below 32+0 gestational age are required to stay at least until they are 32 weeks old. These adjustments ensure a proper fit to guidelines and help explain a larger part of the observed variance.

The regression approach proved most accurate for NICU patients. I suspect this phenomenon partly due to the standardized admission criteria that help homogenize patient profiles. Overall, the regression models were sufficiently precise for representing a broader population as seen in the comparison of mean, min, and max values between actual and predicted LoS of the dataset.

Across all ward levels, I see the highest LoS values for premature and extreme premature neonates. Moreover, any kind of respiratory support – CPAP, oxygen, HFO/conventional ventilation– is strongly linked with an increased LoS. As LoS directly impacts the occupancy rate through a potential increased bed turnover, a possible lever could be the changing the use of these treatments or more in general see the impact of LoS changes for premature patients.

To properly implement the regression models, the used variables need to be incorporated in the modeling. Thus, the following sections will introduce them in more detail and provide insights on how to integrate them in the eventual implementation.

5.1.3 Neonatal Care Pathways

Patient pathways in healthcare are determined by various factors and faces a high level of complexity and uncertainty (Han et al., 2019). Yet, it is still possible to abstract key pathways on a ward level that a patient can take based on the available data and consultation with practitioners. To do so, I categorized hospitals by their ward level and analyzed single stay admissions and afterwards multiple stay admissions. For patients with multiple admissions, I divided into two groups– inside and outside region patients.

The region receives two types of patients: patients with a home zip code in the region, and patients with a home zip code outside the region. Due to the regionalization across the country, each region should be in the position to provide care for all inside region patients. Outside region patients are a sign for capacity shortages in other regions and add additional stress on the region. Patients are assigned to a ward based on their admission criteria and the capacity of the respective ward. As patients can have multiple admissions, it is possible for them to be transferred to another hospital with another respective ward level. These transfers can happen between inside region hospitals or to an outside region hospital. As we only have data for one specific region and neonatal care is governed on a regional level, the system will be bounded by the regional borders. Hence, all outside hospitals are aggregated to one group. By analyzing the perined dataset, I identified the most common pathways of neonates in the care system.

5.1.3.1 Admissions by ward level

Across both patient groups, most patients fortunately are only admitted into one hospital and can be released afterwards as seen in Table 23. While the NICU has the longest LoS, only 4% require such care.

Table 23 Overview of patients with single stay

Path	Proportion of total pathways [%]	Average total LoS in days	Most common admission criteria
NICU	4.00	13.65	Gestational age, Others, Birth weight
High Care	53.00	3.90	Others, Birth weight, maternal medication
Medium Care	39.00	3.10	Others, maternal medication, gestational age

The highest level of neonatal care is provided at the NICU. The easiest and most straightforward source are guidelines that state under which conditions a patient must be admitted to which ward level. However, in the Netherlands such guidelines only exist for NICU admissions. Here, all newborn under 32+0 weeks of gestational age, 1250 gr birth weight, or congenital defect must be admitted to a NICU (NVOG, 2007). Most patients at a high care ward are moderate to late preterm neonates, need specialized care without NICU indications, or are a post NICU admission. All other patients normally only require a medium care ward.

5.1.3.2 Patient pathways with multiple admissions

However, five percent of patients require a transport to a different ward level due to their medical conditions. These pathways can mostly be described by the following groups displayed in Table 24.

Table 24 Comparison of most common paths with more than one stay

Pathway	Proportion of total pathways [%]	Average total LoS in days
NICU-High	2.0	55.40
NICU-Medium	0.4	25.91
Medium-NICU	0.4	9.46
High - NICU – High	0.3	26.84

It can be seen that an additional stay easily leads to a higher LoS by multiple factors. The analysis of these pathways reveals that transitions involving the NICU typically result in longer LoS, emphasizing the critical and intensive nature of NICU care. Especially, the typical post-IC path (NICU-High) leads to a long LoS as these patients are born at the NICU due to extremely low birth weight or being below 32+0 weeks of gestation, necessitating a long initial NICU stay. Following this, they also require an extended high care stay on average until their term day at 40+0 weeks of gestation. Thus, this pathway is particularly interesting for potential interventions aimed at either lowering the LoS or redistributing the pressure from the NICU or high care. Such interventions could help ensure that these patients receive the necessary length of stay without overburdening any single ward level, ultimately improving the efficiency and capacity management within the neonatal care system.

Additionally, there are patient pathways that include hospitals outside the region. This goes in a bidirectional manner, as inside region patients might be transferred to an outside region hospital and at the same time outside region patients might be transferred to an inside region hospital. Patients that moved between regions were mostly linked to the following combinations in Table 25.

Table 25 Overview of most common pathways including other regions

Pathway	Proportion of total pathways [%]	Average total LoS in days
NICU (outside region) – High care (inside region)	0.27	48.74
NICU (inside) – High care (outside)	0.18	68.79

Based on the transfers to outside region hospitals, it is evident that capacity shortages are most likely to occur at the NICU and high care hospitals. Additionally, both pathways (High - NICU - High and NICU - High) have a long total LoS, further emphasizing their impact on the number of available operational beds.

5.1.3.3 Hospital Assignment Process

The ward level is decided by gestational age, birth weight, and any relevant medical condition. However, this does not automatically decide which hospital the patient will be admitted to. The primary goal is to always provide care within the region for patients with a home location inside the region. The secondary goal is to provide care as close as possible to their home location.

To achieve these goals, the six subregions were analyzed to understand the distribution of neonatal home locations, the hospitals within each subregion, and the adjacent subregions. By understanding the percentage of neonatal home locations in each subregion, the hospitals available, and the connections between subregions, the implemented model can provide a more accurate picture of the occupancies across hospitals and identify bottlenecks between hospitals.

Table 26 Overview of subregions

Subregion	Share of inside region patients [%]	Hospitals	Adjacent Subregion
Rotterdam Noordoever	31.00	Erasmus MC, Franciscus Gasthuis & Vlietland, IJsselland Ziekenhuis	Noord-Brabant West, Rotterdam Zuidoever, Zuid-Holland Zuid
Noord-Brabant West	28.00	Bravis, Amphia	Rotterdam Noordoever, Zuid-Holland Zuid, Zeeland
Zuid-Holland Zuid	26.00	Albert Schweitzer Ziekenhuis	Rotterdam Noordoever, Rotterdam Zuidoever, Zuid-Holland Eilanden, Noord-Brabant West
Rotterdam Zuidoever	8.00	Maasstad Ziekenhuis, Ikazia Ziekenhuis	Rotterdam Noordoever, Zuid-Holland Zuid
Zuid-Holland Eilanden	5.00	Van Weel-Bethesda Ziekenhuis	Zuid-Holland Zuid, Zeeland
Zeeland	2.00	Admiraal De Ruyter Ziekenhuis, ZorgSaam Zeeuws-Vlanderen	Noord-Brabant West, Zuid-Holland Eilanden

The subregions within the neonatal care system represent drastically different numbers of neonates. For example, nearly one-third of all admissions are linked to the Rotterdam

Noordoever subregion, while only 2% of patients are based in Zeeland. Consequently, hospitals in subregions with a relatively high percentage of local patients face more potential admissions and a higher risk of capacity shortages.

The process for choosing the most suitable hospital for a patient can be summarized in several steps. First, it is determined if there is an available operational bed at the appropriate ward level within the patient's subregion. If not, the adjacent subregions are checked sequentially until all subregions have been considered. If no suitable bed is found within the region, the patient would then be transferred to a hospital outside the region.

The closest hospital does not always have to be within the patient's subregion; for instance, there is only one NICU in the entire region. If a patient cannot be admitted to their closest hospital with the appropriate ward level, they must be transferred, adding additional stress for both the neonate and the parents.

5.1.3.4 Patient pathways across subregions

The goal of the region is to provide care as close as possible to the home location of patients to minimize travel time and additional stress for families. However, due to the uneven distribution of patients across the region, occupancy rates between hospitals can vary significantly. As a result, some patients are not admitted to the hospital closest to their home. In 2016, this occurred for 8.7% of high care patients and 7.8% of medium care patients. While these patients are not transferred to hospitals outside the region, their admissions still deviate from the optimal care pathway. Hence, the implemented model includes the subregions of patients and determines the closest hospital in relation to the patient’s home location.

5.1.3.5 Conclusion Neonatal Care Pathways

Overall, the neonatal care pathways can take multiple forms, with patients experiencing multiple stays at different ward levels, and sometimes even needing to be admitted to the same ward level multiple times. This complexity adds to the challenges of managing the neonatal care system. The pathways have a significant impact on the LoS of a patient, particularly because a stay in a NICU ward generally increases the LoS. Additionally, a stay in a high care ward following a NICU stay tends to result in a longer LoS to ensure full recovery after intensive care.

Moreover, as pathways are influenced by the home location of the patient, hospitals handle varying amounts of patients, leading to an uneven distribution and the potential for transfers between subregions. This uneven distribution and the necessity for patient transfers further complicate the management of the system.

Two mechanisms were identified that could be used as tested system levers: care pathways, particularly after a NICU stay, and the hospital selection process. These mechanisms are crucial for optimizing patient flow and improving overall system efficiency. By focusing on these areas, the model can help in formulating strategies to better manage patient admissions, distribute the patient load more evenly, and potentially reduce the overall LoS across the system.

5.2 Model Inputs

The previous chapter introduced the main functionalities of the system and how they can be conceptualized. These functionalities are dependent on appropriate input factors that determine how individual functions will play out. Thus, this chapter presents the necessary input variables for an accurate conceptualization and later modeling process.

5.2.1 Gestational Age

Given the impact of gestational age on the ward assignment and the LoS of a patient, there is the need to treat its distribution as a model input factor and find an adequate way to represent it in the model.

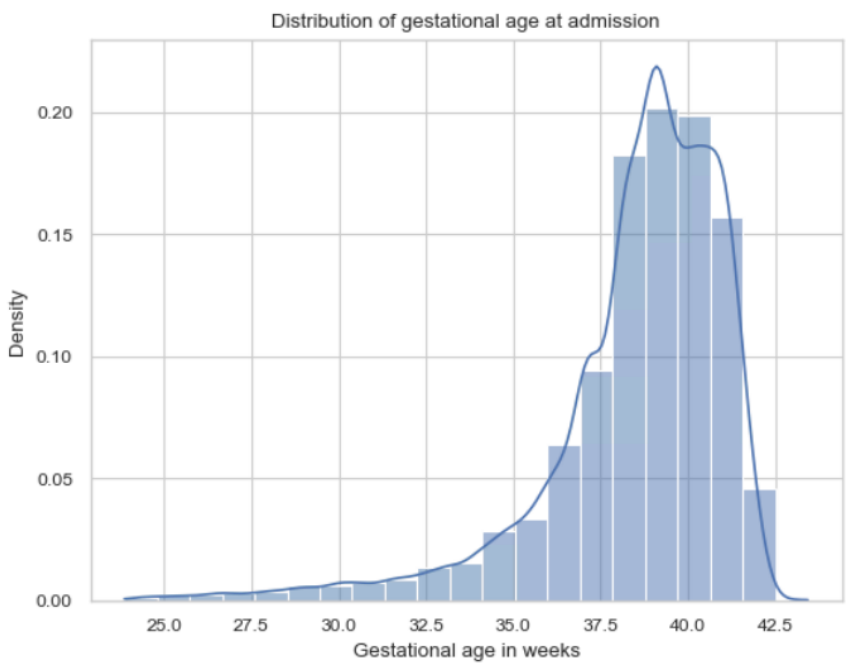


Figure 26 Distribution of gestational age

Figure 26 shows the gestational age distribution across all patients. Most patients have a gestational age around the mean of 38.5 weeks with an observed minimum of 23.85 weeks and maximum of 43.43 weeks. However, there is a noticeable heavy left tail extending down to 24 weeks. Since these patients are linked to NICU admissions, they represent a crucial subgroup for the model and must be accurately accounted for. Therefore, a Gaussian mixture model was applied, which is a weighted sum of n Gaussian distributions. To keep the parametrization of the theoretical distribution as simple as possible and avoid overfitting, the goal was to use as few components as possible. Thus, the performance of the model was tested with various components using the Bayesian Information Criterion (BIC) as an evaluator. The BIC is a criterion for model selection among a finite set of models; it balances model fit and complexity by penalizing the number of parameters in the model (Neath & Cavanaugh, 2012).

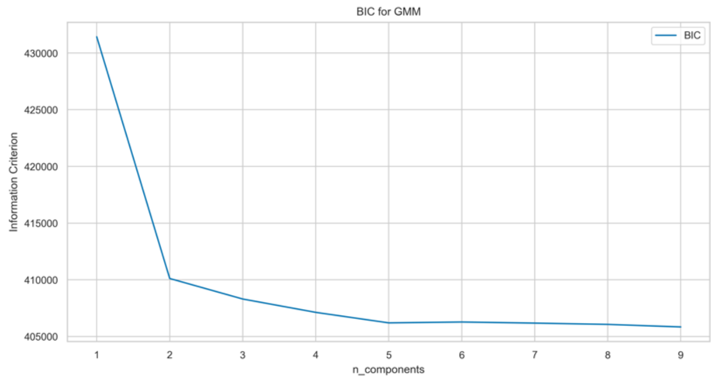


Figure 27 BIC for different number of components for the GMM on gestational age

Based on the results of the BIC evaluation in Figure 25, the model was limited to two components. The analysis showed that adding more components resulted in diminishing returns in model performance. Although using five components was another option, the performance improvement with two components was deemed sufficient for the purpose of the simulation model.

The resulting distribution, as seen in Figure 28, approximates the empirical distribution with an average error of three days, which meets the required accuracy level for the simulation model. Moreover, by limiting the number of components in the mixture model, the approach remains transparent and generalizable, allowing the model to be used for other datasets or regions.

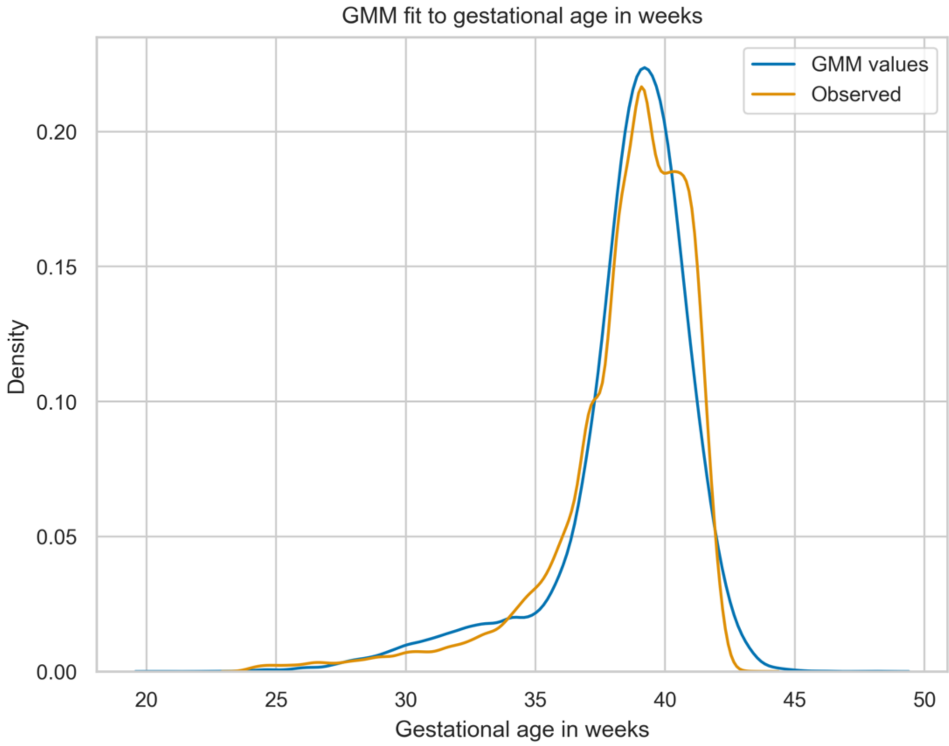


Figure 28 Comparison between modeled and observed gestational age distribution

The model is a combination of one component with a mean of 39+2 weeks and a weight of about 86%, and another component with a mean of 33+6 weeks and a weight of 14%. This effectively illustrates the significant mass of the distribution located in the left tail, capturing the crucial subgroup of extremely premature patients.

Additionally, the approximation is bounded at 24 weeks for the lower bound, as per government guidelines, and 44 weeks for the upper bound, the highest value observed in the dataset. Therefore, the gestational age of each patient in the simulation model is sampled from this described Gaussian Mixture Model.

5.2.2 Birth Weight

Across multiple LoS regression models, we saw that birth weight can have a relevant impact on the LoS. Moreover, various interventions are only applicable for patients above certain weight thresholds. Hence, it is necessary to include the factor in the modeling process.

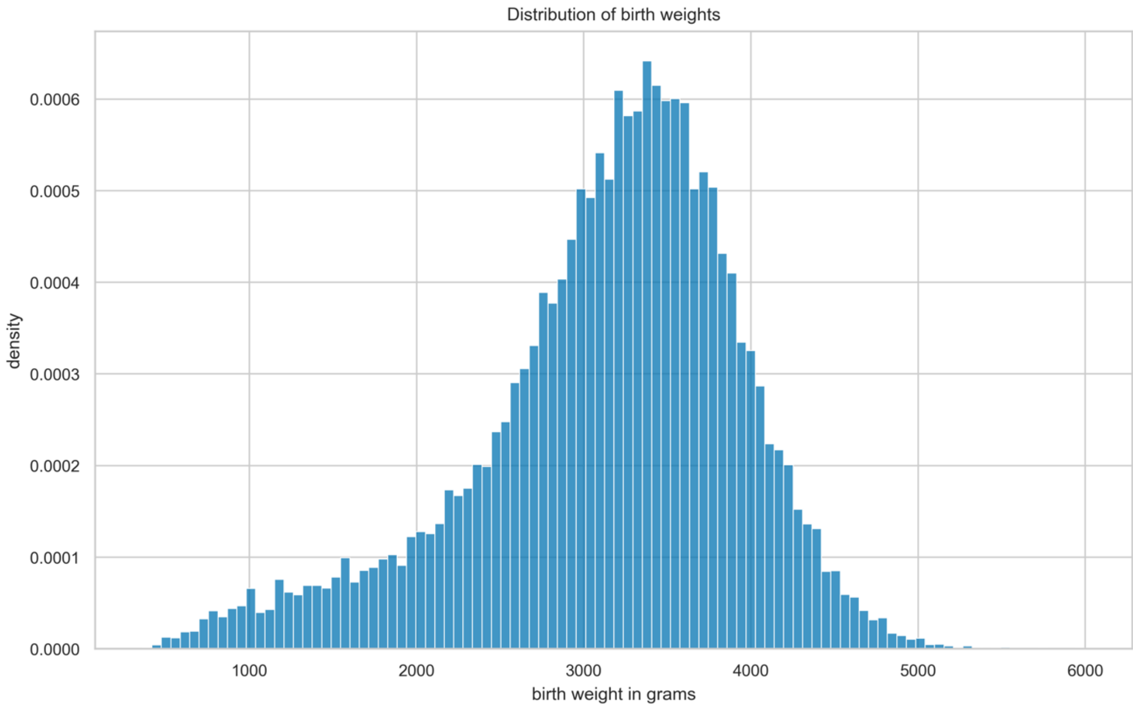


Figure 29 Birth weight distribution for neonatal care patients

The birth weight distribution follows a bell shape with a long, and heavy left tail and a relatively short and light right tail, as seen in Figure 29. The tails of the neonatal birth weight distribution distinguish it from the standard birth weight distribution. Lower birth weights are associated with increased medical complexities, which in turn heighten the likelihood of neonatal admissions. The left tail of this distribution is particularly critical, as it predominantly represents patients who require admission to the NICU.

Analyzing the statical measures in Table 27, we see that most patients are expected to weight around the mean of 3152g, while at the same time birth weight can also be in the range between 450g and 5500g marking a wide range of possible birth weights.

Table 27 Statistical description of birth weight in the dataset

	Mean	Std	min	50%	max
Birth Weight (in grams)	3152	784	450	3260	5500

As discussed in previous chapters, birth weight influences LoS and serves as a criterion for NICU admissions. While sampling directly from the birth weight distribution would yield adequate results at an aggregated level, it may produce implausible samples for individual patients. For instance, it is highly unlikely that an extremely premature neonate would be born with the average birth weight.

To address this, I investigated factors that can be used to express birth weight and found a direct relationship between gestational age and birth weight. This relationship can be linearized by taking the natural logarithm of birth weight, as shown on the right in Figure 31. This approach ensures that the birth weights of individual patients are more realistic, especially for extremely premature neonates, thereby improving the accuracy and reliability of the simulation model.

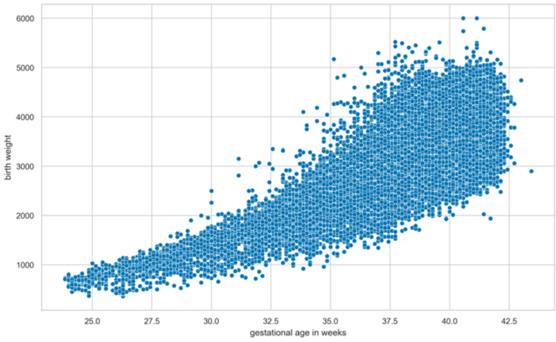


Figure 30 Observed birth weights by gestational age in weeks

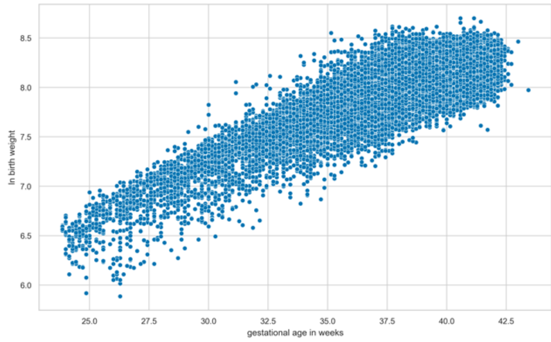


Figure 31 natural logarithm of observed birth weights by gestational age in weeks

A logarithmic OLS regression was used to express birth weight through gestational age. Additional suspected factors like sex had no impact on the regression results and were thus excluded, simplifying the regression for easier implementation. The regression results can be seen in Table 28.

Table 28 Logarithmic OLS regression results of birth weight and gestational age

	Coefficient	Standard error	P-value	Conf min	Conf max
Intercept	4.538	0.009	0.000	4.521	4.556
Gestational Age	0.013	3.4 e-05	0.000	0.013	0.013
Adj. R^2	0.73				
F-statistic	1.5e05				

The regression results show a sufficient level of accuracy with an R^2 of 0.73. Additionally, both the coefficient and the intercept have small confidence intervals and standard errors, confirming the robustness of the regression model. Moreover, the high F-statistic speaks in favor of a statistically significant model.

In the model implementation, an additional standard distributed error term with a mean of zero and a standard deviation of 200 was added. This adjustment covers a wider range of values for the same gestational age, ensuring that the minimum and maximum values for each age are properly captured. A potential further development could be to scale the added random term by gestational age as we see an increasing range for higher gestational age. However, the current implementation is acceptable for the overall purpose of the simulation model.

5.2.3 Treatments

The LoS does not only depend on factors at birth, like gestational age and birth weight, but also what kind of treatment a patient received during their admissions in the neonatal care system. Thus, the following sections will introduce the most relevant treatments and explain how they were incorporated in the modeling process.

5.2.3.1 Days of continuous positive airway pressure (CPAP)

In a neonatal setting, CPAP therapy is often used to support premature infants or newborns with respiratory distress syndrome or other breathing difficulties. A CPAP machine delivers a continuous stream of air into the infant's lungs through small prongs placed in the nostrils or a mask over the nose. This steady airflow helps keep the newborn's airways open, preventing collapse and making breathing easier.

The use of CPAP in neonates can be crucial for reducing the work of breathing, improving oxygenation, and stabilizing the infant's respiratory status. It is often employed as a less invasive alternative to mechanical ventilation, reducing the risk of lung injury and other complications.

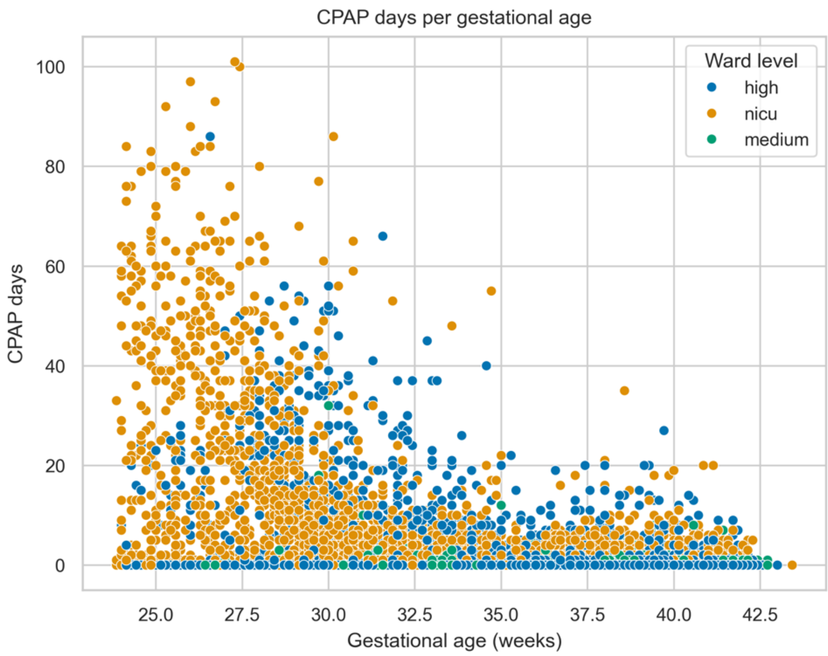


Figure 32 Distribution of CPAP days across gestational age in weeks per ward level

The analysis focuses on NICU and high-care admissions, particularly noting that the days on CPAP increase significantly with decreasing gestational age. CPAP usage can extend up to 100 days in the NICU and up to 85 days in high care. Therefore, I decided to analyze data based on ward level and differentiate by gestational age groups. The theoretical distributions were not able to properly capture the patterns observed in the data. Hence, I developed a piecewise distribution method for both NICU and high care wards:

1. Define probabilities for the initial values for different age groups
2. Use an inverse function to capture the decreasing probability, scaled by gestational age. This ensures that all values are possible, while making extreme values significantly less likely, particularly for higher gestational ages.

For NICU patients, I categorized them into three age groups after visually inspecting the distribution over gestational age: below 28+4 weeks, between 28+4 and 32+0 weeks, and older than 32+0 weeks. For high-care patients, I identified two groups after inspecting the distribution over the duration of stay: 32+0 weeks or less, representing most post-IC patients, and more than 32+0 weeks. For medium care patients, there was no observed need to account for different gestational ages. Thus, I defined probabilities for 0 and 1 days of treatment, with the remaining range following an inverse function for the decreasing probability.

5.2.3.2 Days of mechanical ventilation

In a neonatal setting mechanical ventilation, such as HFO ventilation or conventional ventilation, is an advanced respiratory support techniques used for newborns, especially premature infants or those with severe respiratory conditions like respiratory distress syndrome.

HFO ventilation is a type of mechanical ventilation that delivers very rapid breaths at small volumes, typically hundreds of breaths per minute. This method helps to maintain continuous lung inflation and improves gas exchange while minimizing lung injury. HFO is particularly beneficial for neonates with severe lung disease, as it uses lower pressures and smaller volume changes compared to conventional ventilation (Hibberd et al., 2023). Conventional ventilation in neonates involves using a ventilator to provide a set number of breaths per minute with a controlled volume or pressure of air. Conventional ventilation is commonly used for neonates with moderate to severe respiratory distress who need more support than what CPAP can provide (Tobias, 2010).

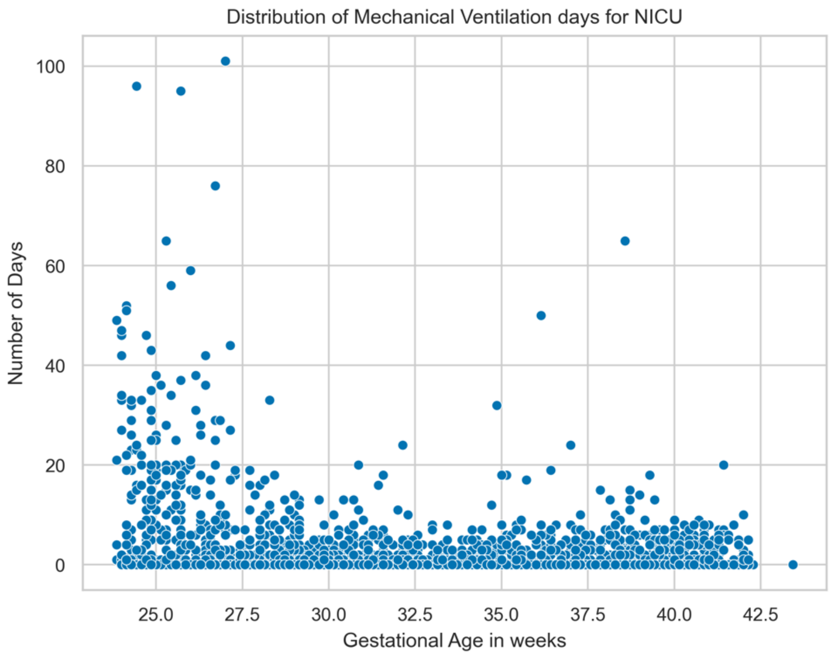


Figure 33 Distribution of mechanical ventilation days by gestational age in weeks

Based on Figure 33, it is evident that an increasing usage with lower gestational age, especially below 200 days. As the variable is only used in the LoS regression models for NICU patients, I only analyzed the usage in this patient group. I decided to split the group by gestational age below and above 27+1 weeks. I defined probabilities for the values 0 to 7 and used an inverse function to capture the decreasing probability, scaled by gestational age. This ensures that all values are possible, while making extreme values significantly less likely, particularly for higher gestational ages.

5.2.3.3 Days of Oxygen Support

Days of oxygen support refers to the duration during which an infant receives supplemental oxygen (>21% room oxygen), provided through methods such as conventional ventilation, HFO, CPAP, or high/low flow cannulas (Goldsmith & Kattwinkel, 2012). This metric is crucial in diagnosing long-term pulmonary problems in preterm infants, particularly those born before 32+0 weeks of gestation. Prolonged oxygen support is an indicator of bronchopulmonary dysplasia, a chronic lung disease prevalent in very preterm infants (Thébaud et al., 2019).

In Figure 34, we see that the use of supplementary oxygen support is distributed differently across the wards. In addition, especially for NICU, we see a strong increase with decreasing gestational age.

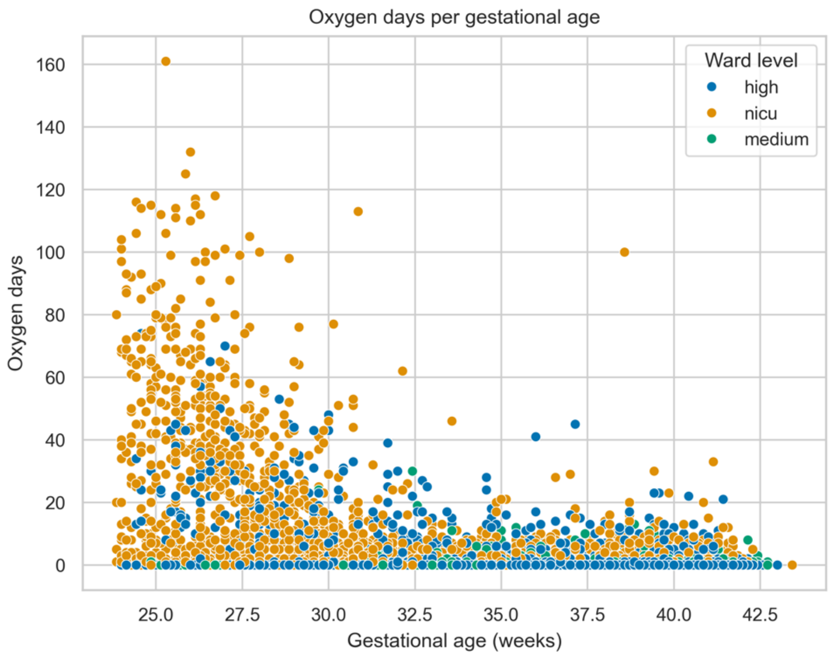


Figure 34 Distribution of oxygen support days by gestational age in weeks

Based on a visual inspection, I decided to have different sampling per ward level. As I did not manage to find a theoretical distribution, I again grouped the observations into different age groups, defined probabilities for the most common values, and the used an inverse function scaled by gestational age for the remaining value range ensuring that the full observed range is included for each group, while also accounting for increasing usage with decreasing gestational age within one age group.

For NICU patients, I divided the groups into those below and above 32+0 weeks of gestation. For those below 32+0 weeks, I defined percentages for 0-10 days, while for those above, I set percentages for 0-5 days. For high care patients, there is a noticeable increase in additional oxygen use below 32+0 weeks. Consequently, I split the groups into below and above this age, defining percentages for 0-5 days for each group. For medium care patients, visual inspection indicated no need to differentiate by gestational age, so I defined probabilities for 0 and 1 days and used an inverse function for the remaining values.

5.2.3.4 Phototherapy Treatment

Phototherapy is a widely used treatment in neonatal care, primarily for managing neonatal jaundice. Jaundice, characterized by yellowing of the skin and eyes, is present to some level in up to 80% of neonates. The underlying reason are high levels of bilirubin in the blood. Bilirubin is a byproduct of red blood cell breakdown, and in newborns, especially preterm infants, the liver may not be mature enough to process it efficiently. Phototherapy helps reduce bilirubin levels and prevent the potential complications of hyperbilirubinemia, primarily potential brain damage. The likelihood for a treatment per ward can be seen in Table 29.

Table 29 Probabilities for phototherapy treatment per ward level

Ward	Treatment Probability
NICU	0.42
High Care	0.09
Medium Care	0.03

5.2.3.5 Antibiotics Treatment within the first 72 hours after birth

One of the most used treatments in neonatal care. Variable includes treatment in the first 72 hours after birth. Based on the available data, I assigned probabilities for each ward level as seen in Table 30.

Table 30 Antibiotics treatment probabilities per ward level

Ward	Treatment Probability
NICU	0.38
High Care	0.40
Medium Care	0.2

5.2.3.6 Clinical Early-Onset Sepsis Treatment

The continuation of antibiotic treatment for clinical early-onset sepsis (EOS) is covered through the variable. EOS in neonates is a severe condition that occurs within the first 72 hours of life, often resulting from bacterial infections acquired during birth. Newborns are particularly vulnerable due to their underdeveloped immune systems. Common symptoms include respiratory distress, temperature instability, and lethargy. Most patients are treated with antibiotics (Simonsen et al., 2014).

Table 31 EOS treatment probabilities per ward level

Ward	Probability
NICU	0.09
High Care	0.06
Medium Care	0.03

To incorporate the treatment into the model, I defined a probability for each ward level based on the observed values in the dataset as seen in Table 31. We see that the probability of treatment increases with increasing level of care.

5.2.3.7 Anemia Treatment

Neonatal anemia is a common condition where a newborn has a lower-than-normal red blood cell count or hemoglobin levels, affecting the oxygen supply to tissues. It can result from prematurity, blood loss, or hemolysis. Symptoms include pallor, rapid heartbeat, and poor feeding. Treatment often involves red blood cell transfusions, especially for moderate to severe cases, to quickly restore healthy blood levels (Aher et al., 2008; Nassin et al., 2015).

Table 32 Probability Overview for Anemia Treatment

Ward	Probability
NICU =< 32+0 weeks	0.24
NICU > 32+0 weeks	0.13
High Care	0.007

After analyzing the data, I decided to assign different probabilities for the relevant wards – NICU and high care and split NICU again in two gestational age groups based on the 32+0 weeks NICU cut-off. This way I maintain a simple implementation, while still accounting for the different probabilities across gestational age.

5.2.3.8 Thrombocytopenia Treatment

Thrombocytopenia is a medical condition characterized by a low platelet count. Platelets are essential for blood clotting, and their deficiency can lead to increased risk of bleeding and bruising. The condition is present in 1-5% of all births and 22-35% of all NICU patients (Roberts, 2003). Treatment can be performed through transfusion, which is also the recorded treatment in the perined dataset. As this treatment was only performed in NICU hospitals in significant numbers, I decided to model the treatment by assigning NICU patients a four percent probability of treatment based on the observed probability in the dataset.

5.2.4 Admission Criteria

The available dataset perined provides 15 admission criteria for each admission. Hospital personnel can decide at the point of admission on up to two admission criteria that are the most suitable for the respective case. However, there are no explicit definitions or requirements for the criteria leaving room for interpretation to the healthcare professionals responsible for registration. As a result, I decided to use percental distributions as inputs based on the empirical data as seen in Table 33.

Table 33 Overview of admission criteria and their probabilities between 2016 and 2017

Criteria	Proportion [%]	Proportion NICU [%]	Proportion High Care [%]	Proportion Medium Care [%]
Others	29.00	40.00	30.50	21.50
Premature	15.50	42.50	12.00	11.00
Birth Weight	14.50	24.50	17.50	11.00
Maternal Medication	14.00	2.00	18.00	13.00
Infection	7.00	5.50	9.50	4.00
Jaundice	3.00	5.00	3.50	0.80
Feeding	0.02	0.60	2.00	0.60
Congenital Abnormalities	0.01	0.03	0.00	0.00
Post IC	0.01	0.00	0.03	0.00
Asphyxia	0.00	0.00	0.00	0.00
Cardiovascular	0.00	0.00	0.00	0.00
Hypoglycemia	0.00	0.00	0.00	0.00
Low Blood Glucose	0.00	0.00	0.00	0.00
Psycho-social symptoms	0.00	0.00	0.00	0.00
Seizures	0.00	0.00	0.00	0.00
Withdrawal symptoms	0.00	0.00	0.00	0.00

The results show that nearly one-third of admissions fall under the "Others" category, indicating that the current criteria do not fully capture the variability of patients. Most premature and low birth weight patients are admitted to a NICU, while those admitted due to maternal medication are more frequently placed in high or medium care hospitals. Moreover, in the selected time period between 2016 and 2017 not all indicators were present.

Based on these results, I decided that for the modeling process, to sample from the overall probabilities of admission indicators for each patient. The sampling is bounded by some guidelines, such as that gestational age indicator is only allowed for births below 37+0 weeks and birth weight indicator below 2000g birth weight. Each patient can have up to two indicators for each admission as this was also the limit for the data entry form of the perinatal birth registry.

5.2.5 Hospitals in the region

As a last input factor, one must decide on the number of hospitals and the respective ward level. This results in the following distribution see in Table 34 across the respective ward levels for the south-west region of the Netherlands.

Table 34 Number of hospitals per ward in the region

Level	Number of hospitals	Number of currently operational beds
NICU	1	23
High care	4	62
Medium care	6	71

Adjusting the number of hospitals of a ward can massively impact the dynamics of the system as it highlights the underlying dependencies. By conceptualizing the system with the number of hospitals per ward, the system becomes more generalizable, and the eventual model implementation can easily be applied to other regions or further extended.

The operational bed capacity of a hospital is defined through the interaction of demand of incoming patients and supply of operational beds. The number of operational beds in the region was acquired through a previous survey and is shown in Table 35. The estimated number of operational beds in 2016 was calculated by taking the maximum number of patients admitted at each hospital and deducting two to account for potential overbeds.

Table 35 Overview of hospitals in the region with physical and operational bed count

Hospital	Ward Level	Estimated number of operational beds (2016)	Number of physical beds (2023)	Number of currently operational beds (2023)
Hospital 1	NICU	29	32	23
Hospital 2	High Care	20	20	17
Hospital 3	High Care	24	22	15
Hospital 4	High Care	28	21	18
Hospital 5	High Care	22	15	12
Hospital 6	Medium Care	13	13	13
Hospital 7	Medium Care	14	14	14
Hospital 8	Medium Care	13	13	13
Hospital 9	Medium Care	5	5	5
Hospital 10	Medium Care	19	8	8
Hospital 11	Medium Care	24	13	13

After consultation with a hospital planner in the field, it was confirmed that there are only minor fluctuations in the number of operational beds over a twelve-month period. Hospital management adjusts staff planning or the hiring process to minimize the risk of short-term bed closures. Therefore, also due to the absence of additional data sources on this aspect for the region, the bed count is assumed to be stable over the simulation period of one year. The initial and the currently operational number of beds serve as the foundation for the experiments, as laid out in out in chapter 7. The estimated bed count for 2016 is used for the validation of the model in chapter 6.4.

6 Model Implementation

As the next step of this simulation study, I implemented the discrete-event simulation model based on the results of the system conceptualization and data analysis. This chapter will first introduce the applied tools and model design with inputs and outputs and afterwards present the validation and verification of all components.

6.1 Salabim: Discrete Event Simulation for Python

There are various packages that provide functionalities to facilitate the implementation of a DES model in the open-source programming language Python. For this study, I decided on using the package *salabim* because of its wide range of relevant functions including holding components and concepts like monitors. In addition, I used statistical package *NumPy* for data preparation and in the data analysis *pandas* for data management and *matplotlib* and *seaborn* for visualization. The model was run using Python version 3.12.2 and Salabim version 24.0.2. The runs were parallelized with Python’s *multiprocessing* functionality to dramatically decrease total run time and use the advantages of modern multi-core processors. Additional details can be found in the associated GitHub repository found at https://github.com/alex-dietz/Discrete-Event-Simulation-for-Neonatal-Care-System.

6.2 Model Design

Based on the previous conceptualization and the functioning of the chosen package *salabim*, I developed the model design seen in Figure 35, which guided the subsequent implementation. Salabim uses an object-oriented programming approach and provides predefined classes for simulation components and resources. In the model, the design was organized into classes for PatientArrival, Hospital, and Patient, which were created as subclasses of Salabim’s component class. These classes were distributed across multiple files to ensure high maintainability and decoupling. In the model, the Hospital class includes a resource *beds* that represent the available capacity. The outside region hospital is modeled through a Hospital object with unlimited amount of the bed resource ensuring that it can always accommodate for an additional patient. Additionally, by establishing distinct classes for each model element, the model can be easily extended to incorporate additional or modified hospitals, patients, and arrival processes. This modular approach enhances the flexibility and scalability of the model, allowing it to adapt to different scenarios and requirements.

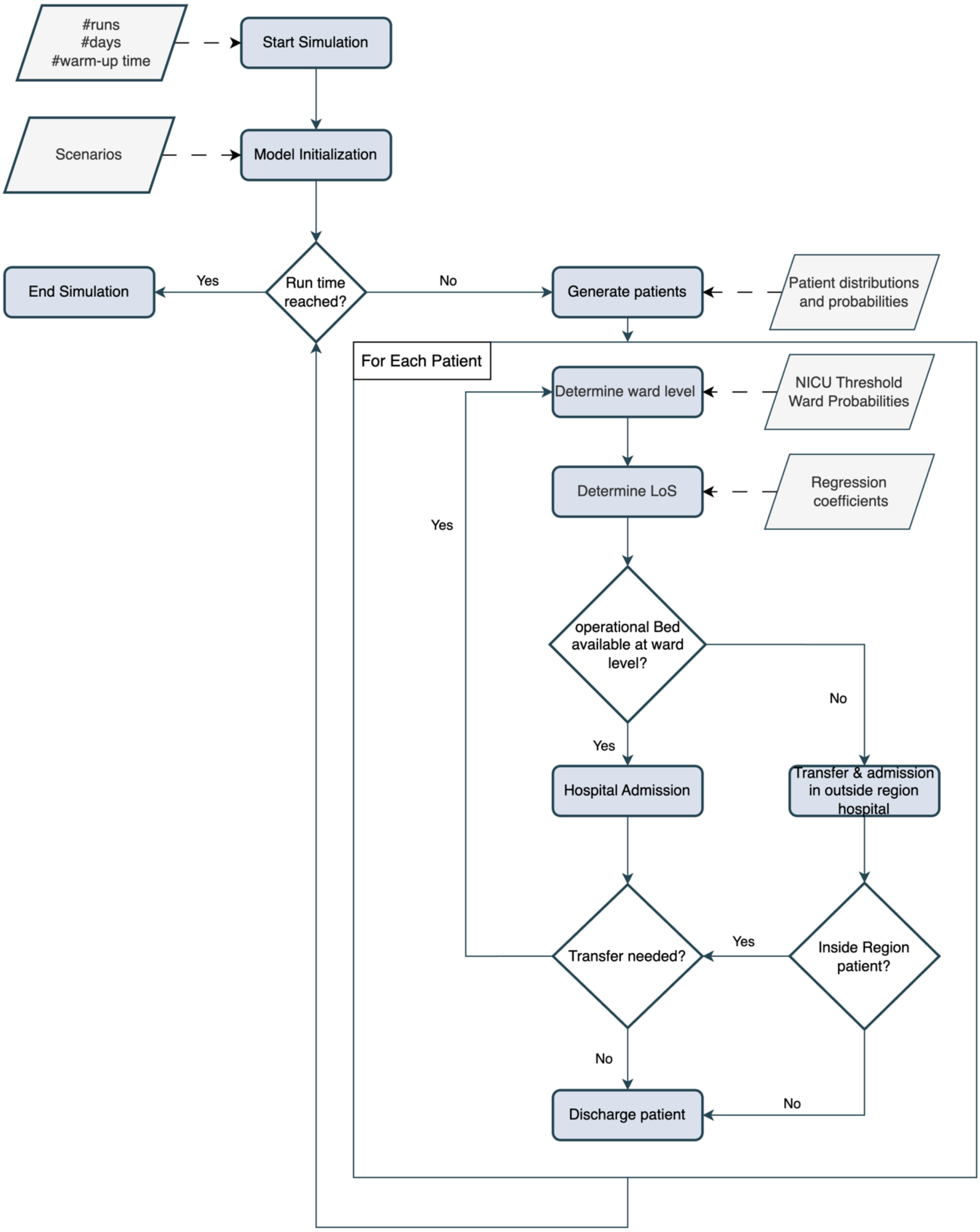


Figure 35 Model design of neonatal care system simulation model implementation

Once the simulation is started, the model is initialized based on the configured settings in *run_config.py* as it creates the necessary hospital and patient generator objects depending on the selected scenarios. The simulation begins with a patient generator that samples the number of daily arrivals as an integer from the specified distributions. For each patient, core characteristics such as birth weight, gestational age, subregion, and admission criteria are sampled to determine the appropriate ward level.

At each time step, the model loops through all patients who are currently active (i.e., not on hold) and processes their next step. If a patient needs to be admitted to a hospital and an operational bed is available, the Patient object claims a bed resource from the respective hospital and occupies it for the determined LoS. Once the patient's LoS has elapsed, the object releases the bed resource, and the system evaluates whether the patient requires an additional stay. If further care is needed, the model checks for bed availability at the requested ward level. If no bed is available, the patient is transferred to an outside region hospital. After each time step, the model checks whether the designated run time has been reached to determine if the simulation should end.

6.2.1 Model Inputs

Based on the model design and conceptualization, multiple inputs must be defined for a model run. These inputs are categorized into run inputs and model inputs. The run input parameters are presented in Table 48.

In addition to the general run inputs, the simulation model requires various input variables to operate effectively. These variables are essential for generating hospitals with the appropriate capacity, defining the patient arrival process, and establishing distributions for patient characteristics, pathways, and treatments. An overview of these variables can be seen in Table 36.

Table 36 Simulation model input variables

Input Variable	Description	Format
Hospitals	List of hospitals with ward level and operative bed count	Dictionary with hospital name, subregion, and operational bed count
Patient arrival Rates	Number of region patients	Mean standard deviation, upper and lower bound for bounded normal distribution
Subregion distribution	Which subregion patient is coming from	Dictionary with share of patients per subregion
Gestational age	Distribution of patient birth age	Weights, means, and covariances of GMM for each component
Birth Weight	Regression coefficients to determine birth weight based on gestational age	Number for coefficient and intercept
Length of Stay	Regression coefficients per ward level and per age subgroup	Dictionaries with variables and coefficients
Admission Criteria	Probabilities for each of the 15 admission criteria	Dictionary with probabilities
O2 support days	Days of treatment, Divided by ward and age groups	Dictionary with probabilities per day
CPAP Treatment	Days of treatment, Divided by ward and age groups	Dictionary with probabilities per day
HFO/Conventional ventilation treatment	Days of treatment, Divided by ward and age groups	Dictionary with probabilities per day
C-Section	Boolean value	Probability
Anemia treatment	Divided by ward and age groups	Probabilities
Antibiotics treatment	Divided by wards	Probabilities
Phototherapy treatment	Divided by wards	Probabilities
Sepsis treatment	Divided by wards	Probabilities

All input variables are based on the results presented in the previous chapter on the system's conceptualization and data analysis. To ensure transferability to other settings, such as different regions, all variables are defined in a separate file. This modular approach allows for easy adaptation and reuse of the model in various contexts.

6.2.2 Model Outputs

Running the simulation model leads to the output files mentioned in Table 37 as they are saved for each simulation in the output folder to facilitate the proceeding analysis.

Table 37 Output files for each simulation

Output variable	Description	Format
Patient admissions	Table of all patient admissions and their characteristics similar to perined format	CSV file including all runs
Occupancy rate	Daily occupancy rate of hospitals and ward levels on each time step	CSV file including all runs

For output analysis and visualization, I created additional Jupyter notebooks that can be run after each simulation. These notebooks provide flexibility to adjust the analysis to individual needs. There are specialized notebooks for validation, analyzing a single simulation, and comparing simulations for tested levers and interventions. This approach ensures that the model is easily extendable for testing additional levers or interventions and allows for direct analysis of their impacts. These notebooks allow to analyze the simulation model outputs described in Table 38.

Table 38 Simulation model outputs

Output variable	Description	Format
Required Beds	Minimum number of beds per ward level required to provide care to all inside region patients Calculated by summing the LoS of all inside region patients divided by 365 for each ward level	Number per ward level
Weekly Occupancy Rate	Weekly moving average occupancy rate of each ward levels on each time step	Percentage per ward level
Capacity Transfer Rate	Percentage of inside region patients per ward level that needed transfer to outside region hospital	Percentage per ward level
Weekly Capacity Transfers	Number of weekly capacity transfers for each occupancy rate (grouped by nearest 2.5%) per ward level	Number per occupancy rate and ward level

The four performance indicators provide a quantitative picture from the hospital and societal perspective and allow to compare any kind of changes in the system.

6.2.3 Number of Runs

The simulation model includes multiple stochastic elements, resulting in different outcomes for each run with a different random seed. Therefore, it is necessary to run the model with various seeds to approximate the most likely values. The appropriate number of runs was determined by analyzing the average occupancy rate per ward level and the average capacity transfer rate per ward level over multiple runs, as shown in Table 39.

Table 39 Comparison of average occupancy rate and average capacity transfer rate per ward level across different numbers of runs using estimated 2016 bed number and 365 days run time

Ward Level	Number of Runs	Average Occupancy Rate [%]	Average Capacity Transfer Rate [%]
NICU	10	87.36	11.18
	25	87.41	10.85
	50	87.33	11.05
	100	87.22	11.04
	250	87.42	11.13
High Care	10	83.09	0.80
	25	82.94	0.76
	50	82.95	0.76
	100	82.73	0.75
	250	82.99	0.81
Medium Care	10	34.06	0.00
	25	33.84	0.00
	50	33.66	0.00
	100	33.71	0.00
	250	33.62	0.00

By comparing the average occupancy and capacity transfer rates per ward level, I decided that 25 runs are sufficient to capture the randomness of the model and provide reliable results as the changes for occupancy and capacity transfer rate were not indicating a trend nor big enough to have an impact on the model’s purpose.

6.2.4 Warm-up time for Simulation Model

A warm-up time is defined as the period required for the system to reach a stable state. Appropriate output data is collected only after reaching this state. Since the simulation starts with no occupied operational beds, a warm-up time is essential to avoid skewed relative data, such as the occupancy rate.

To determine an adequate warm-up time, the model was run for 200 days over 25 runs as seen in Figure 36. By visually inspecting the occupancy rate per ward level, a saturation level was identified, indicating when the system reached stability. This approach ensures that subsequent data collected for analysis accurately reflects the system's performance in a stable state, providing reliable insights into occupancy rates and capacity transfer rates.

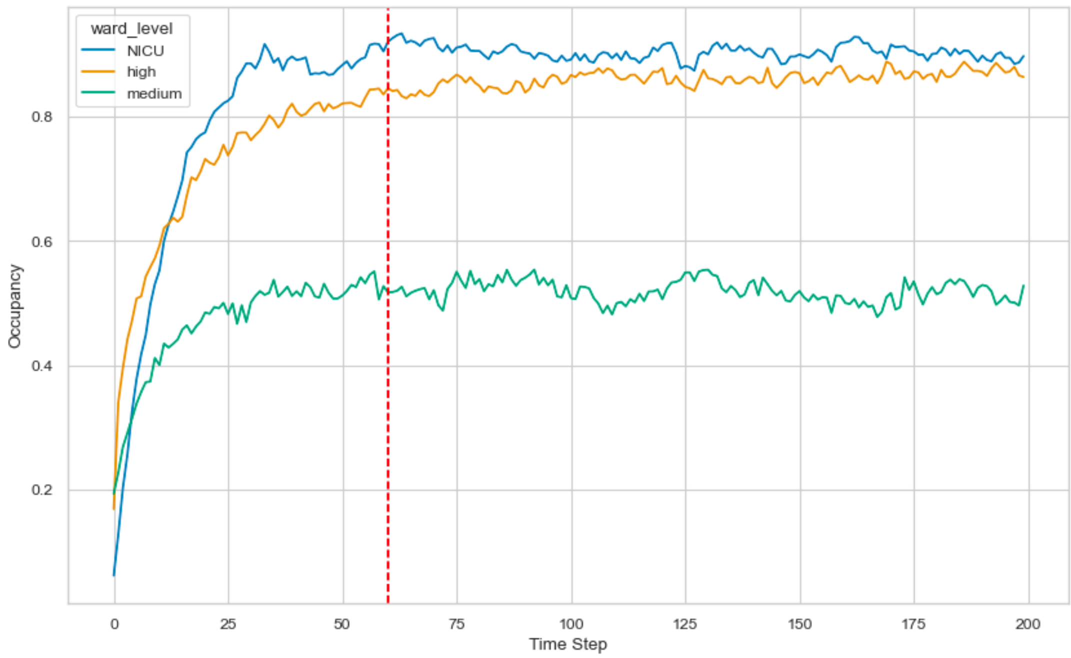


Figure 36 Occupancy rate across wards per time step

This level is reached for each ward at a different time step. Hence, I set the warm-up time at 70 days as on this point also the high care ward starts to stabilize around its average.

6.3 Model Verification

The model verification process is used to confirm that the implemented model accurately follows the results of the conceptualization and adheres to its defined boundaries and assumptions. This step ensures that the model behaves as intended and that its output is consistent with expectations of the real world.

6.3.1 Model Component Verification

At first, the implemented model components were verified. Each component was tested to ensure it exhibited the expected behavior. This step involved checking the functionality of individual parts of the model to confirm that they operated correctly and aligned with the conceptual design.

6.3.1.1 Patient Generator

The patient generator component is designed to create patient objects in the simulation and assign them appropriate characteristics. After generating patients, the generator should pause until the next time step. To verify this, I ensured that the arrivals follow the expected distribution, including checking for minimum and maximum values. This step confirms that the patient generation process accurately reflects the real-world arrival patterns and operates within the defined parameters.

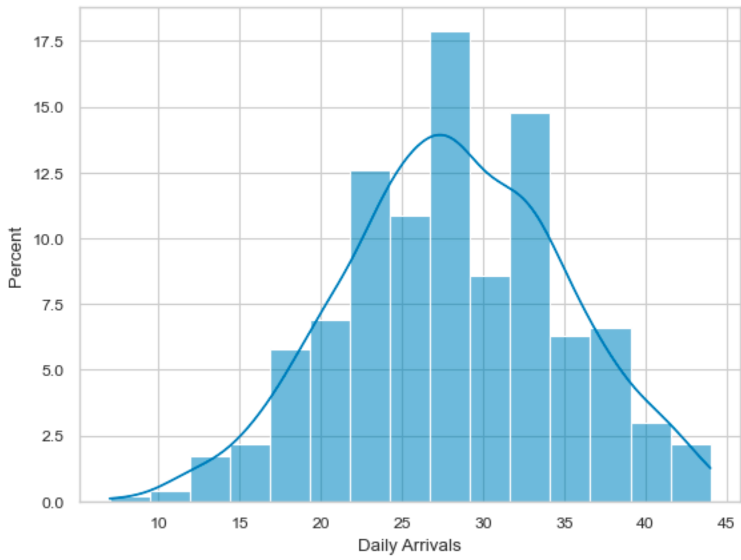


Figure 37 Daily Arrivals at hospitals in the region

The arrivals follow a bounded normal distribution with mean 28 and standard deviation of 7, the minimum bound is 7 and there is no day with more than 44 new patients. In addition, I verified that patients are properly generated for all ward levels as seen in Figure 38, Figure 39, and Figure 40.

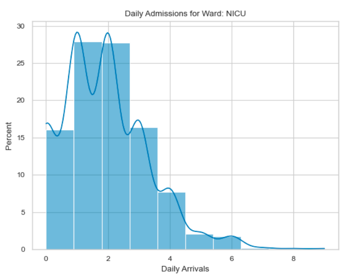


Figure 38 Daily Arrivals for NICU

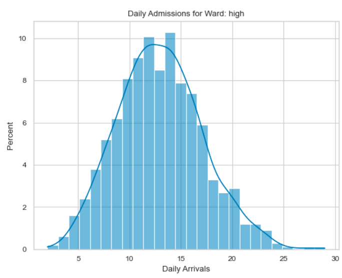


Figure 39 Daily Arrivals for High Care

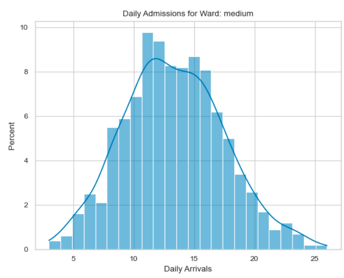


Figure 40 Daily Arrivals for Medium Care

We see that the wards follow different arrival rates, and each ward has minimum and maximum values in feasible ranges. Moreover, as expected, the NICU is the only ward level that also has days with zero admissions.

6.3.1.2 Patient

The generated patient objects need to be assigned their characteristics, admission criteria, and ward level.

id	242
subregion	Rotterdam Zuidover
cesarean_section	1
gestational_age	196
weight	1540
stay_number	1
hospital	Erasmus MC
ward	NICU
hospital_region	Rotterdam Noordoever
cpap	20
o2	2
hfo	2
antibiotics	1
photherapy	1
anemia	0
thrombocytopenia	0
sepsis	1
admission_criteria	premature,weight
length_of_stay	28
start_date	10.0
end_date	38.0

Figure 41 Example NICU patient

id	patient.4648
subregion	Zuid-Holland Eilanden
cesarean_section	1
gestational_age	286
weight	3789
hospital	Maasstad Ziekenhuis
ward	high
hospital_region	Rotterdam Zuidoever
cpap	0
o2	0
hfo	0
antibiotica	0
photherapy	0
anemia	0
thrombocytopenia	0
sepsis	0
admission_criteria	['feeding']
length_of_stay	2
start_date	170.0
end_date	172.0

Figure 42 Example High Care Patient

id	patient.4662
subregion	Rotterdam Noordoever
cesarean_section	0
gestational_age	257
weight	2614
hospital	IJsselland Ziekenhuis
ward	medium
hospital_region	Rotterdam Noordoever
cpap	0
o2	0
hfo	0
antibiotica	1
photherapy	0
anemia	0
thrombocytopenia	0
sepsis	0
admission_criteria	['others']
length_of_stay	5
start_date	171.0
end_date	176.0

Figure 43 Example Medium Care Patient

Figures 32, 33, and 34 show an exemplary patient for each ward level. We see the patient core data, which hospital they were admitted, the start and end date and any kind of treatments as well as the admission criteria.

6.3.1.3 Hospital Generator

In the beginning of the simulation, all hospitals with their respective ward level and operational bed number are generated.

```
RUN ID: 1, SEED: 42
   45                          hospital.0 create data component
                               line numbers prefixed by A refer to  hospital.py
   A6                          Hospital 1_NICU create               capacity=28
   45                          hospital.1 create data component
   A6                          Hospital 2_high create               capacity=20
   45                          hospital.2 create data component
   A6                          Hospital 3_high create               capacity=24
   45                          hospital.3 create data component
   A6                          Hospital 4_high create               capacity=28
   45                          hospital.4 create data component
   A6                          Hospital 5_high create               capacity=22
   45                          hospital.5 create data component
   A6                          Hospital 6_medium create             capacity=13
   45                          hospital.6 create data component
   A6                          Hospital 7_medium create             capacity=14
   45                          hospital.7 create data component
   A6                          Hospital 8_medium create             capacity=13
   45                          hospital.8 create data component
   A6                          Hospital 9_medium create             capacity=5
   45                          hospital.9 create data component
   A6                          Hospital 10_medium create            capacity=19
   45                          hospital.10 create data component
   A6                          Hospital 11_medium create            capacity=24
   52                          hospital.11 create data component
   A6                          outside_region_outside_region create capacity=inf
```

Figure 44 Generated Hospitals with capacity

In Figure 44, we see that different hospitals are created, and that each hospital has a name, ward level, and bed capacity. The beds are modelled as resources of a hospital. Thus, patients should be able to claim a quantity of the bed resource. However, a patient should not be able to claim more than one quantity.

```
                     patient.0                          request 1 from Bravis_medium priority=inf
                     patient.0                          claim 1 from Bravis_medium  priority=inf
                     patient.0 request honor Bravis_medium scheduled for 0.000 @ B111+
0.000 patient.1      current
                     patient.1                          request 1 from Franciscus Gasthuis & Vlietland_high priority=inf
                     patient.1                          claim 1 from Franciscus Gasthuis & Vlietland_high  priority=inf
                     patient.1 request honor Franciscus Gasthuis & Vlietland_high scheduled for 0.000 @ B111+
0.000 patient.2      current
                     patient.2                          request 1 from Amphia_high priority=inf
                     patient.2                          claim 1 from Amphia_high  priority=inf
                     patient.2 request honor Amphia_high  scheduled for 0.000 @ B111+
0.000 patient.3      current
                     patient.3                          request 1 from IJsselland Ziekenhuis_medium priority=inf
                     patient.3                          claim 1 from IJsselland Ziekenhuis_medium  priority=inf
                     patient.3 request honor IJsselland Ziekenhuis_medium scheduled for 0.000 @ B111+
0.000 patient.4      current
                     patient.4                          request 1 from Franciscus Gasthuis & Vlietland_high priority=inf
                     patient.4                          claim 1 from Franciscus Gasthuis & Vlietland_high  priority=inf
                     patient.4 request honor Franciscus Gasthuis & Vlietland_high scheduled for 0.000 @ B111+
0.000 patient.5      current
                     patient.5                          request 1 from IJsselland Ziekenhuis_medium priority=inf
                     patient.5                          claim 1 from IJsselland Ziekenhuis_medium  priority=inf
                     patient.5 request honor IJsselland Ziekenhuis_medium scheduled for 0.000 @ B111+
0.000 patient.6      current
                     patient.6                          request 1 from IJsselland Ziekenhuis_medium priority=inf
                     patient.6                          claim 1 from IJsselland Ziekenhuis_medium  priority=inf
                     patient.6 request honor IJsselland Ziekenhuis_medium scheduled for 0.000 @ B111+
0.000 patient.7      current
                     patient.7                          request 1 from Albert Schweitzer Ziekenhuis_high priority=inf
                     patient.7                          claim 1 from Albert Schweitzer Ziekenhuis_high  priority=inf
                     patient.7 request honor Albert Schweitzer Ziekenhuis_high scheduled for 0.000 @ B111+
```

Figure 45 Trace of patient requesting and claiming beds

Figure 45 shows the trace for the first timestep of a simulation. We see that patients only request and claim one bed at a time. This indicates that the hospital component is functioning correctly, as it processes patient bed requests in a controlled and sequential manner. These examples confirm that the hospital component behaves as expected, ensuring proper bed allocation and patient management within the simulation.

6.3.2 Model Function Verification

As a second verification step, I verified the individual functions in the model. I first checked that patient are admitted to different wards based on their conditions. Secondly, I checked that patients have different LoS depending on their ward level and lastly, I confirmed that patients can have multiple stays across hospitals.

6.3.2.1 Ward Level Admissions

Each patient is admitted to a ward level depending on their conditions. I verify that all patients that fulfill the NICU criteria are admitted to a NICU for their first stay. The ward level for other patients is decided by probabilities.

Table 40 Verification of gestational age and birth weight per ward level

Ward Level	Min Gestational Age	Max Gestational Age	Min Birth Weight	Max Birth Weight
NICU	24+0	42+6	400	5145
High Care	32+1	42+6	1266	5329
Medium Care	32+1	42+6	1256	5266

As seen in Figure 48, patients under 32 weeks of gestational age or under 1250g birth weight have their first stay in a NICU. It is also possible to have older NICU patients as the admission criteria congenital abnormalities also requires NICU care.

6.3.2.2 Length of Stay

Each patient is assigned a different ward level based on their medical conditions and treatments. The next step involved verifying that patients in different ward levels have different LoS and that patients within a single ward level group exhibit variability in their characteristics.

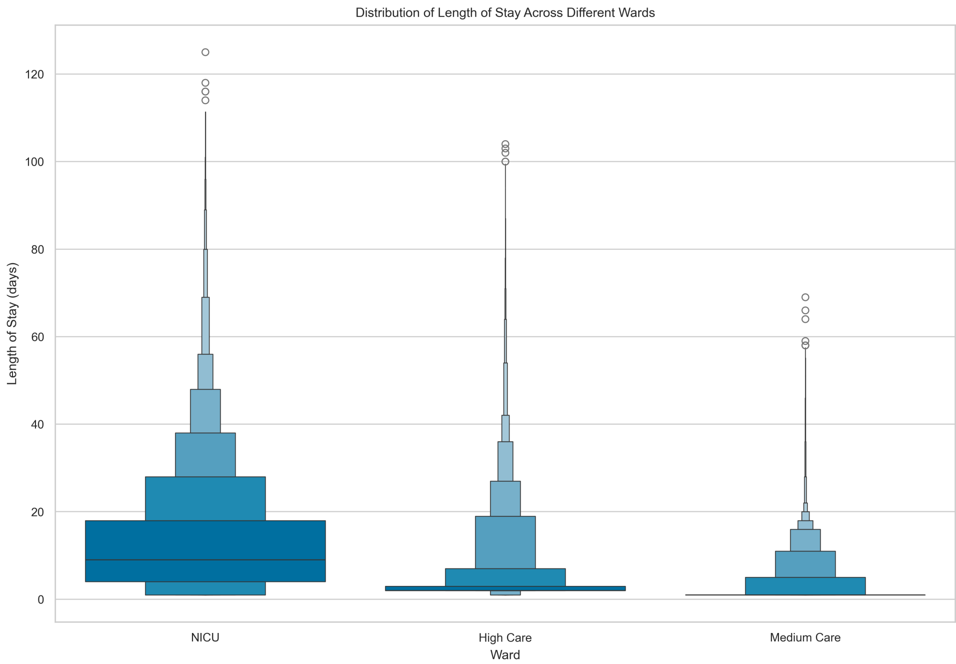


Figure 46 Comparison of simulated LoS distribution across different ward levels

Based on Figure 46, it is evident that the mean and variance of LoS differ between the ward levels. Additionally, each ward level covers a wide range of potential LoS, indicating significant variance among patients within the same ward level group. In addition, NICU and high care patients have patients with a LoS of more than 100 days, hence, also covering the relevant extreme cases of patients.

6.3.2.3 Patient Pathways

The model allows patients to have multiple stays, thus, capturing an additional layer of complexity in the neonatal care system. Patients can be admitted at any hospital of a different ward level compared to their previous stay given set probabilities.

Table 41 Overview of patient pathway for simulation

Patient Pathway	Proportion [%]
High Care	52.43
Medium Care	39.16
NICU	4.79
NICU-High	1.50
High-NICU	0.74
Medium-NICU	0.55
NICU-Medium	0.32
High-NICU-High	0.23

We see the most common paths align with the common paths identified in 5.1.3. Consequently, the model can simulate this mechanism.

6.4 Model Validation

The model validation aims to confirm that the modeled processes are as close as possible to observations in the real world. This will be done in a three-step approach by first comparing the simulated data against the available perined dataset in historical data validation, second, by testing two extreme conditions to identify logic flaws, and third, by gaining a face validation from experts in the field to validate the applicability and interpretability of results.

6.4.1 Historical Data Validation

The first validation step is performed by comparing the simulation results with observed values in the neonatal care system of the south-west of the Netherlands region. All historical comparisons are performed for the 01.01.2016 to 15.10.2017 timeframe for the highlighted data quality issues as presented in chapter 5.

Arrival Process

The patient generator component of the model should adequately be able to create patient components that follow the same distribution as in the historical data. In addition, the daily arrivals need to be accurate for each ward level to properly simulate patient flows. As a first validation step, I visually inspect the daily arrival distribution for each ward level in Figure 47.

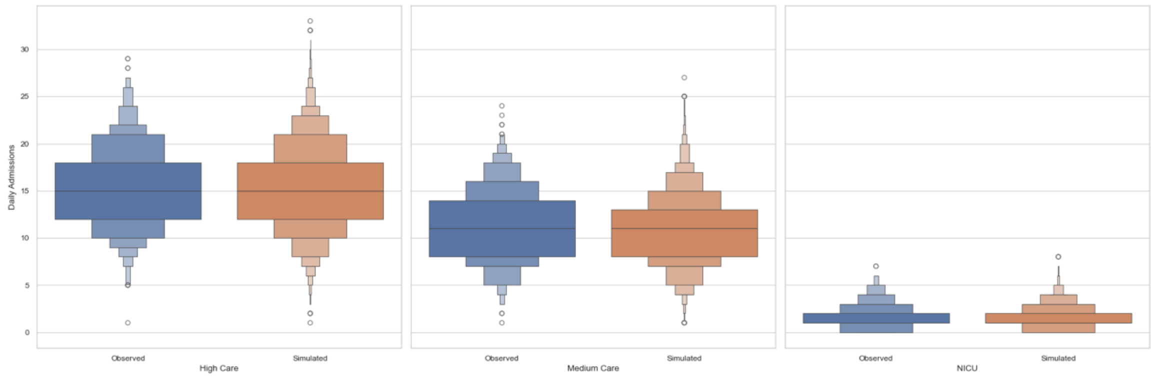


Figure 47 Letter-value plots comparing observed and simulated daily admissions per ward level

Analyzing each ward level, we only see minor differences in the distributions and extreme values are well captured.

As a second validation step, statistical testing was applied to demonstrate that the samples originate from the same distribution. A Kolmogorov-Smirnov test was performed for each ward level to validate that observed and simulated arrivals could come from the same distribution for each ward level. The hypotheses are as follows:

H_0: The observed and simulated daily admissions come from the same distribution.

H_1: The observed and simulated daily admissions come from different distributions.

As seen in Table 42, the actual and simulated daily arrivals are similar, and the p-values indicate that the null hypothesis cannot be rejected. The samples are not statistically significantly different at the 5% level.

Table 42 Comparison actual and simulated average daily arrivals per ward level

Ward Level	Average Daily Arrivals (Perined 2016-2017)	Average Daily Arrivals (Simulation over 25 runs)	KS-Test P-Value
NICU	1.66	1.62	0.79
High Care	15.32	15.30	0.99
Medium Care	11.13	11.05	0.55

Thus, these results indicate that the simulation model can properly simulate the daily arrivals for each ward level.

Length of Stay

While the arrival process defines how many patients enter the system, the LoS calculation determines how long they stay per admission and is, thus, another crucial part of the model. The regression functions were validated by comparing the statistical descriptions and plotting the LoS distribution across gestational ages for each ward level.

For the NICU, the simulated LoS is adequate for each gestational age group and accurately captures the overall trend of increasing LoS for decreasing gestational age below 32 weeks, as seen in Figure 48. This validation ensures that the model effectively represents the relationship between gestational age and LoS, particularly for the critical group of extremely premature neonates.

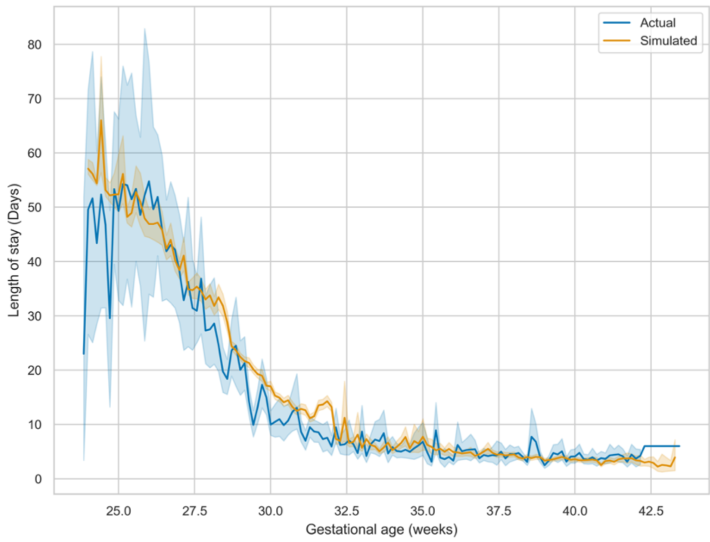


Figure 48 Comparison between actual and simulated LoS for NICU care patients

A comparison between the simulated and observed LoS values resulted in a R^2 of .94 confirming an overall good fit. Differences between actual and simulated LoS can be seen especially for extreme premature patients below 27+0 weeks gestational age. This can be explained as the mortality rate increases drastically for decreasing age leading to potential LoS of just a couple of days. The regression model has been trained including these data points and, thus, on average leads to appropriate values. The model currently does not include a mechanism for mortality but rather those patients stay for their initial LoS and do not have an additional stay based on the pathway probabilities.

For the high care ward level, we see that the simulated LoS is adequate for each gestational age group and captures well the overall trend of increasing LoS for decreasing gestational age below 37+0 weeks but also the downward shift below 30+0 weeks, as seen in Figure 49.

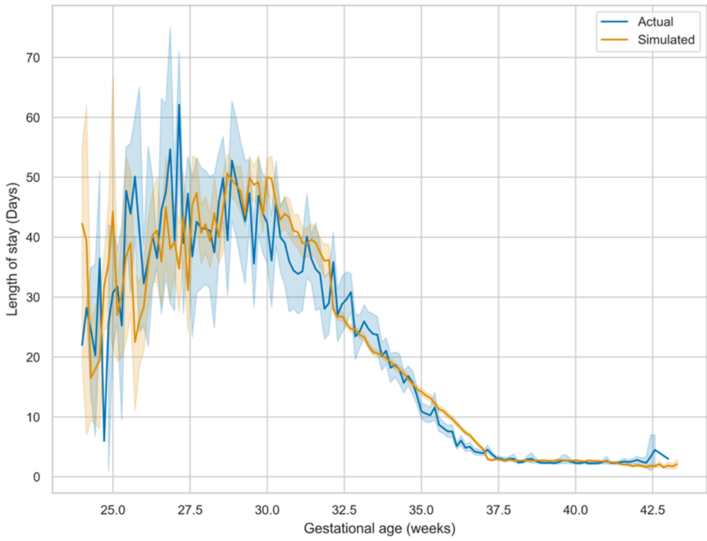


Figure 49 Comparison between actual and simulated LoS for high care patients

A comparison between the simulated and observed LoS values resulted in a R^2 of .94 confirming an overall good fit. However, it is still visible that there are more factors at play than the selected variables in the regression model and the actual data includes a bigger variance for each gestational age.

For medium care, we see that the simulated data follows a similar pattern as the historical data as visualized in Figure 50. The simulated data does not have such enormous fluctuations as the historical data for below 32+0 weeks gestational age, however, the regression does on average still capture the LoS properly for this group.

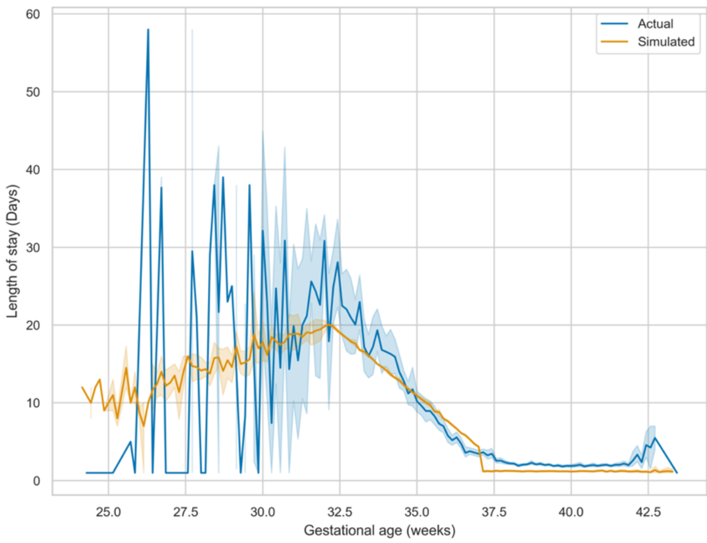


Figure 50 Comparison between actual and simulated LoS for medium care patients

A comparison between the simulated and observed LoS values resulted in a R^2 of .93 confirming an overall good fit. Biggest difference can be observed for patients with gestational age greater than 37+0 weeks. The regression underestimates the LoS as already observed in the data analysis chapter. For this group the dataset did not provide enough correlated factors and, thus, the regression struggled more to explain the variance across patients.

Using the visual inspection, I validated that the LoS follows the expected patterns across different gestational ages for the respective wards. As a next validation step, I compare the average LoS for each ward as displayed in Table 43.

Table 43 Comparison between average observed LoS and simulated LoS per ward level in days

Ward Level	Average observed LoS [days]	Average LoS (Simulation with base scenario over 25 runs) (min-max) [days]
NICU	12.50	12.61 (11.90-13.68)
High Care	5.68	4.72 (4.53-4.90)
Medium Care	3.2	3.21 (3.03-3.41)

The comparison shows that the average LoS across simulation runs is adequately close to the observed values in the perined dataset. High and medium care are slightly underestimated as already mentioned in the visual inspection. This is explained due to the increase variability of patients on these ward levels decreasing the potential for regression models to capture all underlying factors. Overall, the two steps – visual and statistical inspection – showed that the model can simulate LoS for each ward level and, thus, the total patient population in the neonatal care system.

Patient Pathways

As the model aims at capturing the complexity of the neonatal care pathway, it is necessary to confirm the number of patients with more than one admission and the ward combinations for the patient journey. To validate the results of the model, I ran the simulation for 25 runs with the assumed operational bed counts from 2016 to compare it to the accurate timeframe between 01.01.2016 and 15.10.2017 in the perined dataset as seen in Table 44.

Table 44 Comparison of patient pathways between historical and simulated data

Patient Pathway	Perined 2016-2017 [%]	Simulation with 2016 bed counts over 25 runs [%]
NICU	4.37	4.79
High Care	53.29	52.43
Medium Care	38.94	39.16
NICU-High	1.99	1.50
Medium-NICU	0.41	0.55
High-NICU-High	0.3	0.23
High-NICU	0.26	0.74
NICU-Medium	0.18	0.32

The model captures the patient pathways accurately with only small differences for individual pathways that should not have major impact on the model outcomes. Thus, the results indicate that the model mechanism is valid.

Required Beds

The first output variable is the number of required beds for inside region patients per ward level, indicating the theoretical minimum of required operational beds in the region. The numbers are obtained by summing the LoS for all inside region patients per ward level and dividing by 365 days as seen in Table 45.

Table 45 Comparison Required Beds between historical and simulated data per ward level

Ward	Required Beds (Perined 2016-2017)	Average Required Beds (with 2016 bed count over 25 runs) (min-max)
NICU	23.62	26.63 (24.39-29.25)
High Care	68.42	74.32 (70.66-79.26)
Medium Care	35.80	33.35 (31.09-35.38)

The observed and simulated numbers for the required beds for inside region patients are similar, yet the simulation model tends to overestimate the numbers for NICU and high care wards. This can be explained by small deviations in average LoS and arrival rates for these ward levels.

Occupancy Rates

A second output variable is the occupancy per hospital that can be aggregated to the occupancy rates per ward level. Unfortunately, there are no records for the occupancy rate across hospitals or ward levels for the region. Thus, I tried to approximate it by calculating it based on the admissions and the Los of patients in the reliable timeframe of 2016 to fall 2017 as seen in Table 46.

Table 46 Comparison Occupancy Rates between historical and simulated data per ward level

Ward	Average Estimated Occupancy Rate (Perined 2016-2017) [%]	Average Simulated Occupancy Rate (with 2016 bed count over 25 runs) (min-max) [%]
NICU	78.61	87.07 (83.00-89.45)
High Care	81.07	82.59 (79.69-86.65)
Medium Care	31.80	34.82 (32.15-36.97)

Differences can be explained by lower NICU LoS in that time (11.9 compared to 12.5 average over all years), while the LoS regression models were developed over full time period. Personal communication with experts confirmed that NICU LoS is increasing over the last years. To ensure that the model is accurate as possible for today I decided to not adjust the LoS calculation for a 2016 validation.

Capacity Transfers Rate

One of the main indicators of the system's performance is the number of capacity transfers, which refers to the number of patients transferred to an outside region hospital due to capacity shortages. Unfortunately, there are no records of a capacity transfer rate across hospitals or ward levels for the region. Thus, this rate was approximated by calculating the number of capacity transfers divided by the total admissions of inside region patients in the reference timeframe of 2016. The comparison was done using estimated bed counts from 2016. The results are shown in Table 47.

Table 47 Comparison Capacity Transfer Rate between historical and simulated data per ward level

Ward	Capacity Transfer Rate (Perined 2016-2017) [%]	Average Capacity Transfer Rate (Simulation with 2016 scenario over 25 runs) (min-max) [%]
NICU	13.33	11.22 (6.43-15.67)
High Care	0.44	0.72 (0.14-1.54)
Medium Care	0.00	0.00 (0.00-0.00)

We see that the model closely matches the actual observed values. The discrepancies can be attributed to uncertainty about the exact operational bed count in 2016. Additionally, the simulation model does not account for overbeds, which refers to the common practice of accommodating one or two extra patients for a short period when all regular beds are occupied.

Weekly Capacity Transfers

The weekly capacity transfers cannot easily be validated because unfortunately there is no data available that would allow the matching of occupancy rates with the time of capacity transfers. However, as all other model outcomes were validated and as the indicator is a combination of previous information, it can be assumed to also be accurate.

6.4.2 Extreme Conditions Validation

Testing a model under extreme conditions is useful for identifying potential faults in the logic for unexpected values and border cases. Thus, I first tested the impact of setting the operational bed capacity of all hospitals to zero. As expected, each patient had to be transferred to outside-the-region hospitals. Secondly, I tested the workings when no patient was arriving in the system. As expected, all outputs remained empty, and no beds were occupied.

6.4.3 Face Validation

Face validation is performed by talking to experts in the real-world system through the model and having them analyze and question simulated data. This validation was performed with an expert from the Erasmus MC hospital who validated the generated patient characteristics and treatments, compared simulated arrival rates and LoS with currently observed data. Hence, they ensured that the model aligns with the expectations.

7 Experiments

The established model was used to perform experiments on scenarios, system levers, and interventions. The following sections will introduce the individual experiments, explain how they were implemented, and present the respective results.

7.1 Scenario Experiments

The implemented simulation model offers valuable insights into potential future scenarios beyond the hospital or region's direct control. By testing four different scenarios, the model demonstrates its capability to evaluate the impact of these varying futures on the neonatal care system, providing essential information for effective planning and decision-making.

1. Base Scenario: No Capacity Shortage

As a first scenario, the model was run with the currently highest number of physically available beds for each hospital. Thus, this scenario provides a picture of the current best case and analyzes if this setting is enough to sufficiently provide the required care.

2. Current Situation: Capacity Shortage

With the ongoing staffing crises, hospitals are forced to close beds and, thus, lower the number of operational beds. Hence, this scenario experiment used the number of operational beds based on a survey across hospital in 2023. It is assumed that these numbers most closely reflect the current situation. This change in operational beds is assumed as a scenario as the bed closures are driven by a general shortage in healthcare personnel that is beyond the control of individual hospitals.

3. Outside Region Demand Increase

While the data and interview partners (Interview 1,2) showed that there have been no significant demographic developments in the past decade and that there are unlikely any changes in the following years, one factor can influence the number of patients in the region – outside region patients – as already suspected by one interview partner (Interview 2). Through the regionalization of neonatal care, every region should, in theory, be self-sustainable and be able to provide care to all patients living in the region. However, this is not the case due to capacity shortages and patients who are being transferred between regions. In the available dataset, outside region patients accounted for circa 5% of all admitted patients translating to circa 1.5 patients per day on average. Thus, I simulated an increasing capacity shortage in the neighboring regions by increasing the number of outside region patients by 20% leading to a total increase in arriving patients. This, scenario reflects the interdependencies between regions and highlights that capacity shortages are not a phenomenon of just one region but rather a national challenge.

4. Change in Government Guideline for minimum Age to 23 weeks (NICU@23)

Over the last decades, medical care improvements have affected NICU patients and continuously provided a higher probability of survival for lower gestational ages. The current guideline in the Netherlands is a minimum age of 24 weeks; however, there are ongoing discussions about decreasing this value to 23 weeks. A major driver for this development is guidelines in neighboring countries, like Belgium and Germany, that already provide care for under 24-week-old neonates. This change would add highly medically complex patients to the NICU population and potentially add further challenges to existing capacity shortages to the NICU and beyond and patients have an exceptional long LoS and often require additional stays at lower care levels after the initial NICU stay.

7.1.1 Implementation of Scenario Experiments

Each scenario can individually be selected or unselected using the run input parameters, seen in Table 48, in the *run_config.py* file. All scenario experiments were performed by running the model with the determined run time of 365 days, 70 days of warm-up over 25 runs to ensure minimal randomness between runs.

If the base hospital scenario is active the model initiates the hospital objects with the number of currently available physical beds, as described in Section 5.2.5. These numbers were collected from a survey by an Erasmus MC study in 2023 and represent the most accurate numbers still today. For the second hospital scenario addressing capacity shortages, the number of operational beds was changed to the number of available operational beds in 2023, according to the survey. The third scenario addresses another uncertainty: the arrival of outside region patients. Hence, by using an additional patient generator further outside region patients were created that would eventually increase the number of outside region patients by 20%. The generator assumes a Poisson arrival process with an inter arrival time of 3.5 days. For the NICU@23 scenario, I implemented another patient generator with an inter arrival time of 27 days meaning that on average every 27 days a patient with a gestational age of 23 weeks would arrive in the region. The inter arrival time is based on a current impact estimation for the region by Erasmus MC. The demand and NICU@23 scenario are run with the capacity shortage hospital scenario to account for the status quo.

Table 48 Overview of necessary run input parameters for scenario experiments

Run Input variable	Description	No Capacity Shortages	Capacity Shortages	Outside Demand Increase	NICU@23
Number of Runs	How many times should the simulation be repeated	25	25	25	25
Days per Run	How many days should be run and recorded after the warm-up time	365	365	365	365
Warm-Up Time	How many days should be run before starting to record outputs	70	70	70	70
Hospital Scenario	Decides on the number of beds in each hospital (-1: 2023 physical bed count, 1: 2023 operational bed count)	-1	1	1	1
Demand Scenario	Decides if there is an increase in outside region patients	0	0	1	0
NICU@23 weeks	Decides if newborns at 23 weeks of gestation are admitted	0	0	0	1

As each scenario is individually implemented, it is possible to also create new scenarios by combining the previous scenarios, e.g., to investigate the effect of the NICU@23 policy under no capacity shortages.

7.1.2 Results of Scenario Experiments

The results of the scenario experiments can be analyzed using the two introduced perspectives – hospital and society– to assess their impact on capacity shortages. We receive the results for the first three indicators shown in Table 49 ensuring easy comparability of the outcomes.

Table 49 Comparison of outcomes between scenarios

Indicator	Ward Level	No Capacity Shortages	Capacity Shortages	Outside Demand Increase	NICU@23
Required Beds	NICU	26.81	26.97	27.16	29.34
	High Care	75.48	75.12	75.27	76.28
	Medium Care	33.68	33.57	33.81	33.64
Weekly Occupancy Rate [%]	NICU	82.58	91.80	91.84	93.63
	High Care	93.22	97.25	97.31	97.35
	Medium Care	55.62	65.84	66.93	65.98
Capacity Transfers Rate [%]	NICU	5.14	21.56	21.72	26.89
	High Care	7.13	20.46	20.28	21.12
	Medium Care	0.00	0.05	0.05	0.03

The analysis of required beds reveals that, in scenarios without capacity shortages, there would be sufficient beds available to meet demand. However, the current situation is deemed unsustainable, particularly in scenarios involving capacity shortages. The NICU@23 scenario, where neonatal intensive care is provided at full capacity, may still face challenges in accommodating all patients, especially when accounting for varying arrival times and the influx of patients from outside the region as this indicator only accounts for inside region patients at optimal theoretical scheduling.

The weekly occupancy rates exhibit distinct patterns across the different ward levels. The highest occupancy is consistently observed in high care wards, followed closely by NICU wards. Notably, in the absence of capacity shortages, the NICU occupancy rate falls within the optimal range of 80-85%, indicating efficient utilization. In contrast, the high care wards consistently exceed this range, suggesting a strain on resources. Medium care wards, on the other hand, exhibit lower occupancy rates, raising concerns about potential inefficiencies due to an excess of available beds. However, it is worth noting that these beds could be repurposed or shared with pediatric care, thereby optimizing their utilization.

The capacity transfer rate shows significant increases in scenarios with capacity shortages. For medium care wards, capacity transfers remain minimal, even in scenarios involving increased demand. However, in NICU and high care wards, capacity shortages lead to a dramatic rise in transfer rates, increasing by a factor of four and three, respectively. The NICU@23 scenario exacerbates this trend, with an additional 5% increase in NICU transfers, reflecting the extended duration of bed occupancy by these patients.

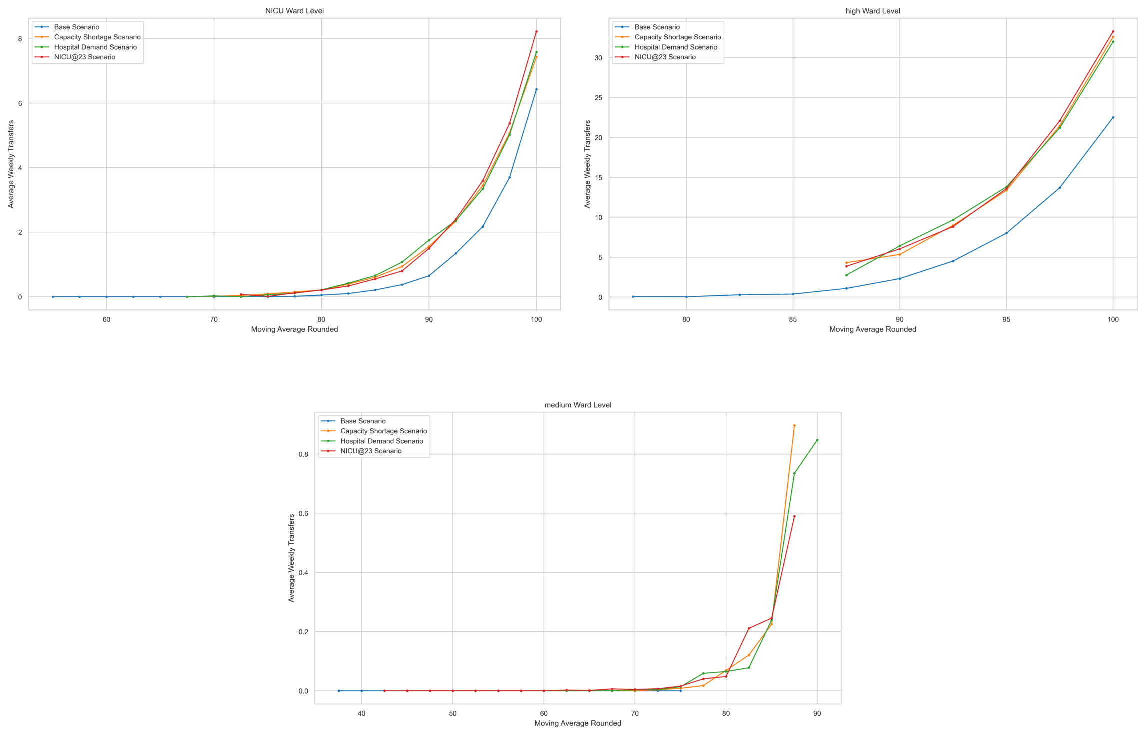


Figure 51 Weekly transfers per weekly occupancy rate for each ward level for different scenarios

In Figure 51, the weekly transfers are displayed for the different scenarios. All scenarios increase the number of weekly transfers across weekly occupancy rates and ward levels. For the NICU, especially the NICU@23 scenario stands out for occupancy rates above 90% leading to more than 8 weekly transfers at full capacity. For high care we can see a similar pattern in which the NICU@23 scenario tends to have a bigger impact in the most critical occupancy rate ranges compared to the other scenarios. These results further indicate the tremendous impact the scenario would have on the already existing capacity shortages.

7.2 System Lever Experiments

As we have seen across the scenarios, the neonatal care system in the south-west of the Netherlands is facing massive challenges linked to operational bed capacity shortages. These challenges are evident in a hospital and, more importantly, on a system-wide aggregation level. In the system conceptualization and literature, we have seen multiple categories of levers that can be assessed as they address different mechanisms in the model. Hence, I tested the impact of changing selected system levers on the overall performance, as seen in Table 50.

Table 50 Overview on tested system levers

System Lever	Description	Model Mechanism
Change in LoS	What if the LoS decreases	Length of Stay
Change in Admission Rate	What if less patients require NICU care, What if less patients require high care	Patient Ward Assignment
Change in Pathways	What if more NICU patients have a post IC stay at a medium care hospital instead of high care	Patient Pathway

The following paragraphs introduce each lever and its justification:

1. Change in LoS

The data analysis has shown the variability in LoS for patients often also leading to stays of multiple months, especially at already challenged high care and NICU wards. Thus, this system lever investigates the effect magnitude of decreasing LoS for each ward level. While it is expected that a decrease in LoS will have a direct positive effect on all performance indicators, it is unclear if this effect is similar for all ward levels.

2. Change in Ward Arrival Rates

Previous analysis has shown that the NICU and high care wards have the most urgent capacity shortages and contribute most to capacity transfers. Thus, I tested the impact of decreasing demand for these ward levels. This lever could inspire interventions of early discharge policies or prediction models that assess the actual required care prior birth.

3. Change in Patient Pathways

Around five percent of all patients require more than one stay. In the data analysis section of this chapter, the most typical pathways were presented. As most capacity shortages occur at the NICU and high care ward levels, changing pathways to decrease the burden on these hospitals can be considered by transferring patients earlier to a medium-care hospital or home. The effect of transferring NICU patients who require a post-IC stay to a medium care hospital instead of a high care hospital was tested.

The next section describes the implementation of the system lever experiments followed by the analysis of the results. The levers will be assessed by their impact on the performance indicators for each of the relevant – the hospital management and the societal – perspective.

7.2.1 Implementation of System Lever Experiments

The following sections describes the necessary run input parameters and any changes in the model logic for each system lever experiment. Each system lever can individually be selected or unselected using the run input parameters, seen in Table 51, in the *run_config.py* file. All system lever experiments were performed by running the model with the determined run time of 365 days, 70 days of warm-up over 25 runs.

Table 51 Overview of run input parameters for system lever experiments

Experiment Factor	Change in LoS	Change in Admission Rate NICU	Change in Admission Rate High Care	Change in Pathways
Number of Runs	25	25	25	25
Days per Run	365	365	365	365
Warm-Up Time	70	70	70	70
Hospital Scenario	1	1	1	1
LoS Lever	1	0	0	0
LoS Lever Change	[-10, -20, -30, -40]	0	0	0
Pathway Lever	0	0	0	1
Pathway Lever Additional LoS	0	0	0	[4,6,8,10,12]

High Care Assignment Lever	0	0	1	0
High Care Assignment Lever High Care Percentage	0	0	[-5, -10, -15, -20]	0
Assignment Lever NICU	0	1	0	0
Assignment Lever NICU Percentage	0	[-5, -10, -15, -20]	0	0

The following paragraphs describe specific changes in the model functionality for each system lever:

1. System Lever: Length of Stay

As a first system lever, the impact of changes in LoS was investigated. Initially, it was assumed that a stepwise percentage decrease in LoS would affect the average occupancy rate and capacity transfer rate. The first test involved examining the effects of a general decrease in LoS across all patients to assess the overall impact on the system's performance. The simulation was run 25 times under a capacity shortage scenario over 365 days, with LoS reductions of 10%, 20%, 30%, and 40%, and the outcomes were compared to the initial baseline results.

2. System Lever: Arrival Rates

As a second system lever, a decrease in arrival rates was tested by gradually reducing the number of arrivals for both the NICU and high care, with reductions ranging from 5% to 20%. For the NICU, this was implemented by not assigning the NICU ward level to an increasing percentage of patients in the age group above 28+0 weeks of gestation. Below this gestational age, the medical complexities are considered too high to permit alternatives to NICU care. For high care, the implementation involved gradually decreasing the percentage of high care assignments within the overall assignment process, which is based on empirical probabilities. Patients were then reassigned to the next lower ward level—high care for those initially assigned to NICU and medium care for those initially assigned to high care.

3. System Lever: Patient Pathway

The model includes a function that determines whether a patient requires an additional admission and at what ward level, based on empirical probabilities. This function was modified to redirect all NICU patients, who would typically require an additional stay at high care, to medium care instead. However, since the medium care hospital cannot provide the same level of medical support, these patients must first stay additional days at the NICU before being transferred. This adjustment involves holding the patient object for the specified additional number of days after their initial stay before beginning the additional admission. The impact was tested for different lengths of the additional stay at the NICU, ranging from 4 to 12 days, in two-day increments.

7.2.2 System Lever Results: Length of Stay

For the hospital management perspective, I analyzed the change in average required bed count for inside region patients and average weekly occupancy rate, as seen in Figure 52 and Figure 53, respectively. The reference values for the required bed graph are the number of operational beds in the selected scenario.

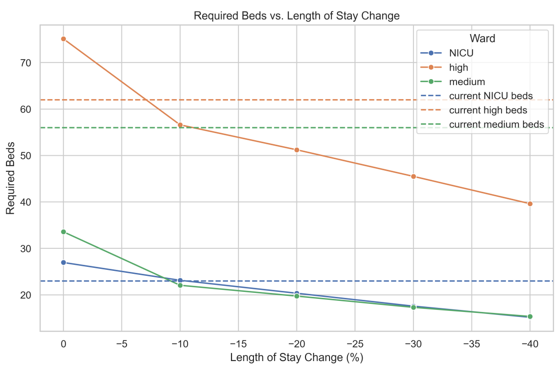


Figure 52 Number of required beds for inside region patients across LoS change

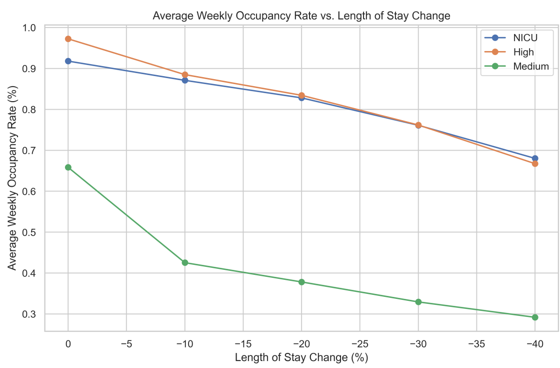


Figure 53 Average weekly occupancy rate per ward level across LoS change

As expected, decreasing LoS has a positive effect on all ward levels. Already a 10% reduction LoS significantly impacts the required number of beds across different ward levels. For high care, this reduction brings the required beds directly under the current number of operational beds. In the NICU, the reduction decreases the required beds to exactly match the number of currently available operational beds. Notably, NICU exhibits a constant linear decrease in bed requirements, whereas high care and medium care experience a more pronounced drop in required beds with the initial 10% reduction in LoS. This disparity can be attributed to the shorter average LoS in high care (4.8 days) and medium care (3.2 days) compared to NICU, which has an average LoS of 12.5 days. As a result, a 20% reduction in LoS has a diminishing relative effect because more patients fall within a calculated LoS of between 0 and 1 day, which the model rounds up to 1 day. Consequently, the LoS distribution for high care and medium care shifts toward a single day, reducing the impact of further LoS decreases.

Regarding occupancy rates, a 10% reduction in LoS lowers the weekly occupancy rates for both NICU and high care below 90%. This decrease continues similarly across both care levels, eventually bringing occupancy rates down to below 70% with a 40% reduction in LoS. In contrast, medium care experiences a more significant decrease in occupancy rates with the initial 10% LoS reduction, followed by smaller declines with further reductions. This suggests that, beyond a certain point, reducing LoS in medium care leads to occupancy levels where it becomes inefficient to maintain operational beds.

For the societal perspective, I first analyzed the changes in capacity transfer rate as seen in Figure 54 and afterwards investigated the effects on the weekly capacity transfers per ward level seen in Figure 55.

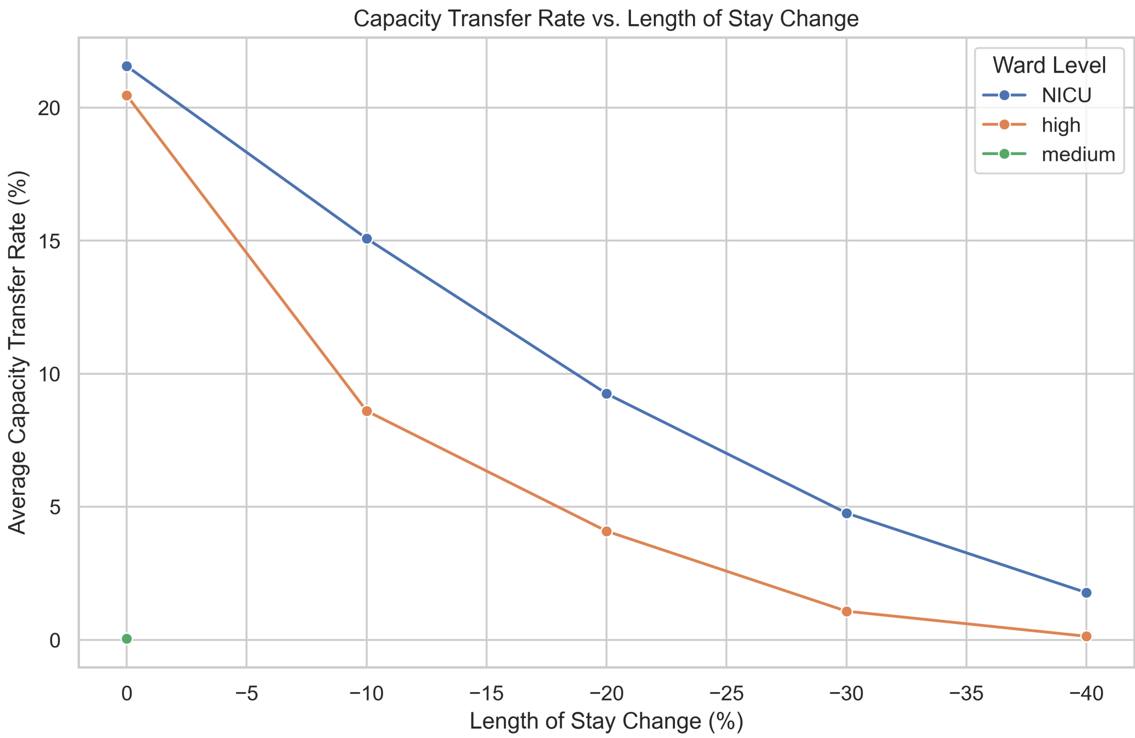


Figure 54 Average capacity transfer rate for LoS lever

The 10% LoS decrease leads to a more than 10% decrease in capacity transfer rate for the high care ward, while the NICU capacity transfer rate decreases with a more constant linear slope. This suggests that capacity transfers at the high care level frequently occur shortly before the release of a previous patient. Thus, even a 10% reduction in the patient's LoS would often free up a bed. These findings recommend investigating an early discharge policy.

As a second step, the average weekly transfers were calculated for each ward level as seen in Figure 55. The results show that each LoS reduction leads to a decrease in the number of weekly transfers across all occupancy rates. However, the magnitude of this effect varies across different ward levels.

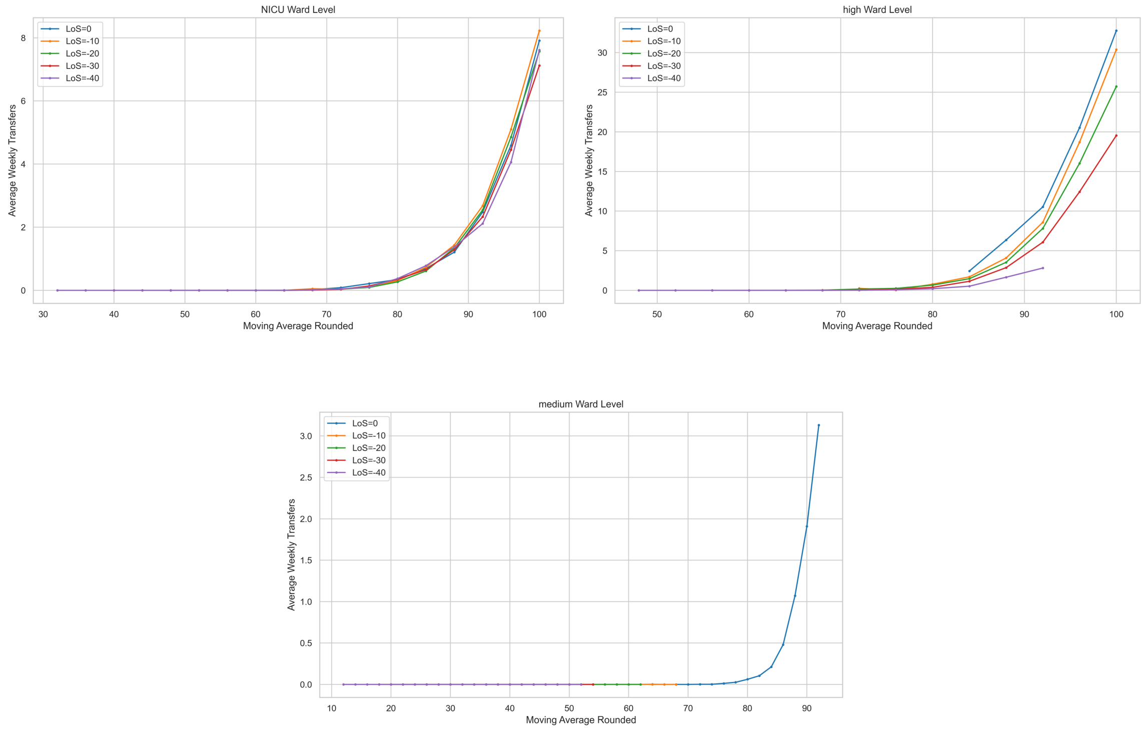


Figure 55 Average weekly transfers per average weekly occupancy rate for each ward level for LoS Lever

For the NICU, even a 40% decrease in LoS still results in approximately 7 weekly transfers at a 100% weekly occupancy rate. In contrast, for high care, each step of LoS reduction amplifies the effect, leading to an absolute difference of more than 10 weekly transfers between the initial rate and the 40% decrease. This translates to over 520 patients per year who would no longer need to be transferred outside the region. The medium care level initially experiences a very limited number of transfers, and a mere 10% LoS decrease eliminates the need for capacity transfers altogether.

Overall, this section demonstrates the substantial impact of LoS on the system's performance indicators from both hospital management and societal perspectives. While it is not surprising to see a positive effect on all indicators when decreasing the LoS, the experiment has shown that already a 10% decrease could bring substantial benefits across the indicators highlighting the need for interventions that decrease the LoS.

7.2.3 System Lever Results: Patient Ward Assignment

As a second system lever experiment, the effect of changing the admission rate for NICU and high care ward was tested. The following sections present the results of the lever experiments. First, the results for the NICU admission lever and afterwards the results for the high care admission lever are presented.

7.2.3.1 Decrease in NICU admissions

From a hospital's management perspective, the relevant indicators – required beds and weekly occupancy rate – can be seen in Figure 56 and Figure 57, respectively.

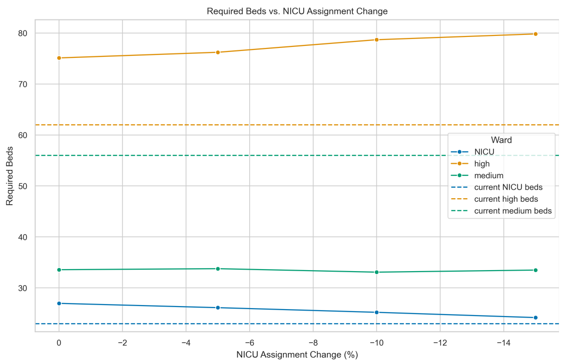


Figure 56 Required operational beds for decrease in NICU admissions

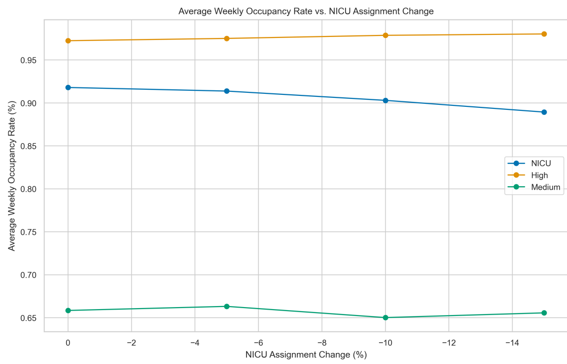


Figure 57 Average weekly occupancy rate for decrease in NICU admissions

For the NICU, we observe a consistent decrease in the number of required beds, approaching the current operational capacity at a 15% reduction in ward assignment. Concurrently, the number of required beds for high care increases by approximately three beds but stabilizes between the 10% and 15% reduction levels. This pattern is likely due to variations in how the LoS is calculated for each ward level, as stays in high care tend to be shorter than those in the NICU. Additionally, the shift of NICU patients to high care results in fewer post-IC high care stays, which further explains the modest increase in high care indicators.

As seen in Figure 57, the average weekly occupancy rate decreases for the NICU to below 90% for the highest lever change of -15%. These results stress what impact individual patients at the NICU have due to their long LoS. At the same time, the weekly occupancy rate for high care only increases slightly, mostly due to the reason that at the already extremely high level, additional patients are more likely to be transferred to an outside region hospital.

For the societal perspective, first the capacity transfer rate per ward level as seen in Figure 58 was analyzed.

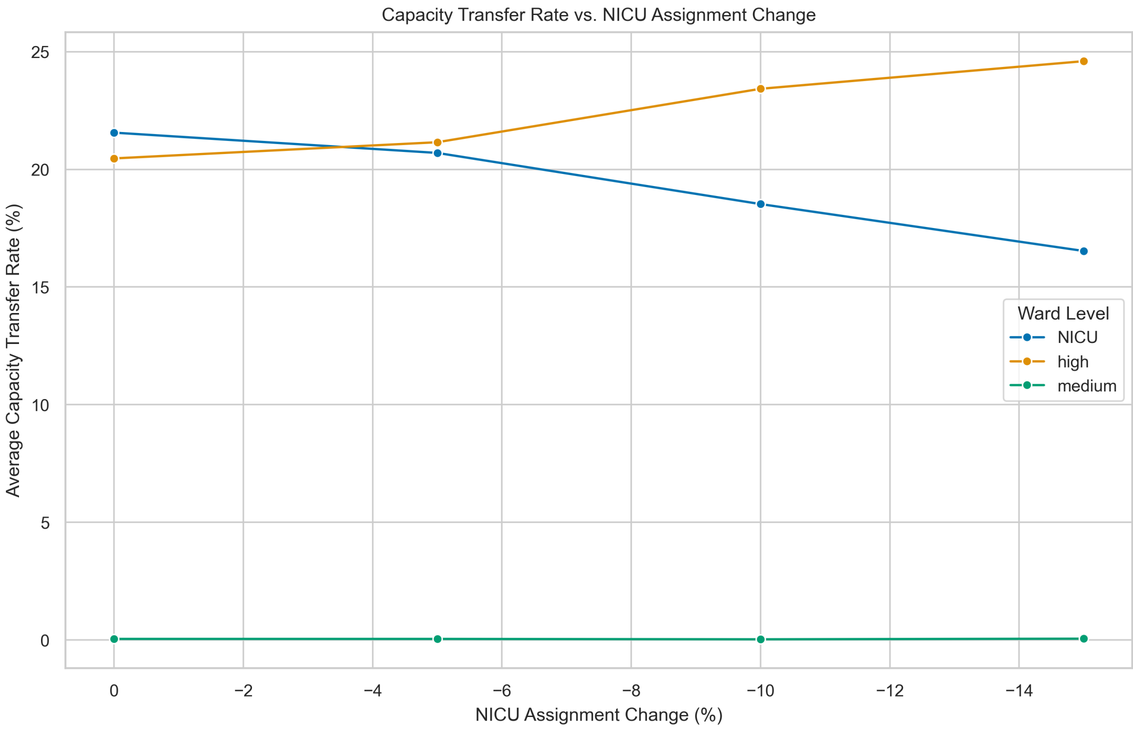
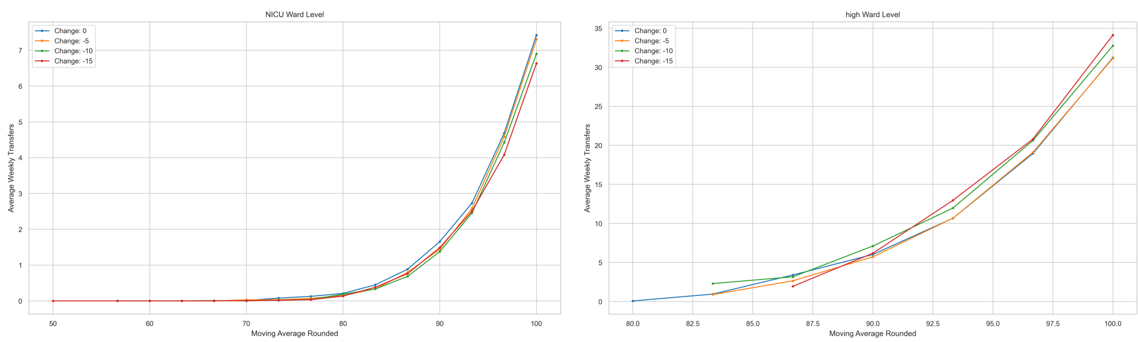


Figure 58 Average capacity transfer rate per NICU admission decrease per ward level

Reducing the NICU assignment rate results, as anticipated, in a linear decrease in NICU capacity transfers and a corresponding increase in high care transfer rates. Notably, the increase in high care transfers is significantly more pronounced when the assignment rate is reduced by 5% to 10%, compared to reductions of 0% to 5% or 10% to 15%. This suggests the presence of tipping points, where surpassing a certain threshold leads to a sharper increase in transfer rates. Overall, this lever creates a trade-off between NICU and high care capacity transfers, as a decrease in one directly leads to an increase in the other.

The results of weekly transfers per ward level, as illustrated in Figure 59, indicate that the increase in high care admissions is especially noticeable at high occupancy rates of above 95%. This effect is most pronounced in the -15% setting, shown in red, where it leads to a difference of approximately three additional weekly transfers.



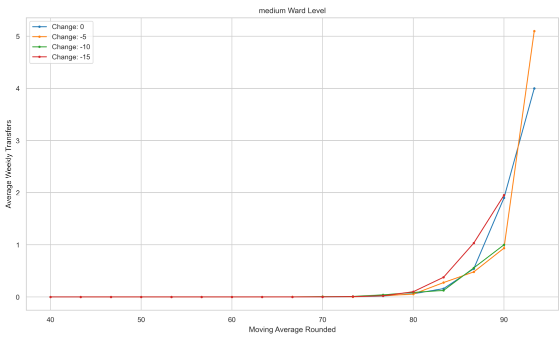


Figure 59 Average weekly transfers per average weekly occupancy rate for each ward level

The weekly transfers to the NICU follow an expected pattern corresponding to the different levels of the system lever. Additionally, the lever causes an increase in weekly transfers for medium care, which is particularly noticeable when the occupancy rate is between 80% and 90%.

The results of the system lever experiment highlight the trade-offs involved when shifting patients between ward levels, as there is no option that provides benefits to all. In this example, the NICU experienced a decrease across all measures, resulting in additional efforts for medium and high care ward levels. This is particularly problematic at the high care ward level as this ward level already faces the strongest capacity shortages.

7.2.3.2 Decrease in High Care Admissions

As a second step, the experiment was repeated for a change in high care admission rates. In Figures 60 and 61, we see the effect of the lever on required bed number and weekly occupancy rate. As expected, shifting demand from high care to medium care increases the occupancy rate for the medium care ward.

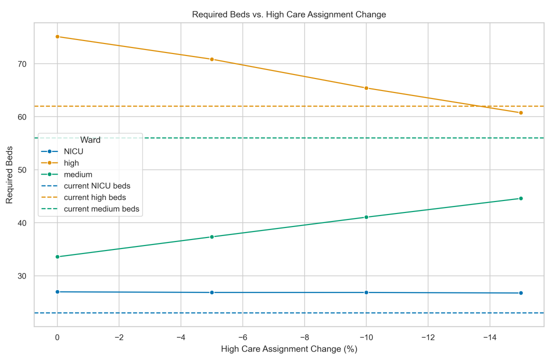


Figure 60 Required beds per ward level for high care admission lever

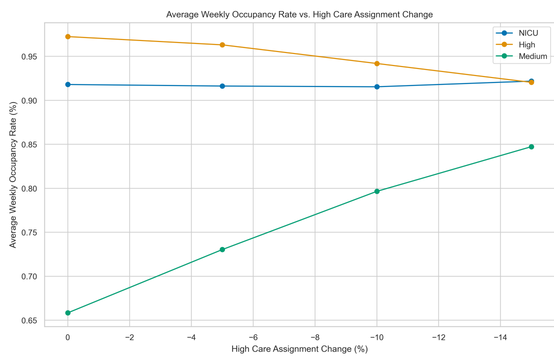


Figure 61 average weekly occupancy rate per ward level for high care admission lever

The lever does not seem to have a noticeable effect on the NICU, neither for required beds nor occupancy rate. This can be explained as medium care patients have the same probability to have an additional stay at the NICU as high care patients, thus, it does not matter whether a patient have their first stay at a high or medium care ward.

For the societal perspective, the capacity transfer rate and number of weekly transfers was analyzed as seen in Figure 62 and Figure 63, respectively. The linear decrease in the capacity transfer rate in high care is not matched with a similar increase in medium care capacity transfer rate This suggests that medium care ward can effectively manage the additional patient load. For instance, a 5% decrease in high care admissions results in a nearly 4-percentage point reduction in the capacity transfer rate for high care, without placing significant strain on medium care.

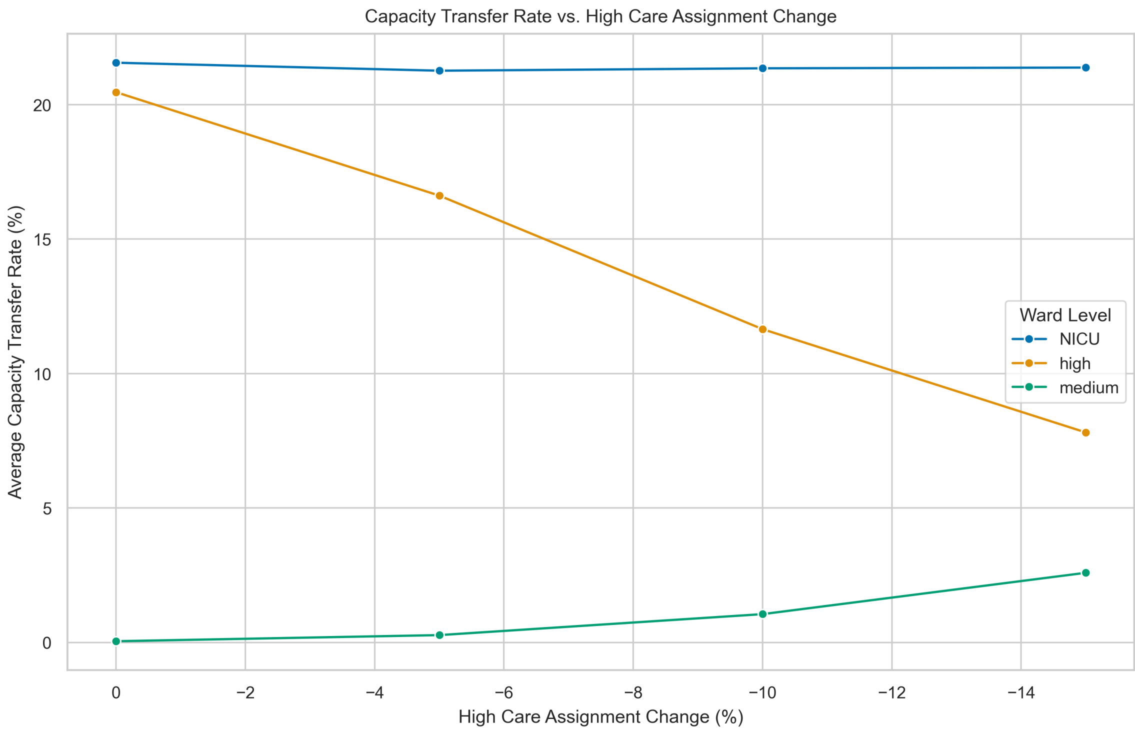


Figure 62 Average capacity transfer rate per ward level for high care admission lever

This analysis reveals the unbalanced distribution of patients across wards, suggesting that, where medically appropriate, it may be beneficial to explore interventions that redistribute patients between ward levels.

As expected, there are no significant differences in weekly transfers for the NICU. However, weekly transfers for high care consistently decrease, while those for medium care increase. At the highest level of a 15% reduction in admissions, the medium care ward experiences several days with a weekly moving average occupancy rate of 100%, resulting in more than 17 weekly transfers of medium care patients.

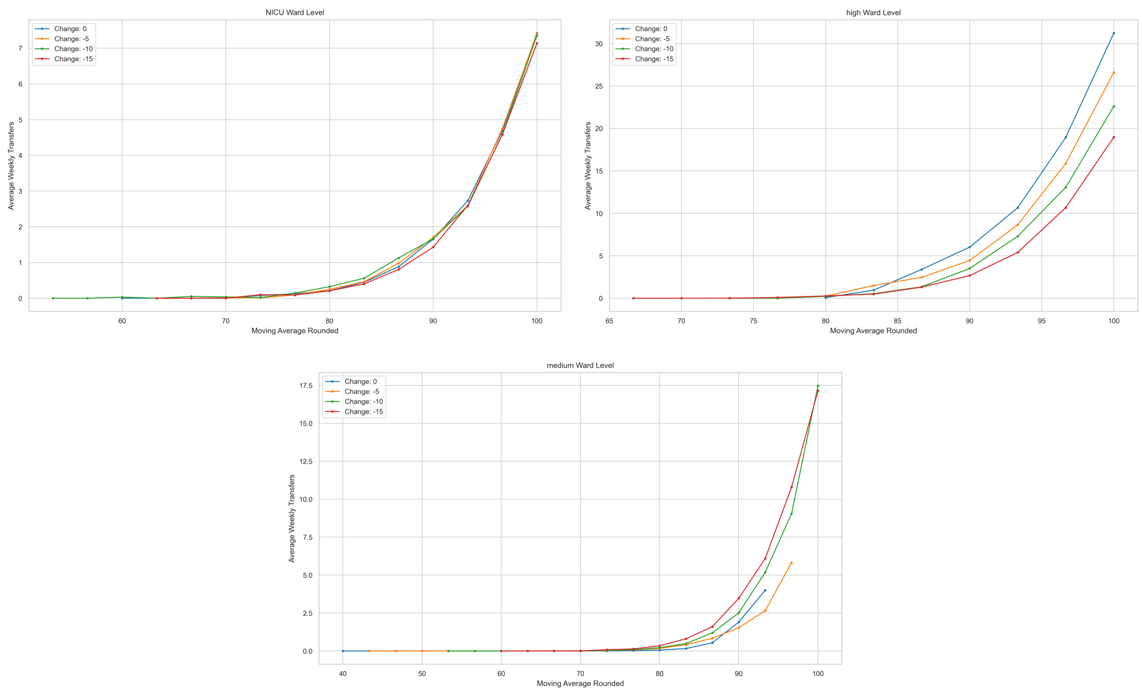


Figure 63 Average weekly transfers per rounded weekly occupancy rate and ward level for high care admission lever

The analysis of this lever supports the importance of the high care ward level to find solutions to existing capacity shortages within staffing limitations. While in practice it might not always be feasible to shift admit patients rather in medium care than in high care due to medical complexity and required treatments, the lever still indicates the possible effects and, thus, it should be considered if there are patient groups (e.g. above a certain gestational age) to be shifted to the medium care ward.

7.2.4 System Lever Results: Patient Pathway

The following section presents the outcomes of the system lever experiment, analyzing the output data from the two introduced perspectives. Since all NICU patients requiring an additional stay are transferred to the medium care ward instead of high care, this lever is expected to significantly impact the indicators for the high care ward level. Additionally, it may place an extra burden on the NICU, due to the extended LoS, and on medium care, due to the increased number of patients.

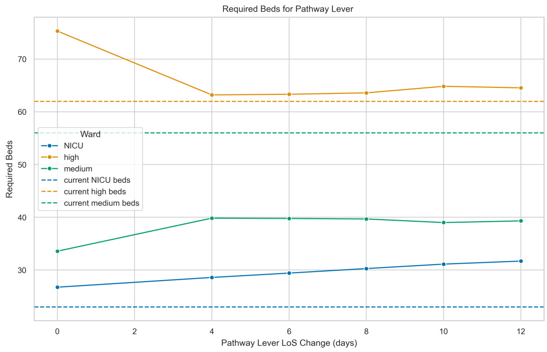


Figure 64 Required beds per ward level for pathway lever with different LoS at NICU

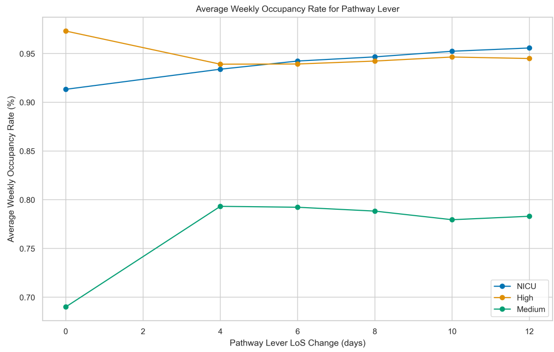


Figure 65 average weekly occupancy rate per ward level for pathway lever with different LoS at NICU

From a hospital's perspective, the drastic decrease, from 75 to circa 63 beds, in required beds for high care demonstrates the significant impact of the addressed patient group on the high care ward level, as shown in Figure 64. These patients tend to have a disproportionately high LoS, directly leading to higher bed requirements. However, the results also show that this lever alone would not be enough to move the number of required beds below the number of available beds. We see a linear increase for the NICU from initially circa 27 to eventually 32 due to the additional days a patient would stay at the NICU before the transfer. The medium ward level can easily handle the additional number of required beds.

For the weekly occupancy rate, we see similar patterns of clear drop in high care occupancy with a simultaneous increase in medium care and NICU occupancy. Medium care sees an increase of around 10%-points, while the NICU rate increases linearly, with an initial increase of 2%-points an additional stay of 4 days. We also see that this lever could at most get the high care ward to around 94% occupancy rate, hence, the high care ward remains under pressure of capacity shortages.

From a societal perspective, the changes in the average capacity transfer rate, see in Figure 66, highlight that for the NICU again a linear increase up to more than 35% capacity transfer rate at most. At the same time, the rate for high care drops close to 10%, with only minor increases for medium care.

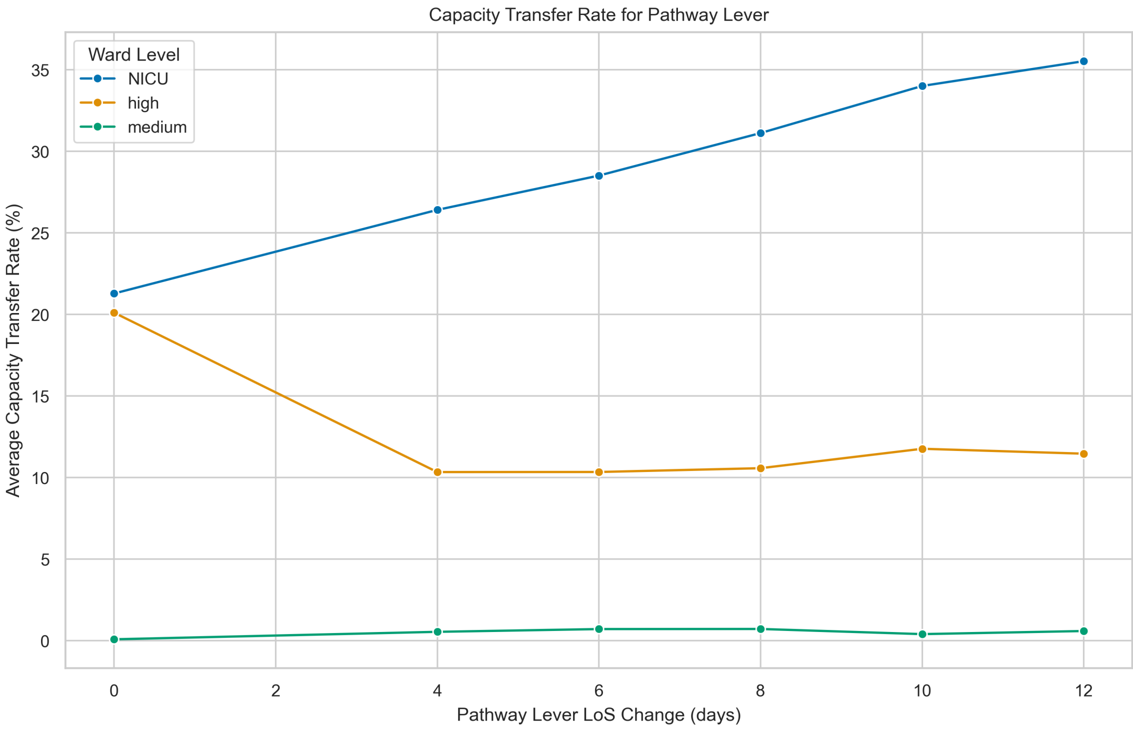
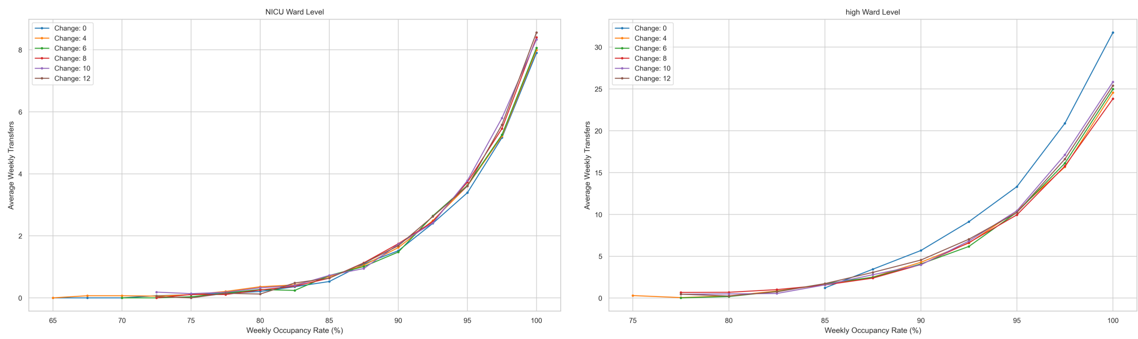


Figure 66 Average capacity transfer rate per ward level for pathway lever

Looking at the average weekly transfers in Figure 67, only minor differences are observed for the NICU level. However, at full capacity, high care experiences a 25% decrease in weekly transfers. This improvement comes at the cost of a significant increase in transfers for medium care, especially with low additional stays at the NICU, as this reduces the arrival rate to medium care.



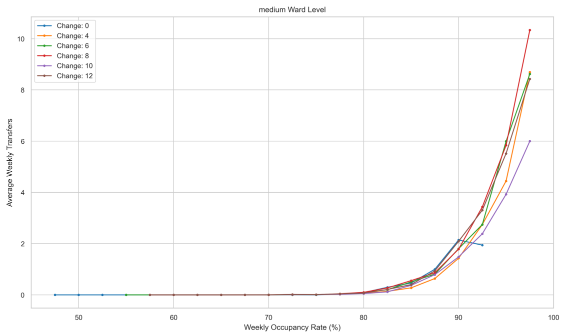


Figure 67 Weekly transfers per weekly occupancy rate per ward level for high pathway lever

This lever highlights the trade-off between reducing pressure on high care hospitals and increasing pressure on medium care and, to some extent, NICU wards. While the lever clearly demonstrated how significant this group of patients is for capacity shortages in high care, the impact on other wards needs careful consideration. It would be beneficial to combine this lever with other approaches, such as adjusting the number of NICU admissions by initially shifting some patients to high care to balance the effects of the respective levers.

7.3 Intervention Experiments

The background section of this work has provided an overview of current innovative developments in neonatal care interventions. Given the ongoing and increasing operational bed capacity shortages driven by staffing limitations, there is an urgent need for change. By modifying mechanisms in the model, key system levers that can impact the system's key performance indicators have been identified: required bed count, weekly occupancy rate, capacity transfer rate, and average weekly transfer.

While the obvious recommendation would be to implement interventions addressing all these impactful levers, such interventions might not yet exist. Therefore, the following chapter will introduce in detail three currently relevant interventions that are promising for clinical outcomes but have an unclear impact on operational bed capacity. Two interventions affect the LoS lever of the model and one the distribution across wards. These interventions are based on literature review results and interviews with field experts and are currently in the implementation or trial phase in the region. In addition, the impact of a combined intervention using the previous intervention, and the patient pathway lever was tested.

Table 52 Overview of tested interventions and corresponding system lever

Intervention	System Lever
Phototherapy at home for jaundice	Decrease LoS
Changing from intravenous to oral antibiotics for EOS	Decrease LoS
Changing NICU gestational age threshold	NICU admission rate
Combined Intervention Strategy	Decrease LoS, NICU admission rate, Pathway Lever

1. Phototherapy at home for jaundice

Jaundice is a common medical condition for newborns in which the skin and whites of the eyes turn yellow. Between 60 and 80% of neonates have some form of jaundice. The underlying reason is linked to low development of the liver and resulting high bilirubin count – a yellowish pigment – in the blood. The most common treatment is phototherapy. Currently, it is provided in hospitals, but research has shown that it can also be safely applied at home. Thus, current trials in high-income countries test the potential of releasing patients without any other condition than jaundice.

2. Changing from intravenous to oral antibiotics for EOS

Antibiotics is a commonly used treatment for various conditions. The transition from intravenous to oral antibiotics for early-onset sepsis in neonates represents a significant intervention aimed at optimizing antibiotic use and improving patient outcomes. This approach not only reduces hospital stay and healthcare costs but also aligns with current guidelines advocating for oral switch therapy. The intervention is based on the results of the RAIN study that tested for clinical outcomes across multiple hospitals in the Netherlands (Keij et al., 2022). The study showed a decrease in average LoS from 7 days to 3.5 days when using oral treatment.

3. Changing NICU gestational age threshold

The NICU is the only ward level with direct guidelines specifying when a patient requires that level of care. In the Netherlands, any patient below 32+0 weeks of gestation must be admitted to a NICU. However, there have been discussions in the region about lowering that threshold to 31 or even 30 weeks (Interview 1). In the previous chapter on system levers, the ward assignment mechanism and the potential impact of decreasing the number of NICU admissions were described. This intervention directly addresses that mechanism. While the 32-week guideline is currently a national standard, the region has the authority to establish its own guidelines, as other regions currently oppose such a change (Interview 1). By exploring the potential benefits and trade-offs of lowering the threshold, the region can make informed decisions about optimizing NICU capacity and improving overall neonatal care.

4. Combined Intervention Strategy

Interventions that address the interactions between ward levels lead to trade-offs between patient groups and hospitals. Since there is no silver bullet, the region should combine interventions to harness their positive effects while countering respective downsides. Thus, a last experiment was performed by combining the previous interventions to see aggregated effects. In addition, the previously identified pathway lever was added, hence, all post-IC patients were transferred to the medium care level instead of the high care level.

7.3.1 Implementation of Intervention Experiments

The following section describes the implementation of the intervention experiments with any changes in the model and the required variables in *run_config.py*, as seen in Table 53, for each experiment.

Table 53 Overview of run input parameters for intervention experiments

Experiment Factor	Phototherapy at home for jaundice	Changing from intravenous to oral antibiotics for EOS	Changing NICU gestational age threshold	Combined Intervention Strategy
Number of Runs	25	25	25	25
Days per Run	365	365	365	365
Warm-Up Time	70	70	70	70
Hospital Scenario	1	1	1	1
Pathway Lever	0	0	0	1
Pathway Lever LoS Change	0	0	0	0
Phototherapy Intervention	1	0	0	1
Sepsis Intervention	0	1	0	1
NICU Threshold Intervention	0	0	1	1
NICU Threshold Intervention Change	0	0	[-1, -2]	-1
Pathway Lever	0	0	0	1
Pathway Lever Additional LoS	0	0	0	4

All other variables in *run_config.py* that are not mentioned in the table above are set to zero. The following paragraphs describe in detail any changes in the model due to the individual interventions.

1. Phototherapy at home for jaundice

For the phototherapy intervention, it involved filtering patients born at or after 35+0 weeks of gestational age who were admitted solely for jaundice, without any other conditions requiring hospital care. Since each patient had to be at least one day old, the LoS was set to a minimum of one day, and no additional hospital stays were permitted afterward. This intervention specifically targeted a subgroup of patients, modifying their treatment pathways by reducing the likelihood of additional hospital stays. In this initial implementation, the maximum potential impact was assessed by including all patients who met these criteria and preventing any readmissions.

2. **Changing from intravenous to oral antibiotics for EOS**

For the EOS intervention, patients were identified by filtering for those born at or after 35+0 weeks gestational age and only having the jaundice admission criteria, with no other conditions requiring hospital care. As each patient must be at least one day alive, the LoS was set to one day, and no additional stays were allowed afterward. This intervention works on the LoS mechanism for a specific patient subgroup and changes the pathways by lowering the chances for additional stays. In this first implementation, the maximum potential impact was assessed. Therefore, all patients meeting the previously mentioned criteria were included, and no readmissions were allowed.

3. Changing NICU gestational age threshold

For the NICU threshold intervention, the age threshold for NICU admission was lowered from 32 weeks to 31 weeks and then to 30 weeks in the model. Consequently, patients born at 31 or 30 weeks gestational age were no longer required to be admitted to the NICU unless they met other NICU criteria, such as a birth weight below 1250g or the presence of congenital abnormalities. These patients were instead distributed across high-care hospitals. The intervention was tested in the capacity shortage scenario, first with the threshold lowered to 31 weeks and then to 30 weeks.

4. Combined Intervention Strategy

Finally, the combined intervention strategy was implemented by combining the adjustments for phototherapy, sepsis treatment, and NICU threshold changes. This comprehensive intervention involved accepting only patients below 31 weeks of gestation into the NICU while adding the pathway lever, described in detail in 7.2.4, moving post-IC patients to medium care instead of high care.

7.3.2 Intervention Results: Phototherapy at home for jaundice

The results for each intervention are again analyzed by the introduced indicators. The results for phototherapy at home can be seen in Table 54.

Table 54 System performance indicators for phototherapy at home intervention per ward level

Indicator	Ward Level	Without Intervention	With Intervention
Required Bed Count		135.65	134.80
	NICU	26.97	26.59
	High Care	75.12	75.19
	Medium Care	33.57	33.03
Weekly Occupancy Rate			
	NICU	91.80	91.33
	High Care	97.25	97.22
	Medium Care	65.84	64.92
Capacity Transfer Rate			
	NICU	21.56	21.12
	High Care	20.46	20.13
	Medium Care	0.05	0.01

The intervention implemented across all hospitals in the region has resulted in only a marginal decrease in the total required bed count, from 135.65 beds to 134.80 beds, representing a minimal reduction of 0.63%. This slight change indicates that the intervention did not substantially alleviate the overall demand for beds. Notably, the NICU and high care units saw even smaller reductions in bed count, with NICU beds decreasing from 26.97 to 26.59 and high care beds slightly increasing from 75.12 to 75.19, respectively. These results suggest that the intervention did not significantly impact the bed demand in these critical care areas.

The effects of the intervention on the weekly occupancy rate across different ward levels are also minimal. The NICU's occupancy rate decreased slightly from 91.80% to 91.33%, while high care saw an even smaller reduction from 97.25% to 97.22%. The most notable change occurred in the medium care unit, where the occupancy rate decreased by nearly one percentage point, from 65.84% to 64.92%. Although the reduction in medium care occupancy is more pronounced, the overall effect on the weekly occupancy rates in the

NICU and high care units remains negligible, indicating that the intervention had limited success in easing the occupancy pressure in these wards.

The intervention's impact on the capacity transfer rate shows some modest improvements, particularly in the high care ward level. Here, the transfer rate decreased from 20.46% to 20.13%, translating to approximately 22 fewer capacity transfers per year. The NICU also experienced a small reduction in transfer rates, from 21.56% to 21.12%. However, the medium care ward saw an almost negligible change, with the transfer rate dropping from 0.05% to 0.01%. Despite these changes, the overall effect of the intervention on reducing capacity transfers is limited, indicating that the intervention was insufficient to address the broader issue of capacity shortages across the region effectively.

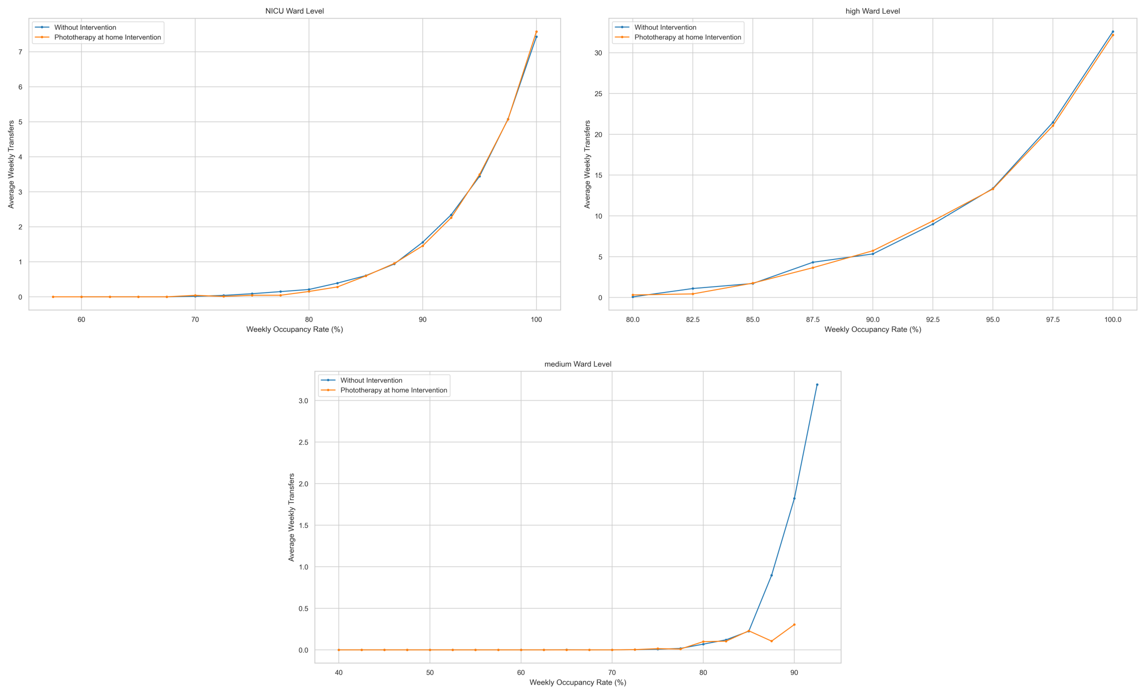


Figure 68 Weekly transfers per weekly occupancy rate per ward level for phototherapy at home

The weekly transfers, presented in Figure 68, reveal that the curves for NICU and High Care exhibit similar patterns both with and without the intervention. Notably, for the NICU, the intervention tends to result in a lower curve for occupancy rates below 92.5%, while at full capacity, the values converge to similar levels. This suggests that the intervention has a limited impact on reducing transfers under high occupancy conditions. However, in the medium care level, the intervention appears more effective, successfully keeping the weekly occupancy rate below 90%. This outcome reduces the likelihood of capacity transfers, indicating a stronger impact of the intervention in managing capacity at this level.

The intervention is currently in multiple trial phases and there are ongoing discussions in the region and beyond on a potential implementation strategy (Interview 2). While the simulation model suggests that the intervention does not have a major impact on the existing capacity shortages, it can still lead to an increase in the quality of care for individual patients and increase the child-parent relationship. Thus, despite not having a large impact on capacity, it can be worth to further test the implementation from a quality improvement perspective. One of the biggest remaining questions for the implementation is the financing as hospitals and insurance companies are in discussing about reimbursement rates as the patient does not occupy any bed or use hospital resources (Interview 2). In addition, it is important to acknowledge that current trials report up to 2% of readmissions. Additionally, 3% of the parents speak neither Dutch nor English and are also excluded from this intervention, as it is assumed they would not understand the instructions. The effectiveness of this intervention is also constrained by the limitations in the quality of the initial dataset. Specifically, jaundice was frequently not among the two most prominent indicators, which suggests that there may be more patients affected than currently accounted for in the simulation model. This potential underestimation could lead to inaccuracies in assessing the intervention's true impact. Additionally, there is room for improvement by considering a further reduction in the age restriction from 35 weeks of gestation to possibly 34 weeks. Such an adjustment could increase the number of patients addressed by the intervention, potentially enhancing its overall effectiveness.

7.3.3 Intervention Results: Changing to oral antibiotics for EOS

The following section describes the experiment results for changing from intravenous to oral antibiotics for EOS. The outcomes for average required beds, weekly occupancy rate, and capacity transfer rate can be seen in Table 55.

Table 55 System performance indicators for oral antibiotics at home intervention per ward level

Indicator	Ward Level	Without Intervention	With Intervention
Average Required Bed		135.65	132.47
	NICU	26.97	26.63
	High Care	75.12	74.36
	Medium Care	33.57	31.48
Average Weekly Occupancy Rate			
	NICU	91.80	91.13
	High Care	97.25	97.10
	Medium Care	65.84	61.63
Average Capacity Transfer Rate			
	NICU	21.56	21.12
	High Care	20.46	19.70
	Medium Care	0.05	0.01

The intervention implemented across the hospitals led to a reduction in the average required bed count, decreasing from 135.65 to 132.47 beds, reflecting a moderate improvement with an approximate 2.34% reduction. Specifically, the NICU saw a slight reduction in the average required beds from 26.97 to 26.63, while high care beds decreased from 75.12 to 74.36. The most significant reduction occurred in medium care, where the average required bed count dropped from 33.57 to 31.48. These changes suggest that the intervention had a more pronounced effect on medium care, though the overall impact on bed demand across all ward levels was modest.

The average weekly occupancy rate also showed some improvements due to the intervention, although these were relatively small. In the NICU, the occupancy rate slightly decreased from 91.80% to 91.13%, and in high care, it dropped marginally from 97.25% to 97.10%. The most notable reduction occurred in medium care, where the occupancy rate decreased from 65.84% to 61.63%, a more significant decline compared to the other wards. This indicates that the intervention was more effective in reducing occupancy pressures in medium care, although the impact on NICU and high care was less substantial.

The intervention's effect on the average capacity transfer rate demonstrated some improvement, particularly in high care. The transfer rate in the NICU decreased slightly from 21.56% to 21.12%, while high care experienced a more noticeable reduction from 20.46% to 19.70%. Medium care, with an already low transfer rate, saw a reduction from 0.05% to 0.01%. These results suggest that the intervention contributed to a decrease in the frequency of capacity transfers, especially in high care, though the overall effect remains modest across all ward levels.

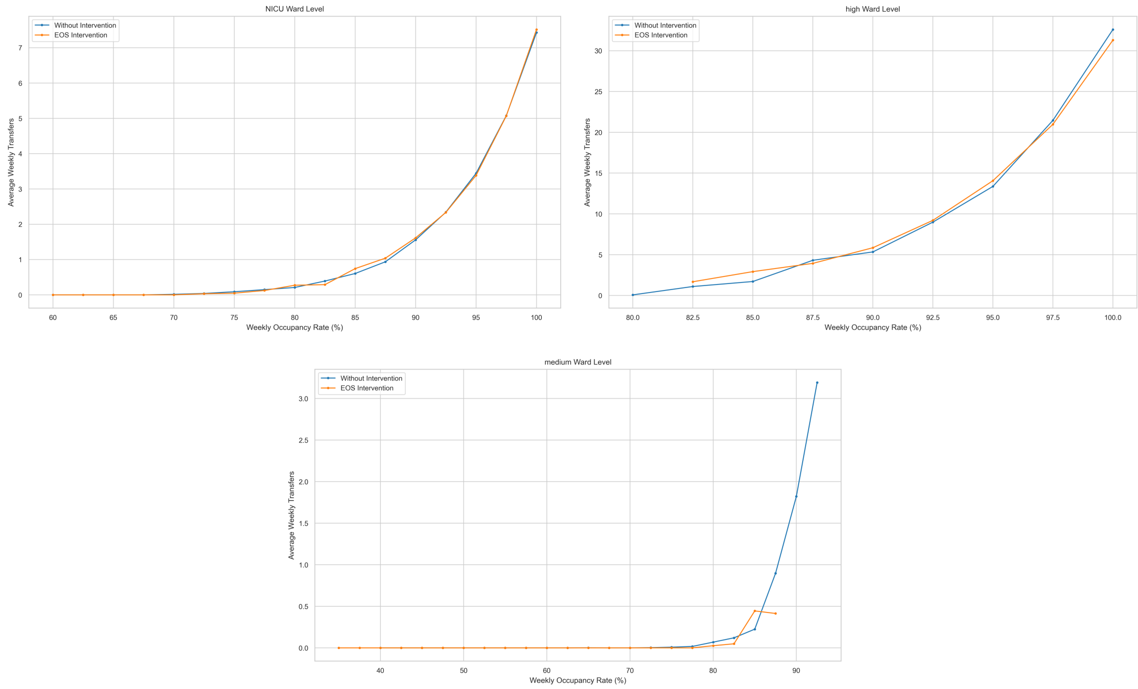


Figure 69 Weekly transfers per weekly occupancy rate per ward level for changing from intravenous to oral antibiotics for EOS

The weekly transfers, presented in Figure 71, reveal that the curves for NICU and High Care exhibit similar patterns both with and without the intervention. Notably, in high care, the intervention results in a higher curve for occupancy rates below 96%, but at full capacity, it leads to a lower curve. This shift is particularly significant given that high care has an average occupancy rate of 97%, meaning the intervention brings improvements in the most critical range. In the medium care level, the intervention appears more effective, successfully maintaining the weekly occupancy rate below 90%. This outcome reduces the likelihood of capacity transfers, indicating a stronger impact of the intervention in managing capacity at this level.

The intervention demonstrated a promising impact on capacity indicators and can be implemented easily without incurring additional costs, as most hospitals in the region participated in the initial study and implementations are already underway at various locations (Interview 3). The results of the simulation model support these efforts as they not only have the potential to enhance medical outcomes and improve the quality of care but also contribute to alleviating existing capacity shortages.

7.3.4 Intervention Results: Changing the NICU Gestational Age Threshold

The third intervention experiment assess the impact of changing the NICU gestational age threshold from 32 weeks to 31 or 30 weeks. For the impact on hospitals, I analyzed the number of required beds for inside region patients and the average weekly occupancy rate, each per ward level, as seen below. Decreasing the threshold by one week to 31 weeks would achieve that the current operational bed count would be sufficient to accommodate for all inside region patients.

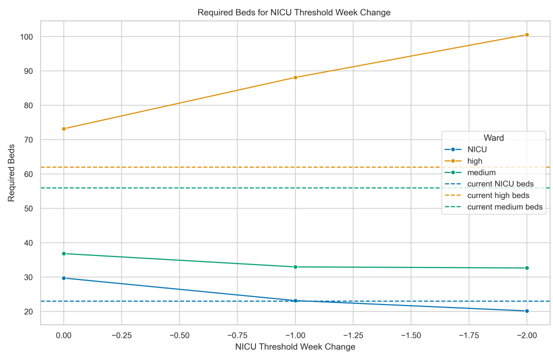


Figure 70 Required beds per ward level for different gestational age NICU thresholds changes

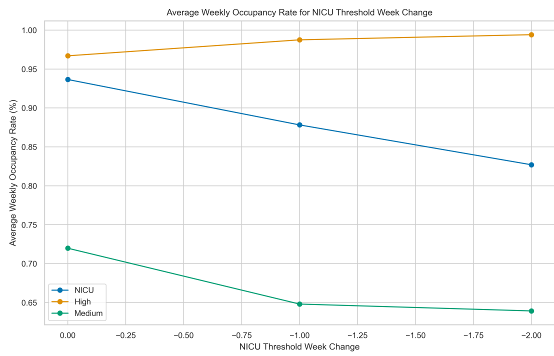


Figure 71 Average weekly occupancy rate per ward level for different gestational age NICU threshold changes

From the hospital's perspective, this intervention would have a significant impact on the NICU, potentially alleviating a substantial portion of the current shortages. However, it is crucial to assess the extent to which high care hospitals can accommodate the additional patient load, as the model indicates an increase in the required beds for high care that far exceeds the currently available capacity. Given that medium care remains well below its required bed count, there could be an opportunity for improvement if fewer patients in other age groups were admitted to high care and instead received treatment at a medium care facility, provided it is medically appropriate.

The weekly occupancy rate for high care rises to 98.75% for the 31-week threshold and surpasses 99% for the 30-week threshold. In contrast, the NICU occupancy rate experiences a sharp decline, dropping below 90% for the 31-week threshold. Additionally, the occupancy rate for medium care also decreases, as fewer NICU patients result in fewer subsequent transfers to medium care following their initial NICU stay. This shift suggests that while the intervention effectively reduces the burden on NICU, it simultaneously places increased pressure on high care.

For the societal impact, I first examined the capacity transfer rate per ward level, as seen level as seen in Figure 72. As expected, the intervention led to a significant decrease in the average capacity transfer rate for the NICU, dropping from approximately 26% to below 10% at the 30-week threshold. However, this reduction is accompanied by an increase in the capacity transfer rate for high care, which rises by up to approximately 38% at its peak. This highlights an inherent trade-off between reducing NICU capacity transfers and managing the consequent increase in transfers within high care.

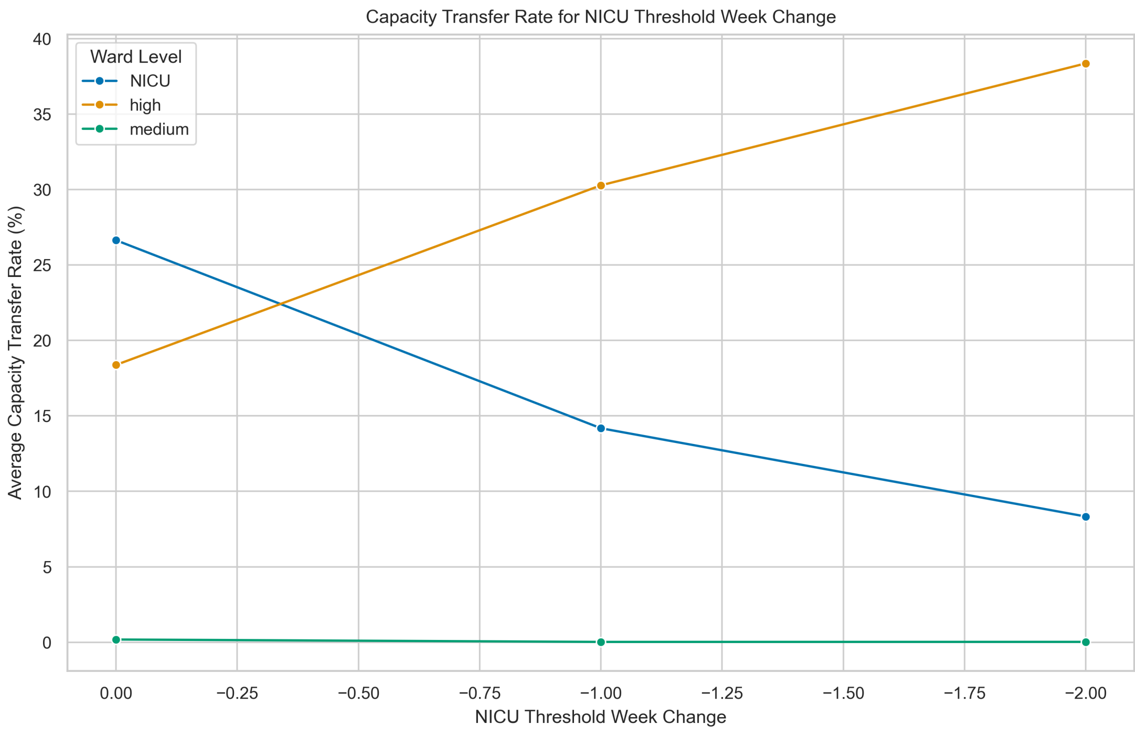


Figure 72 Comparison of average capacity transfer rate for decrease in NICU age threshold per ward level

Capacity transfers create additional stress for both the patient and their parents, and are therefore particularly important to avoid for highly vulnerable patients, such as those in the NICU. Given this context, one could argue that the average high care patient may not experience as significant an impact from a transfer as the average NICU patient. Consequently, the trade-off between reducing NICU transfers at the expense of increasing high care transfers could be justified, especially when the overall goal is to provide the best possible care for the patients with the greatest need. This approach prioritizes minimizing disruptions for the most vulnerable patients, aligning with the principle of delivering care where it is most critical.

In addition, I analyzed the impact on the number of weekly transfers per ward level as seen in Figure 73. As anticipated, the average weekly transfer rate for the NICU decreases, while it increases for high care. Particularly under the 30-week setting, the high care ward's weekly occupancy rate would fluctuate between 95% and 100%, underscoring the significant strain placed on this ward level. This fluctuation highlights the substantial pressure the high care unit would face, reflecting the trade-offs involved in managing occupancy across different ward levels.

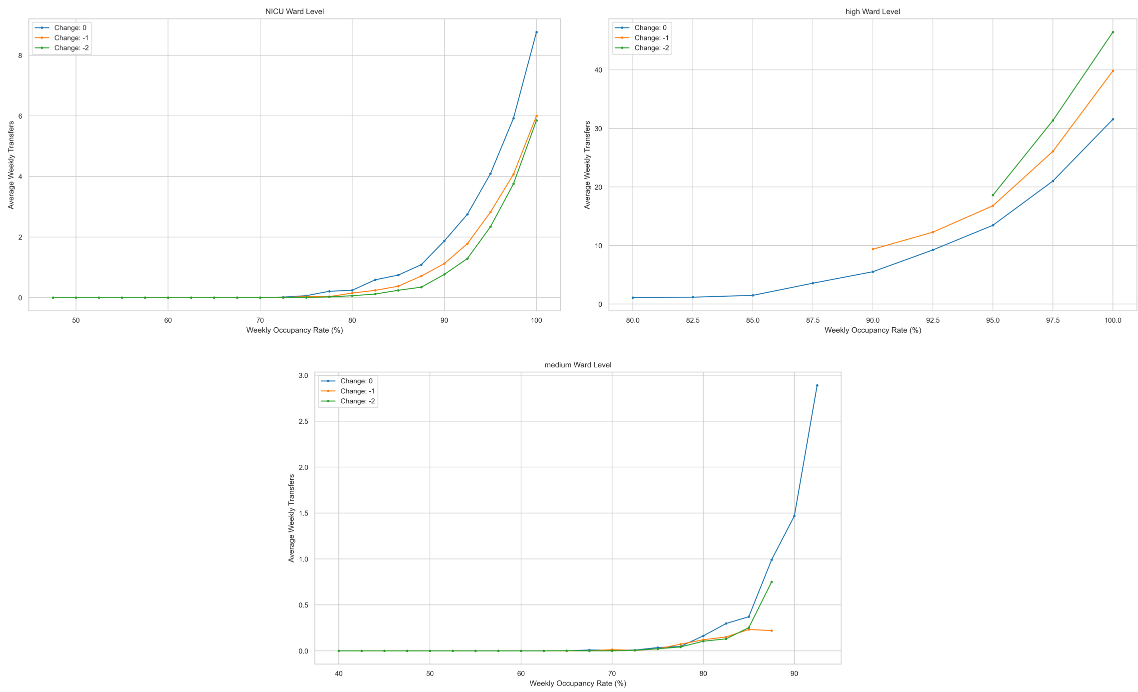


Figure 73 Weekly transfer per ward level and weekly occupancy rate for different NICU threshold changes

This analysis helps quantify the trade-off between NICU and non-NICU transfers. Notably, at full capacity, there is only a minor difference in weekly transfers at the NICU between the 31-week and 30-week settings. Therefore, even at the 30-week setting, the intervention would result in more than two fewer NICU capacity transfers per week. However, this reduction comes at the cost of eight additional high care capacity transfers. This trade-off highlights the balance between reducing NICU strain and potentially increasing the burden on high care.

7.3.5 Intervention Results: Combined Intervention Strategy

As the last experiments, the previous insights from levers and interventions were used to conceptualize a combined intervention strategy. The following section provides the results for the performed experiment as seen in Table 56.

Table 56 Overview of indicators for combined intervention strategy experiment results

Indicator	Ward Level	Without Intervention	With Intervention
Average Required Bed Count		135.65	134.03
	NICU	26.97	24.37
	High Care	75.12	73.31
	Medium Care	33.57	36.35
Average Weekly Occupancy Rate			
	NICU	91.80	89.71
	High Care	97.25	97.10
	Medium Care	65.84	73.74
Average Capacity Transfer Rate			
	NICU	21.56	17.92
	High Care	20.46	19.54
	Medium Care	0.05	0.16

The intervention resulted in a reduction in the overall average required bed count, decreasing from 135.65 to 134.03 beds. This decrease is most pronounced in the NICU, where the average required bed count dropped from 26.97 to 24.37, indicating a significant decrease in demand for this critical ward. High care also saw a reduction in required beds, from 75.12 to 73.31. In contrast, the medium care ward experienced an increase in the required bed count, rising from 33.57 to 36.35. This suggests that while the intervention effectively reduced pressure on the NICU, it shifted some of the demand toward medium care.

The average weekly occupancy rate showed varied outcomes following the intervention. In the NICU, the occupancy rate decreased from 91.80% to 89.71%, demonstrating the intervention’s impact on reducing occupancy pressure in this ward. High care, however, saw only a slight change, with the occupancy rate decreasing marginally from 97.25% to 97.10%. Meanwhile, the medium care ward experienced a notable increase in occupancy, from 65.84% to 73.74%. This increase suggests that while the intervention reduced overcrowding in the NICU, it led to higher occupancy in medium care.

The intervention's impact on the average capacity transfer rate differed across ward levels. The NICU saw a significant reduction in the transfer rate, dropping from 21.56% to 17.92%, indicating the intervention's success in reducing capacity transfers in this critical ward. High care also experienced a decrease in the transfer rate, from 20.46% to 19.54%, showing some relief in patient transfers. However, the medium care ward saw an increase in the transfer rate, rising from 0.05% to 0.16%. This increase suggests that while the intervention helped reduce transfers in the NICU and high care, it also led to a slight rise in transfers within medium care.

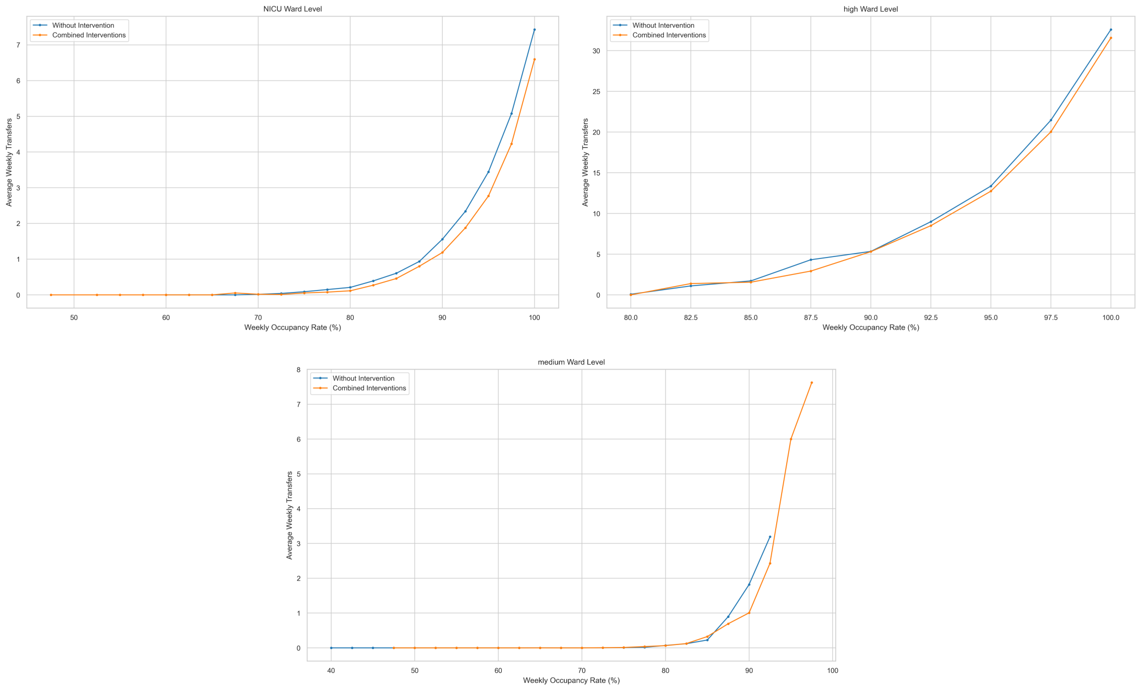


Figure 74 Weekly transfer per ward level and weekly occupancy rate for combined intervention strategy

The weekly transfers, displayed in Figure 74, further support the previous findings, showing a clear reduction in numbers for NICU and high care across all occupancy rates. Although there is a noticeable increase in medium care weekly transfers for occupancy rates above 90%, this is less concerning because the average occupancy rate for medium care remains around 74%. As a result, the weekly average for medium care is unlikely to frequently exceed 90%.

Overall, the experiment highlighted the potential of combining interventions, as it allows for leveraging individual strengths and compensating for shortcomings to achieve a better overall outcome. However, the findings also underscore the inherent trade-offs between ward levels even with combined interventions. This intervention strategy prioritized reducing capacity shortages at the most medically critical levels of care, focusing on NICU and high care, which consequently increased the burden on medium care. Nonetheless, considering that the medium care ward is currently well below its capacity limits, redistributing efforts in this manner appears to be a reasonable approach.

8 Discussion

In the previous chapters, the neonatal care system was conceptualized, a suitable computer simulation model was implemented, and various scenarios, system levers, and interventions were tested in the context of operational bed capacity shortages. The following chapter discusses the findings and provides academic and societal implications. Afterwards, the results are put into context with the identified limitations of this study.

8.1 Interpretation of Findings

A large portion of this study relied on the data analysis of the perinatal birth registry, which played a crucial role in driving model decisions and implementation. While modelers often attempt to express arrival rates through inter-arrival rates, this approach was not feasible for the neonatal care system due to the time unit being measured in days, with multiple patients arriving each day. Therefore, I employed an alternative approach to determine an overall distribution, specifically using a bounded normal distribution, leading to an easy implement and understandable arrival process. Additionally, the data did not provide sufficient evidence for seasonality, which contrasts with the commonly assumed seasonality of births, where more births occur in summer than in winter (Lam & Miron, 1991). One possible explanation for this discrepancy is that, while only a small percentage of newborns require neonatal care, this percentage might fluctuate across seasons, resulting in a steady demand throughout the year. However, further data is needed to validate this hypothesis. Moreover, the p-value of the conducted test was relatively low, suggesting that the selected time period could have been an outlier, further emphasizing the need for additional data to draw more definitive conclusions.

The analysis of LoS for each ward level emphasized the vast differences between medical conditions and their complexities across patients. Some patients require only a one-day stay, while others may remain in care for nearly half a year. Additionally, the analysis revealed an exponential increase in LoS as gestational age decreases, underscoring the critical nature of specialized ward levels tailored to different patient groups. These findings also illustrate the varying turnover rates across ward levels. In the NICU, most beds are occupied for several months, whereas high and medium care wards experience more frequent patient turnover.

Interestingly, the modeling of LoS based on medical and patient variables proved most effective for the NICU. Despite the medical complexity of NICU patients, they tend to share common admission criteria—such as being born before 32 weeks of gestation, weighing less than 1250 grams at birth, or having congenital abnormalities. This consistency in criteria might explain the success of the LoS model for NICU patients. Given this success, it may be worth considering whether additional guidelines could be defined for high and medium care to achieve further specialization within these ward levels, potentially improving patient outcomes and resource allocation by having more predictable stay durations.

In addition, the Dutch neonatal care network is characterized by bidirectional patient pathways between the ward levels. The data analysis showed that while only 4-5% of neonatal patients required a second stay, this has a tremendous impact on LoS, with the average increasing to over 50 days for patients admitted to a high care hospital after a NICU stay. Consequently, this group of patients tends to occupy beds disproportionately long and significantly contributes to capacity shortages. These results suggest the importance of differentiating between patient groups and recognizing the patient pathway more explicitly in discussions on capacity shortages. Understanding these pathways could lead to more targeted strategies for managing capacity and improving overall care.

When analyzing the dataset for the performance indicators, the results revealed that even during the 2016 to 2017 period, the region had to transfer patients from NICU and high care wards due to capacity shortages. This indicates that either the number of physical beds or the number of operational beds, constrained by staffing levels, was insufficient for the region's needs. While specific data on the ratio of physical to operational beds at that time is unavailable, making it difficult to fully address the issue, these findings suggest that capacity shortages in neonatal care are not a recent phenomenon. However, a comparison of bed numbers between 2016 and 2023 shows a consistent decrease across all wards, highlighting increasing pressure and challenge. The analysis also demonstrated that the NICU and high care wards bear the greatest burden. At the regional level, it is rare for a medium care patient to be transferred outside the region, underscoring the critical nature of NICU and high care wards. Since NICU and high care patients are among the most vulnerable, they are at greater risk of adverse outcomes from transfers, making these capacity issues particularly concerning.

The implemented simulation model was used to explore various "what-if" scenarios, system levers, and interventions, providing insights into the effects of different strategies on the neonatal care system. The scenarios underscored the severity of the current capacity shortages, revealing that approximately 21.5% of NICU patients and 20.5% of high care patients are being transferred to hospitals outside the region. Additionally, the average weekly occupancy rates indicate that these ward levels consistently operate above the recommended occupancy levels of 80 to 85% (Planningsbesluit Bijzondere Perinatologische Zorg, 2018). While hospitals require a minimum number of patients to operate efficiently, consistently running at such high occupancy levels is unsustainable and leaves the system vulnerable to potential shocks.

Given that both NICU and high care wards are operating well above the recommended guidelines, the utility of relying solely on a single occupancy rate goal is questionable. It is essential to consider occupancy rates in context, such as by combining them with metrics like weekly capacity transfers, to gain a more comprehensive understanding of the system's resilience and capacity challenges. Furthermore, capacity transfers create fluctuations in occupancy rates, making them unstable and posing additional challenges for hospitals. I also suspect that the drop in occupancy after a peak is likely to be larger for the NICU due to the relatively high LoS of its patients. When a patient with a long LoS is transferred, it frees up a bed for an extended period, leading to a more significant drop in occupancy. These fluctuations are problematic because they hinder hospitals' efforts to maintain stable occupancy levels, which are crucial for both planning and financial stability. The goal should be to smooth out these fluctuations. Capacity transfers increase variability, as irregular arrivals disrupt the balance between patient admissions and discharges, leading to greater unpredictability in bed availability.

When testing system levers—changing LoS, admission rates, and patient pathways—it was shown that all three can significantly impact the system’s performance indicators and help reduce capacity shortages. The most substantial effect was observed by decreasing LoS across all patients, with a more pronounced impact in high and medium care compared to the NICU. However, reducing LoS on a large scale may be challenging due to the inherent differences in patients' medical conditions and the various factors influencing their length of stay, resulting in varying admission durations. Adjusting admission rates for a ward or modifying patient pathways are strategies designed to shift bed demand between wards, aiming to optimize resource utilization. However, when using these levers, it’s crucial to consider the trade-offs between hospitals and among different patient groups. Given the varying medical complexities across ward levels, the focus should be on minimizing the risk of transfers for NICU patients. In the worst-case scenario, transferring an extremely premature neonate could pose significant risks and lead to potential negative outcomes, making it imperative to prioritize stability for these highly vulnerable patients.

As a final set of experiments the model was used to test currently discussed interventions. The two clinical interventions – phototherapy at home and oral antibiotics for EOS – aimed at decreasing the LoS for specific patient groups. While the absolute percentage changes for capacity transfer rates – 0.44%-points for NICU and 0.33%-points for high care, might appear small and for phototherapy at home are also below initial expectations from experts, the change still represents 22 less high care patient transfers to per year to outside the region. Given the unpredictability of arrivals, the number of patients could also include post-IC patients that would have the biggest negative effects from a transfer at the high care level. Thus, the results show the phenomenon that interventions aimed at one group can indirectly also aid other patient groups which increases their overall value. The results for oral antibiotics for EOS seem to be more promising and the intervention is also further in the implementation stage.

The adjustment in NICU thresholds has demonstrated encouraging results in improving the performance of the NICU ward but has also been associated with negative impacts on high care services. This highlights a secondary phenomenon where interventions may create a trade-off between the interests of different patient groups. The individual effects on high care indicators are significant; for example, the capacity transfer rate increases to 30% when set at 31 weeks. In contrast, the same threshold adjustment can reduce the capacity transfer rate for the NICU to below 15%, marking a decrease of more than 10 percentage points. Consequently, this intervention could be justified, as NICU patients generally require more critical medical attention than the average high care patient. Given the significantly increased mortality rate of up to 50% for extremely premature NICU patients, it is essential to prioritize ensuring the availability of NICU beds first (Glass et al., 2015). Therefore, the priority should be to minimize the risk of capacity transfers in the NICU. However, this intervention should not be implemented in isolation; it must be accompanied by additional measures to alleviate the burden on the high care ward for other patient groups.

The last intervention – combining previous interventions with the pathway lever of shifting post-IC patients to medium care instead of high care, showed promising results as the individual elements can partially overcome respective disadvantages of other elements. Overall, this combined intervention strategy achieved strong results on NICU and high care indicators as it would reduce the capacity transfers rate by 3.5%-point and 1%-point, respectively. This comes at a cost of an 0.1%-point increase in the medium care capacity transfers. However, it can be assumed that medium care patients are medically more stable and, hence, are more in the position to accomplish such a transfer. The results highlight the importance of assessing interventions rather in an intervention package than individually. Assessments should not ignore the interaction effects between individual interventions as combined they can lead to more desired outcomes. In addition, the combined intervention strategy emphasizes the importance of evaluating interventions beyond clinical interventions focused on medical outcomes and encourages to include dynamics between hospitals and ward levels in intervention design.

8.2 Academic Implications

The study contributed to academic literature by filling the earlier described knowledge gap in the fields of modeling and simulation in healthcare.

This study contributed to the small field of simulation studies of neonatal care systems and, to the best of my knowledge, was the first to be conducted in a Dutch setting accounting for different ward levels and bidirectional transfers in a regional setting. The Dutch neonatal care system provides unique characteristics in definition of care levels and the patient journey across hospitals in a region, by accounting for all these settings the developed model can serve as comparison tool for the impact of different system designs. Moreover, the developed simulation model considers the regional setting, multiple hospital with different care levels, and complexities of medical conditions and bidirectional patient transfers, thus, also further extending on previous limitations (Adeyemi & Demir, 2020; Demir et al., 2014; Lebcir & Atun, 2021). While these model features increased the model complexity, they also provide opportunities for different levers than typically tested ones like an increase in operational beds. It answered the call in the field for using simulation models to perform impact assessments, going beyond mere simulation model building to link it back to real-life interventions and test their impact (Adeyemi & Demir, 2020). The results show how the strengths of modeling and simulation – such as easily answering what if questions – provide value to the healthcare domain.

New performance indicators were introduced in the context of capacity shortages, considering the temporal aspect of transfers, thus extending the work of Harper and Shahani (2002). By grouping indicators into two perspectives – hospital management and societal – we can highlight the complexity and dimension of capacity shortages. Moreover, the linking the number of weekly transfers to the respective weekly occupancy rate, it was possible to identify how scenarios, system levers, and interventions perform at a given occupancy rate. This combination of indicators provides valuable insights as the indicators are normally only assessed individually.

In the healthcare literature, this study performed impact assessments for currently discussed interventions in neonatal care. This provided an additional perspective when evaluating interventions and highlighted the importance of including the impact on the system's capacity in future studies, helping to assess the scalability of interventions (Zamboni et al., 2019). Additionally, the data analysis provided insights into the influential factors of LoS for neonates across different ward levels (Seaton, Barker, Jenkins, et al., 2016). Lastly, the study demonstrated the potential for ridge regression models to capture multicollinearity and the medical complexity of patients to estimate LoS. In particular, the more accurate LoS sampling offers more potential ways of interaction and higher usability across various levers or interventions. Still, the model is easily adjustable and can be used to extend other simulation models or be applied to other regions, offering additional value to interdisciplinary studies.

Based on these findings, the works contributes to bigger questions that go beyond the initial scope of this study as the following discusses the value and goals of different performance indicators and their meaning for health system performance assessments.

In the process of determining relevant model outcomes, it became evident that there are various stakeholders interested in the discussion of capacity shortages in the neonatal care system. In my observation, the current literature on capacity shortages focuses on analyzing occupancy rates and numbers of beds (Jones, 2011). However, this study suggests that using the number of beds and occupancy rates as individual performance indicators for health systems has limited value.

While bed numbers are straightforward to visualize and communicate to various stakeholders, they fall short in capturing the uncertainties associated with patient arrivals and LoS. In this study, one indicator focused on the number of beds required for patients within the region, emphasizing the minimum number of operational beds needed. It is important to note that this figure is not intended as a recommendation but rather illustrates the potential gap between the minimum bed requirement and the current situation, given capacity constraints. However, this indicator alone offers limited insights, as it lacks temporal information and, therefore, cannot account for the uncertainties related to patient arrival times and LoS.

Moreover, the results demonstrate that an occupancy rate alone offers only limited insights into the actual capacity and dynamics of a ward. While occupancy rates are easy to compare across wards and hospitals and can be communicated as general guidelines, the same occupancy rate can reflect different situations in practice. For instance, a 95% occupancy rate in the NICU, as shown in the case study, would mean that 22 out of 23 beds are occupied. This leaves only one bed available, meaning that admitting just one more patient would push the NICU to full capacity, increasing the risk of capacity transfers for subsequent patients. In contrast, at the high care level, with 62 operational beds, a 95% occupancy rate translates to about 59 beds being occupied. This means that the ward could still accommodate three additional patients before reaching full capacity, compared to only one additional patient at the NICU, despite both wards initially having the same occupancy rate. This example highlights that occupancy rates must be interpreted in context, as they do not uniformly convey the same level of strain or risk across different ward levels.

Based on these realizations, the work was extended by indicators that address the impact on society through the capacity transfer rate and the weekly capacity transfers. These indicators provide additional value through translating bed numbers and occupancy rates into real world impact on patients.

These indicators can contribute to the wider field of health system performance assessments. In the quest of guiding healthcare organizations and policymakers toward enhanced health system performance, the concept of the Triple Aim was initially developed by Berwick et al. (2008). This framework aimed to improve the patient care experience, enhance population health, and reduce per capita healthcare costs. Recognizing the critical importance of workforce well-being, the Triple Aim was later expanded into the Quadruple Aim, which adds a fourth goal: improving the work life of healthcare personnel (Bodenheimer & Sinsky, 2014). While the proposed framework provides valuable guidance it is often difficult to quantify and compare interventions across these dimensions as each field of healthcare can lead to different indicators for the dimensions (Seow & Sibley, 2014).

The introduced indicators could provide additional insights ensuring a further implementation of the framework in neonatal care. The cost dimension is addressed by the number of required beds and weekly occupancy rates, which hospitals use to guide financial planning. The dimension of population health is considered through a societal lens, using the capacity transfer rate and weekly capacity transfers as indicators. The objective should be to minimize these transfers due to their potential negative impact on patient outcomes and, consequently, on population health. Additionally, occupancy rates offer insights into the quality of care dimension, as higher rates can lead to increased stress levels, a higher risk of errors, and potentially reduced time per patient. The final dimension, workforce well-being, is addressed by multiple indicators. An increasing number of beds necessitates either additional staff or a higher staff-to-patient ratio, while occupancy rates serve as a proxy for the workload, which can lead to heightened emotional stress. The capacity transfer rate also highlights the additional work required to manage transfers between hospitals and reflects the emotional burden associated with transferring patients due to capacity shortages. Thus, the indicators used in this model could contribute to further operationalizing the Quadruple Aim, leading to a more sophisticated approach to assessing health system performance in neonatal care.

8.3 Societal Implications

This work was characterized by a strong link to an ongoing practice problem with high societal relevance and close collaboration with practitioners in the field. Thus, it contributed to practice in multiple ways.

Firstly, this work highlights the inherent value of collecting admission data across hospitals. By doing so, the increased number of data points can be used to identify underlying factors and patterns, such as for LoS, providing a means to learn across hospitals rather than acting in isolation. An analysis of the existing data over the past years identified key constraints and factors in the region. The pathways patients take were mapped, revealing the uneven occupancy rates across hospitals. The data and scenario analysis underscored the magnitude of the ongoing capacity shortages, serving as a clear call to action for stakeholders in the field and external stakeholders, such as the national government. The challenges are not only faced by individual hospitals but are visible at a system level, necessitating a collaborative approach across stakeholders.

The designed and implemented simulation model is open-source and can easily be extended or adjusted for use in different regions or similar settings in high-income countries. In this context, the model provides various ways to test possible interventions that could influence any of the underlying mechanisms in the model. Moreover, the simulation model can be used beyond the scientific community by hospital planning and management teams as a communication tool to drive evidence-based decision-making in the healthcare sector.

Additionally, this work identified system levers and their working mechanisms that have the potential to impact the existing operational bed capacity shortages in the region. These levers should inspire researchers and practitioners to identify or develop appropriate interventions. In this context, the results reveal trade-offs between patient groups, and the model aids in quantifying these trade-offs during the decision-making process. For example, it helps determine the acceptable increase in capacity transfer rate for high care in exchange for a specific decrease in the capacity transfer rate for the NICU. Additionally, we observed that interventions targeting one particular patient group can have unintended effects—either positive or negative—on other patient groups due to the interaction effects within the model.

Furthermore, the simulation model was used to test relevant interventions that are currently implemented or under discussion, with the promise of impacting capacity shortages. The results show that phototherapy at home is not effective as previously thought, while changing antibiotics treatment and lowering the age threshold for NICU ward level could significantly improve the current situation. However, it is also evident that there is no silver bullet intervention; each intervention comes with its drawbacks and trade-offs. Therefore, the region is advised to combine interventions and approaches and assess their collective impact to address the current capacity shortages effectively.

Overall, the scenario experiment results underscore that the current situation of limited operational bed capacity poses significant risks to the most vulnerable patients, as the number of NICU and high care beds is insufficient to accommodate all patients. Currently, both NICU and high care are experiencing capacity transfer rates above 20%, meaning that, on average, every fifth patient would need to be transferred outside the region. Given the unpredictability of incoming patients, there is a risk that an extremely premature infant, under 27 weeks of gestation, might need to be transferred, which could lead to severe long-term negative outcomes. Further lowering the minimum NICU age to 23 weeks of gestation would likely exacerbate the current crisis, and based on the capacity assessment, such a policy cannot be recommended at this time.

Therefore, a recommendation is to reconsider the 32-week guideline for NICU admissions, potentially lowering it, while simultaneously implementing other interventions to increase the number of available beds in high care to accommodate the additional incoming patients. One option would be test out moving some of post-IC patients to the medium care level instead of high care. Furthermore, clinical interventions such as oral antibiotics for EOS should be continued in implementation. However, it is unlikely that the current challenges can be overcome with just clinical interventions, and it is necessary to work on interventions using the patient pathways. This balanced approach would help manage capacity more effectively across different ward levels.

8.4 Limitations

This work comes with multiple limitations that are inherent in the research design or have become evident over time.

Firstly, the model is inherently stochastic, and each run can produce slightly different results. Therefore, each part of this research was conducted across multiple runs to provide a range of outcome values.

Most of the model implementation and assumptions are based on the perinatal birth registry data for the region. While the dataset includes around 50,000 admissions over six years, there were challenges due to incomplete time periods as not all hospitals reported their admissions consistently over the entire period. Additionally, it was not possible to validate the model with data from another region, leading to the risk of overfitting to the specific region’s settings.

Furthermore, the model assumed that the number of operational beds remains constant over the simulation period of one year. This assumption, confirmed in a private conversation with a hospital planner, allowed for clear comparisons across scenarios and runs. However, it might not fully reflect reality.

Another assumption of this work is that a patient with the same characteristics and treatments would have the same LoS regardless of the specific hospital at the ward level where they are admitted. However, analysis and consultations showed that individual hospital protocols and factors outside the model's scope, such as the socio-demographic composition of the patient population, can lead to different outcomes.

All tested levers and interventions were assessed solely on the introduced performance indicators linked to capacity shortages. While feasibility challenges and the potential for interventions were acknowledged, the model does not account for other factors. Healthcare systems do not operate in isolation and have significant societal and economic impacts. Potential side effects, costs of interventions, and impacts on quality of care are not considered but should be kept in mind when interpreting the results and making decisions.

These limitations should be considered when using the model and interpreting its results.

9 Conclusion

Linking back to the main research question of "How can operational bed capacity shortages in neonatal care be reduced within staffing limitations" and its sub-questions, multiple conclusions can be found. Based on these results multiple avenues of future research are opened. This chapter will provide concluding remarks as well as provide an outlook into where research should go from here.

9.1 Answers to Research Questions

At first, I provide detailed conclusions for each sub-question. The sub-questions followed the research flow and addressed all stages from conceptualization, implementation, to simulation experiments and their interpretation.

Sub-Question 1: What factors and constraints influence the operational bed capacity shortages in the neonatal care pathway within staffing limitations?

The first sub-question aimed to identify the factors and constraints influencing operational bed capacity shortages in the neonatal care pathway within the limitations of staffing. This question was addressed using a mix of qualitative and quantitative methods. A conceptualization of the neonatal care system in the region was provided, encompassing different ward levels and the concept of regionalization.

The data analysis revealed that daily arrivals in the region could be estimated using a normal distribution and that the LoS of patients could be expressed through ridge regression models. These regression models highlighted that the driving factors for LoS vary by ward level and age group, with common factors often including gestational age, birth weight, and respiratory treatments like CPAP and oxygen support days. Further modeling demonstrated how these factors can be distributed across different ward levels and age groups, offering insights into approximations for simulation models. Additionally, the analysis revealed the added complexity of patients being transferred between ward levels, who typically experience a longer total LoS, leading to further capacity constraints. Based on these findings, a capacity transfer rate was defined as a performance measure. This rate accounts for the number of inside region patients that need to be transferred to an outside region hospital – a clear sign of capacity shortages.

Sub-Question 2: Which levers in the neonatal care system have the biggest impact on reducing operational bed capacity shortages within staffing limitations?

The second sub-question focused on identifying levers in the neonatal care system that have the biggest impact on operational bed capacity shortages within staffing limitations. This part of the research was answered through using insights from the data analysis and literature to propose levers in the system that could be addressed. These levers have then been tested using the simulation model. The levers used the following model mechanism – LoS, ward admission rate, and patient pathway. Changing the LoS for all patients showed the biggest effect especially for patients with relatively lower LoS, hence, mostly at high and medium care wards. Adjusting admission rates leads to demand shifting and trade-offs between ward levels and patient groups. However, it still showed the potential to decrease the burden at the NICU by admitting less patients at that level. As part of the neonatal care system's complexity originates from the patient's pathway, I developed an additional lever that would assess the impact of changing pathways for specific patient groups. Shifting post-IC patients to the medium care instead of high care at the cost of some additional days at the NICU can become valuable depending on the amount of additional days at the NICU. Thus, I showed with these levers that impact on capacity shortages is not only found in medical aspects that would potentially impact the LoS but can also be found in the interactions and coordination between parts of the system.

Sub-Question 3: Which interventions in the neonatal care system can address the levers with the biggest impact on reducing operational bed capacity shortages within staffing limitations?

To answer the third subquestion, I used insights gained from the system levers, literature, and interviews with experts in the field to identify currently relevant intervention and test them for their impact on capacity shortages. For interventions that focus on decreasing the LoS, I have found that phototherapy at home has only a minor influence on the capacity shortages and thus, cannot serve as potential solution. However, changing the way of providing treatment for antibiotics from intravenous to oral can have a noticeable impact on the region and is also easy to implement without additional cost. In addition, I tested changing the NICU age threshold from 32 weeks to 31 or 30 weeks and, thus, admitting those patients to other ward levels. This intervention had a large impact on all indicators for the NICU yet bringing the high care ward close to full capacity. Thus, a combination of interventions that can tackle each other's trade-offs would be the most suitable option to overcome the current capacity shortages within staffing limitations. Such a combined intervention strategy was tested – using the previous interventions together with the patient pathway lever – leading to promising results for NICU and high care ward level indicators in a trade-off for acceptable burden for the medium care ward level.

9.2 Future Research

The results of this thesis have been developed over a time range of half a year. In this process, multiple limitations and additional ideas have been identified. Thus, there are various pathways for future research following the limitations and results of this study.

Based on the limitations of this study, at first, it would be beneficial to validate and expand the model with other regions in the Netherlands or even beyond. This should be done on a general model level but also for submodels such as the regression models. Doing so, insights could be generalized and be applied to a large variety of settings. Moreover, the reproducibility of the results depends on access to *perined* data which must be obtained through a partnering hospital or research institution.

The *perined* dataset provided a great starting resource for building the simulation model. However, a detailed analysis of the data and discussions with practitioners revealed inherent weaknesses related to the data collection process and the willingness of hospitals to contribute to a high-quality database. The digitalization of healthcare in recent years has increased the quality of electronic health records. These advancements can become valuable in validating and extending the healthcare system simulation model without additional efforts from hospitals and healthcare personnel. Therefore, future research should take advantage of easier access to high-quality data in building additional simulation models or confirming the existing one.

The inherent links between neonatal departments, pediatrics, and obstetrics by multiple stakeholders suggests the inclusion of these aspects in a future model. This would allow for a more comprehensive investigation of the healthcare system supporting the days before and after birth. Future research should aim to integrate related medical fields into the model to provide a more holistic understanding of neonatal care and its interdependencies within the healthcare system.

In addition, the results of this work open additional points for future research.

First, additional studies should investigate the feasibility and costs of the proposed intervention strategy. Evidence should be collected in similar contexts to gain more experience on potential benefits and disadvantages. Based on this, the next questions would be how to implement the interventions further, in which order, at which hospitals, at what point, and how to communicate these changes effectively.

In the current movement towards a One Health approach, scholars should invest more into factors outside the neonatal care system that influence admissions and stay duration. One prime example is the effects of climate change. With increasing extreme weather conditions, the risks for preterm and low birth weight increase (Basu et al., 2018). It is unknown what the effect would be on the already challenged neonatal care system in the context of capacity shortages. The simulation model of this study is open-source and can easily serve as a basis for these assessments. Individual functions, such as gestational age and birth weight prediction, can be easily adjusted to fit the setting of a climate change scenario.

Moreover, future research should extend this work by including socio-demographic aspects in decision-making and modelling. Even in high-income countries, like the Netherlands, we still see vast socio-economic differences between parts of cities and regions, potentially leading to different outcomes during pregnancy and in the first days of life. These insights could also inform the field of urban science to account more for healthcare-related factors in city planning. Thus, there is a call for more interdisciplinary work that incorporates the modelling approach of one system, like this work, with other systems and contexts to provide more holistic answers to the challenges of our time.

References

Adeyemi, S., & Demir, E. (2020). Modelling the neonatal system: A joint analysis of length of stay and patient pathways. *The International Journal of Health Planning and Management*, *35*(3), 704–717. https://doi.org/10.1002/hpm.2928

Aher, S., Malwatkar, K., & Kadam, S. (2008). Neonatal anemia. *Seminars in Fetal and Neonatal Medicine*, *13*(4), 239–247. https://doi.org/10.1016/j.siny.2008.02.009

Arnold, R. D., & Wade, J. P. (2015). A Definition of Systems Thinking: A Systems Approach. *Procedia Computer Science*, *44*, 669–678. https://doi.org/10.1016/j.procs.2015.03.050

Asaduzzaman, M., & Chaussalet, T. J. (2008). Modelling and Performance Measure of a Perinatal Network Centre in the United Kingdom. *2008 21st IEEE International Symposium on Computer-Based Medical Systems*, 506–511. https://doi.org/10.1109/CBMS.2008.50

Bai, J., Brunner, J., & Gerstmeyr, S. (2020). Simulation and Evaluation of ICU Management Policies. *2020 Winter Simulation Conference (WSC)*, 864–875. https://doi.org/10.1109/WSC48552.2020.9383958

Bai, J., Fügener, A., Schoenfelder, J., & Brunner, J. (2018). Operations research in intensive care unit management: A literature review. *Health Care Management Science*, *21*(1), 1–24. https://doi.org/10.1007/s10729-016-9375-1

Basu, R., Rau, R., Pearson, D., & Malig, B. (2018). Temperature and Term Low Birth Weight in California. *American Journal of Epidemiology*, *187*(11), 2306–2314. https://doi.org/10.1093/aje/kwy116

Beltempo, M., Bresson, G., & Lacroix, G. (2023). Using machine learning to predict nosocomial infections and medical accidents in a NICU. *Health and Technology*, *13*(1), 75–87. https://doi.org/10.1007/s12553-022-00723-1

Berwick, D. M., Nolan, T. W., & Whittington, J. (2008). The Triple Aim: Care, Health, And Cost. *Health Affairs*, *27*(3), 759–769. https://doi.org/10.1377/hlthaff.27.3.759

Birta, L. G., & Arbez, G. (2019). *Modelling and Simulation: Exploring Dynamic System Behaviour*. Springer International Publishing. https://doi.org/10.1007/978-3-030-18869-6

Bodenheimer, T., & Sinsky, C. (2014). From Triple to Quadruple Aim: Care of the Patient Requires Care of the Provider. *The Annals of Family Medicine*, *12*(6), 573–576. https://doi.org/10.1370/afm.1713

Bonifacio, S. L., & Van Meurs, K. (2019). Neonatal Neurocritical Care: Providing Brain-Focused Care for All at Risk Neonates. *Seminars in Pediatric Neurology*, *32*, 100774. https://doi.org/10.1016/j.spen.2019.08.010

Braithwaite, M. (2008). Nurse Burnout and Stress in the NICU. *Advances in Neonatal Care*, *8*(6), 343–347. https://doi.org/10.1097/01.ANC.0000342767.17606.d1

British Association Of Perinatal Medicine. (2010). *Service standards for hospitals providing neonatal care*. https://www.bapm.org/resources/32-service-standards-for-hospitals-providing-neonatal-care-3rd-edition-2010

Cassidy, R., Singh, N. S., Schiratti, P.-R., Semwanga, A., Binyaruka, P., Sachingongu, N., Chama-Chiliba, C. M., Chalabi, Z., Borghi, J., & Blanchet, K. (2019). Mathematical modelling for health systems research: A systematic review of system dynamics and agent-based models. *BMC Health Services Research*, *19*(1), 845. https://doi.org/10.1186/s12913-019-4627-7

College Perinatale Zorg. (2020, December 9). *Rapport RIVM over perinatale sterfte vraagt om verbreding inzet geboortezorg*. https://www.kennisnetgeboortezorg.nl/nieuws/rapport-rivm-over-perinatale-sterfte-vraagt-om-verbreding-inzet-geboortezorg/#:~:text=Perined%2Dcijfers%20over%202019,4.6%20per%201000%20geboren%20kinderen.

Committee on Fetus and Newborn. (2004). Levels of Neonatal Care. *Pediatrics*, *114*(5), 1341–1347. https://doi.org/10.1542/peds.2004-1697

Currie, C. S. M., Fowler, J. W., Kotiadis, K., Monks, T., Onggo, B. S., Robertson, D. A., & Tako, A. A. (2020). How simulation modelling can help reduce the impact of COVID-19. *Journal of Simulation*, *14*(2), 83–97. https://doi.org/10.1080/17477778.2020.1751570

Curry, J., McGregor, C., & Tracy, S. (2006). A Communication Tool to Improve the Patient Journey Modeling Process. *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, 4726–4730. https://doi.org/10.1109/IEMBS.2006.259481

Davahli, M. R., Karwowski, W., & Taiar, R. (2020). A System Dynamics Simulation Applied to Healthcare: A Systematic Review. *International Journal of Environmental Research and Public Health*, *17*(16), 5741. https://doi.org/10.3390/ijerph17165741

Demir, E., Lebcir, R., & Adeyemi, S. (2014). Modelling length of stay and patient flows: Methodological case studies from the UK neonatal care services. *Journal of the Operational Research Society*, *65*(4), 532–545. https://doi.org/10.1057/jors.2013.51

DeRienzo, C. M., Shaw, R. J., Meanor, P., Lada, E., Ferranti, J., & Tanaka, D. (2017). A discrete event simulation tool to support and predict hospital and clinic staffing. *Health Informatics Journal*, *23*(2), 124–133. https://doi.org/10.1177/1460458216628314

Dickson, K. E., Simen-Kapeu, A., Kinney, M. V., Huicho, L., Vesel, L., Lackritz, E., De Graft Johnson, J., Von Xylander, S., Rafique, N., Sylla, M., Mwansambo, C., Daelmans, B., & Lawn, J. E. (2014). Every Newborn: Health-systems bottlenecks and strategies to accelerate scale-up in countries. *The Lancet*, *384*(9941), 438–454. https://doi.org/10.1016/S0140-6736(14)60582-1

Dixon, K. L., Carter, B., Harriman, T., Doles, B., Sitton, B., & Thompson, J. (2021). Neonatal Thermoregulation: A Golden Hour Protocol Update. *Advances in Neonatal Care*, *21*(4), 280–288. https://doi.org/10.1097/ANC.0000000000000799

Donnellan, D., Moore, Z., Patton, D., O'Connor, T., & Nugent, L. (2020). The effect of thermoregulation quality improvement initiatives on the admission temperature of premature/very low birth-weight infants in neonatal intensive care units: A systematic review. *Journal for Specialists in Pediatric Nursing*, *25*(2), e12286. https://doi.org/10.1111/jspn.12286

Eriksson, C. O., Stoner, R. C., Eden, K. B., Newgard, C. D., & Guise, J.-M. (2017). The Association Between Hospital Capacity Strain and Inpatient Outcomes in Highly Developed Countries: A Systematic Review. *Journal of General Internal Medicine*, *32*(6), 686–696. https://doi.org/10.1007/s11606-016-3936-3

Feldman, K., & Rohan, A. J. (2022). Data-Driven Nurse Staffing in the Neonatal Intensive Care Unit. *MCN: The American Journal of Maternal/Child Nursing*, *47*(5), 249–264. https://doi.org/10.1097/NMC.0000000000000839

Fiske, E. (2018). Nurse Stressors and Satisfiers in the NICU. *Advances in Neonatal Care*, *18*(4), 276–284. https://doi.org/10.1097/ANC.0000000000000514

Forbus, J. J., & Berleant, D. (2022). Discrete-Event Simulation in Healthcare Settings: A Review. *Modelling*, *3*(4), 417–433. https://doi.org/10.3390/modelling3040027

Fournier, D. L., & Zaric, G. S. (2013). Simulating neonatal intensive care capacity in British Columbia. *Socio-Economic Planning Sciences*, *47*(2), 131–141. https://doi.org/10.1016/j.seps.2013.01.001

Franck, T., Bercelli, P., Aloui, S., & Augusto, V. (2020). A Generic Framework to Analyze and Improve Patient Pathways within a Healthcare Network Using Process Mining and Discrete-Event Simulation. *2020 Winter Simulation Conference (WSC)*, 968–979. https://doi.org/10.1109/WSC48552.2020.9384021

Frazer, M., Ciarlo, A., Hinderer, K. A., & Briere, C.-E. (2022). Reducing Admission Hypothermia in Neonates Born at Less Than 32 Weeks or 1500 g. *Advances in Neonatal Care*, *22*(2), 99–107. https://doi.org/10.1097/ANC.0000000000000865

Garnier, A., Chavez-Demoulin, V., Hameri, A., Niemi, T., & Wasserfallen, B. (2016). Patient flow congestion—Predictive modelling to anticipate bottlenecks. *International Journal of Healthcare Technology and Management*, *15*(4), 352–373. https://doi.org/10.1504/IJHTM.2016.084137

Gievers, L. L., Sedler, J., Phillipi, C. A., Dukhovny, D., Geddes, J., Graven, P., Chan, B., & Khaki, S. (2018). Implementation of the sepsis risk score for chorioamnionitis-exposed newborns. *Journal of Perinatology*, *38*(11), 1581–1587. https://doi.org/10.1038/s41372-018-0207-7

Gill, A. B. (2004). Perinatal transport: Problems in neonatal intensive care capacity. *Archives of Disease in Childhood - Fetal and Neonatal Edition*, *89*(3), F220–F223. https://doi.org/10.1136/adc.2003.028159

Glass, H. C., Costarino, A. T., Stayer, S. A., Brett, C. M., Cladis, F., & Davis, P. J. (2015). Outcomes for Extremely Premature Infants. *Anesthesia & Analgesia*, *120*(6), 1337–1351. https://doi.org/10.1213/ANE.0000000000000705

Goldsmith, J. P., & Kattwinkel, J. (2012). The Role of Oxygen in the Delivery Room. *Clinics in Perinatology*, *39*(4), 803–815. https://doi.org/10.1016/j.clp.2012.09.003

Gopakumar, B., Wang, S., Khasawneh, M., Srihari, K., Gandhi, T., & Saunders, N. (2009). A Systems Approach for Hospital Inpatient Bed Capacity Planning. *2009 IEEE International Conference on Industrial Engineering and Engineering Management*, 744–748. https://doi.org/10.1109/IEEM.2009.5372930

Guttmann, K., Patterson, C., Haines, T., Hoffman, C., Masten, M., Lorch, S., & Chuo, J. (2020). Parent Stress in Relation to Use of Bedside Telehealth, an Initiative to Improve Family-Centeredness of Care in the Neonatal Intensive Care Unit. *Journal of Patient Experience*, *7*(6), 1378–1383. https://doi.org/10.1177/2374373520950927

Han, P. K. J., Babrow, A., Hillen, M. A., Gulbrandsen, P., Smets, E. M., & Ofstad, E. H. (2019). Uncertainty in health care: Towards a more systematic program of research. *Patient Education and Counseling*, *102*(10), 1756–1766. https://doi.org/10.1016/j.pec.2019.06.012

Harper, P., & Shahani, A. (2002). Modelling for the planning and management of bed capacities in hospitals. *Journal of the Operational Research Society*, *53*(1), 11–18. https://doi.org/10.1057/palgrave.jors.2601278

Hibberd, J., Leontini, J., Scott, T., Pillow, J. J., Miedema, M., Rimensberger, P. C., & Tingay, D. G. (2023). Neonatal high-frequency oscillatory ventilation: Where are we now? *Archives of Disease in Childhood - Fetal and Neonatal Edition*, 467–474. https://doi.org/10.1136/archdischild-2023-325657

Hussain, A., Rivers, P. A., Glover, S. H., & Fottler, M. D. (2012). Strategies for dealing with future shortages in the nursing workforce: A review. *Health Services Management Research*, *25*(1), 41–47. https://doi.org/10.1258/hsmr.2011.011015

Jacobson, S. H., Hall, S. N., & Swisher, J. R. (2013). Discrete-Event Simulation of Health care Systems. In R. Hall (Ed.), *Patient Flow* (Vol. 206, pp. 273–309). Springer US. https://doi.org/10.1007/978-1-4614-9512-3_12

Jie Liu, Kaimeng Kong, Yexuan Tao, & Wei Cai. (2015). Optimal Timing for Introducing Enteral Nutrition in the Neonatal Intensive Care Unit. *Asia Pacific Journal of Clinical Nutrition*, *24*(2). https://doi.org/10.6133/apjcn.2015.24.2.14

Jones, R. (2011). Volatility in bed occupancy for emergency admissions. *British Journal of Healthcare Management*, *17*(9), 424–430. https://doi.org/10.12968/bjhc.2011.17.9.424

Jun, J. B., Jacobson, S. H., & Swisher, J. R. (1999). Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society*, *50*(2), 109–123. https://doi.org/10.1057/palgrave.jors.2600669

Kanai, Y., & Takagi, H. (2021). Markov chain analysis for the neonatal inpatient flow in a hospital. *Health Care Management Science*, *24*(1), 92–116. https://doi.org/10.1007/s10729-020-09515-3

Katsaliaki, K., & Mustafee, N. (2011). Applications of simulation within the healthcare context. *Journal of the Operational Research Society*, *62*(8), 1431–1451. https://doi.org/10.1057/jors.2010.20

Keij, F. M., Kornelisse, R. F., Hartwig, N. G., Van Der Sluijs-Bens, J., Van Beek, R. H. T., Van Driel, A., Van Rooij, L. G. M., Van Dalen-Vink, I., Driessen, G. J. A., Kenter, S., Von Lindern, J. S., Eijkemans, M., Stam-Stigter, G. M., Qi, H., Van Den Berg, M. M., Baartmans, M. G. A., Van Der Meer-Kappelle, L. H., Meijssen, C. B., Norbruis, O. F., … Tramper-Stranders, G. A. (2022). Efficacy and safety of switching from intravenous to oral antibiotics (amoxicillin–clavulanic acid) versus a full course of intravenous antibiotics in neonates with probable bacterial infection (RAIN): A multicentre, randomised, open-label, non-inferiority trial. *The Lancet Child & Adolescent Health*, *6*(11), 799–809. https://doi.org/10.1016/S2352-4642(22)00245-0

Kokangul, A., Akcan, S., & Narli, M. (2017). Optimizing nurse capacity in a teaching hospital neonatal intensive care unit. *Health Care Management Science*, *20*(2), 276–285. https://doi.org/10.1007/s10729-015-9352-0

Komashie, A., Hinrichs-Krapels, S., & Clarkson, P. J. (2021). Systems Approaches to Healthcare Systems Design and Care Delivery: An Overview of the Literature. *Proceedings of the Design Society*, *1*, 2941–2950. https://doi.org/10.1017/pds.2021.555

Kox, J. H. A. M., Groenewoud, J. H., Bakker, E. J. M., Bierma-Zeinstra, S. M. A., Runhaar, J., Miedema, H. S., & Roelofs, P. D. D. M. (2020). Reasons why Dutch novice nurses leave nursing: A qualitative approach. *Nurse Education in Practice*, *47*, 102848. https://doi.org/10.1016/j.nepr.2020.102848

Kringos, D. S., Boerma, W. G., Hutchinson, A., Van Der Zee, J., & Groenewegen, P. P. (2010). The breadth of primary care: A systematic literature review of its core dimensions. *BMC Health Services Research*, *10*(1), 65. https://doi.org/10.1186/1472-6963-10-65

Lam, D. A., & Miron, J. A. (1991). Seasonality of births in human populations. *Biodemography and Social Biology*, *38*(1–2), 51–78. https://doi.org/10.1080/19485565.1991.9988772

Lane, D. C., & Oliva, R. (1998). The greater whole: Towards a synthesis of system dynamics and soft systems methodology. *European Journal of Operational Research*, *107*(1), 214–235. https://doi.org/10.1016/S0377-2217(97)00205-1

Lebcir, R., & Atun, R. (2020). Should doctors use their judgment? How a system dynamics model elicited knowledge in neonatal care services. *Journal of the Operational Research Society*, *71*(7), 1113–1123. https://doi.org/10.1080/01605682.2020.1730252

Lebcir, R., & Atun, R. (2021). Resources management impact on neonatal services performance in the United Kingdom: A system dynamics modelling approach. *The International Journal of Health Planning and Management*, *36*(3), 793–812. https://doi.org/10.1002/hpm.3118

Liu, J., Wu, S., & Zhu, X. (2022). Advances in the Prevention and Treatment of Neonatal Hypothermia in Early Birth. *Therapeutic Hypothermia and Temperature Management*, *12*(2), 51–56. https://doi.org/10.1089/ther.2021.0036

Lowery, J. C., Hakes, B., Lilegdon, W. R., Keller, L., Mabrouk, K., & McGuire, F. (1994). Barriers to implementing simulation in health care. *Proceedings of Winter Simulation Conference*, 868–875. https://doi.org/10.1109/WSC.1994.717447

Manani, M., Jegatheesan, P., DeSandre, G., Song, D., Showalter, L., & Govindaswami, B. (2013). Elimination of Admission Hypothermia in Preterm Very Low-Birth-Weight Infants by Standardization of Delivery Room Management. *The Permanente Journal*, *17*(3), 8–13. https://doi.org/10.7812/TPP/12-130

Manktelow, B., Draper, E. S., Field, C., & Field, D. (2010). Estimates of length of neonatal stay for very premature babies in the UK. *Archives of Disease in Childhood - Fetal and Neonatal Edition*, *95*(4), F288–F292. https://doi.org/10.1136/adc.2009.168633

Marsden, J. R., & Pingry, D. E. (2018). Numerical data quality in IS research and the implications for replication. *Decision Support Systems*, *115*, A1–A7. https://doi.org/10.1016/j.dss.2018.10.007

McAdams, R. M., Kaur, R., Sun, Y., Bindra, H., Cho, S. J., & Singh, H. (2022). Predicting clinical outcomes using artificial intelligence and machine learning in neonatal intensive care units: A systematic review. *Journal of Perinatology*, *42*(12), 1561–1575. https://doi.org/10.1038/s41372-022-01392-8

McCall, E. M., Alderdice, F., Halliday, H. L., Vohra, S., & Johnston, L. (2018). Interventions to prevent hypothermia at birth in preterm and/or low birth weight infants. *Cochrane Database of Systematic Reviews*, *2018*(2). https://doi.org/10.1002/14651858.CD004210.pub5

McDonald, G. C. (2009). Ridge regression. *WIREs Computational Statistics*, *1*(1), 93–100. https://doi.org/10.1002/wics.14

Mielczarek, B. (2016). Review of modelling approaches for healthcare simulation. *Operations Research and Decisions*. https://doi.org/10.5277/ORD160104

Minton, S., Allan, M., & Valdes, W. (2014). Teleneonatology: A Major Tool for the Future. *Pediatric Annals*, *43*(2). https://doi.org/10.3928/00904481-20140127-11

Mohamed, I., El-Henawy, I., & El-Din, R. (2017). An early discharge approach for managing hospital capacity. *International Journal of Modeling Simulation and Scientific Computing*, *8*(1). https://doi.org/10.1142/S1793962317500064

Myers, M. D. (2013). *Qualitative research in business & management* (2nd ed). SAGE.

Najibi, S., Seyedi, S., Farhadi, P., Kharazmi, E., Shojaei, P., Delavari, S., Lotfi, F., & Kavosi, Z. (2022). Development of a model for predicting hospital beds shortage and optimal policies using system dynamics approach. *BMC Health Services Research*, *22*(1). https://doi.org/10.1186/s12913-022-08936-w

Nassin, M. L., Lapping-Carr, G., & De Jong, J. L. O. (2015). Anemia in the Neonate: The Differential Diagnosis and Treatment. *Pediatric Annals*, *44*(7). https://doi.org/10.3928/00904481-20150710-08

Neath, A. A., & Cavanaugh, J. E. (2012). The Bayesian information criterion: Background, derivation, and applications. *WIREs Computational Statistics*, *4*(2), 199–203. https://doi.org/10.1002/wics.199

Neonatologie Netwerk Nederland. (n.d.). Homepage of Neonatologie Netwerk Nederland. *Homepage of Neonatologie Netwerk Nederland*. Retrieved July 20, 2024, from https://www.neonatology.eu/

Nguyen, M.-N. R., Mosel, C., & Grzeskowiak, L. E. (2018). Interventions to reduce medication errors in neonatal care: A systematic review. *Therapeutic Advances in Drug Safety*, *9*(2), 123–155. https://doi.org/10.1177/2042098617748868

NVOG. (2007). *Nota Verwijzing naar een perinatologisch centrum*. https://www.nvog.nl/wp-content/uploads/2017/12/Nota-Verwijzing-naar-een-perinatologisch-centrum-1.0-19-09-2007.pdf

O'Callaghan, N., Dee, A., & Philip, R. K. (2019). Evidence-based design for neonatal units: A systematic review. *Maternal Health, Neonatology and Perinatology*, *5*(1), 6. https://doi.org/10.1186/s40748-019-0101-0

OECD. (2023). *Ready for the Next Crisis? Investing in Health System Resilience*. OECD. https://doi.org/10.1787/1e53cf80-en

Patel, R. (2016). Short- and Long-Term Outcomes for Extremely Preterm Infants. *American Journal of Perinatology*, *33*(03), 318–328. https://doi.org/10.1055/s-0035-1571202

Perera, T. S., & Calis, B. (2022). Simulation Analysis of a Neonatal Unit with Complex Patient Flow Patterns – An Enhanced Model for Capacity Planning. *South African Journal of Industrial Engineering*, *33*(4). https://doi.org/10.7166/33-4-2621

Pettersson, M., Eriksson, M., Albinsson, E., & Ohlin, A. (2021). Home phototherapy for hyperbilirubinemia in term neonates—An unblinded multicentre randomized controlled trial. *European Journal of Pediatrics*, *180*(5), 1603–1610. https://doi.org/10.1007/s00431-021-03932-4

Planningsbesluit Bijzondere Perinatologische Zorg, Pub. L. No. CSZ/ZT/2192014, BWBR0032383 (2018). https://wetten.overheid.nl/BWBR0032383/2018-08-01#:~:text=Een%20centrum%20voor%20bijzondere%20perinatologische,voorafgaat%20aan%20de%20neonatologische%20IC.

Pomare, C., Churruca, K., Ellis, L. A., Long, J. C., & Braithwaite, J. (2019). A revised model of uncertainty in complex healthcare settings: A scoping review. *Journal of Evaluation in Clinical Practice*, *25*(2), 176–182. https://doi.org/10.1111/jep.13079

Qin, S., Thompson, C., Bogomolov, T., Ward, D., & Hakendorf, P. (2017). Hospital occupancy and discharge strategies: A simulation-based study. *Internal Medicine Journal*, *47*(8), 894–899. https://doi.org/10.1111/imj.13485

Quinn, J. M., Sparks, M., & Gephart, S. M. (2017). Discharge Criteria for the Late Preterm Infant: A Review of the Literature. *Advances in Neonatal Care*, *17*(5), 362–371. https://doi.org/10.1097/ANC.0000000000000406

Ranu, J., Sauers-Ford, H., & Hoffman, K. (2021). Engaging and supporting families in the Neonatal intensive care unit with telehealth platforms. *Seminars in Perinatology*, *45*(5), 151426. https://doi.org/10.1016/j.semperi.2021.151426

Rasmussen, M. K., Clemensen, J., Zachariassen, G., Kidholm, K., Brødsgaard, A., Smith, A. C., & Holm, K. G. (2020). Cost analysis of neonatal tele-homecare for preterm infants compared to hospital-based care. *Journal of Telemedicine and Telecare*, *26*(7–8), 474–481. https://doi.org/10.1177/1357633X19843753

Roberts, I. (2003). Neonatal thrombocytopenia: Causes and management. *Archives of Disease in Childhood - Fetal and Neonatal Edition*, *88*(5), 359F – 364. https://doi.org/10.1136/fn.88.5.F359

Robinson, C., Gund, A., Sjöqvist, B., & Bry, K. (2016). Using telemedicine in the care of newborn infants after discharge from a neonatal intensive care unit reduced the need of hospital visits. *Acta Paediatrica*, *105*(8), 902–909. https://doi.org/10.1111/apa.13407

Robinson, S. (2014). *Simulation: The practice of model development and use* (Second edition). Palgrave Macmillan.

Robinson, S. (2015). A tutorial on conceptual modeling for simulation. *2015 Winter Simulation Conference (WSC)*, 1820–1834. https://doi.org/10.1109/WSC.2015.7408298

Ryan, G. M. Jr. (1975). Toward Improving the Outcome of Pregnancy: Recommendations for the Regional Development of Perinatal Health Services. *Obstetrics & Gynecology*, *46*(4). https://journals.lww.com/greenjournal/fulltext/1975/10000/toward_improving_the_outcome_of_pregnancy_.1.aspx

Sauers-Ford, H. S., Marcin, J. P., Underwood, M. A., Kim, J. H., Nicolau, Y., Uy, C., Chen, S. T., & Hoffman, K. R. (2019). The Use of Telemedicine to Address Disparities in Access to Specialist Care for Neonates. *Telemedicine and E-Health*, *25*(9), 775–780. https://doi.org/10.1089/tmj.2018.0095

Savigny, D. de, Blanchet, K., & Adam, T. (2017). *Applied systems thinking for health systems research: A methodological handbook*. McGraw-Hill Education. https://researchonline.lshtm.ac.uk/id/eprint/4646083/

Seaton, S. E., Barker, L., Draper, E. S., Abrams, K. R., Modi, N., Manktelow, B. N., & UK Neonatal Collaborative. (2016). Modelling Neonatal Care Pathways for Babies Born Preterm: An Application of Multistate Modelling. *PLOS One*, *11*(10), e0165202. https://doi.org/10.1371/journal.pone.0165202

Seaton, S. E., Barker, L., Jenkins, D., Draper, E. S., Abrams, K. R., & Manktelow, B. N. (2016). What factors predict length of stay in a neonatal unit: A systematic review. *BMJ Open*, *6*(10), e010466. https://doi.org/10.1136/bmjopen-2015-010466

Segers, E., Ockhuijsen, H., Baarendse, P., Van Eerden, I., & Van Den Hoogen, A. (2019). The impact of family centred care interventions in a neonatal or paediatric intensive care unit on parents' satisfaction and length of stay: A systematic review. *Intensive and Critical Care Nursing*, *50*, 63–70. https://doi.org/10.1016/j.iccn.2018.08.008

Seow, H.-Y., & Sibley, L. M. (2014). Developing a dashboard to help measure and achieve the triple aim: A population-based cohort study. *BMC Health Services Research*, *14*(1), 363. https://doi.org/10.1186/1472-6963-14-363

Shahani, A., Ridley, S., & Nielsen, M. (2008). Modelling patient flows as an aid to decision making for critical care capacities and organisation. *Anaesthesia*, *63*(10), 1074–1080. https://doi.org/10.1111/j.1365-2044.2008.05577.x

Shields, L. B., Davydov, Y., Glyder, A., Weymouth, C., Udwin, M., & Eakins, M. (2023). Impact of Technology on Neonatal Intensive Care Unit Admissions and Length of Stay: A Retrospective Study. *Cureus*. https://doi.org/10.7759/cureus.40813

Simonsen, K. A., Anderson-Berry, A. L., Delair, S. F., & Davies, H. D. (2014). Early-Onset Neonatal Sepsis. *Clinical Microbiology Reviews*, *27*(1), 21–47. https://doi.org/10.1128/CMR.00031-13

Singh, H., Cho, S. J., Gupta, S., Kaur, R., Sunidhi, S., Saluja, S., Pandey, A. K., Bennett, M. V., Lee, H. C., Das, R., Palma, J., McAdams, R. M., Kaur, A., Yadav, G., & Sun, Y. (2021). Designing a bed-side system for predicting length of stay in a neonatal intensive care unit. *Scientific Reports*, *11*(1), 3342. https://doi.org/10.1038/s41598-021-82957-z

Stahl, J. E. (2008). Modelling Methods for Pharmacoeconomics and Health Technology Assessment: An Overview and Guide. *PharmacoEconomics*, *26*(2), 131–148. https://doi.org/10.2165/00019053-200826020-00004

Stark, A. R., Pursley, D. M., Papile, L.-A., Eichenwald, E. C., Hankins, C. T., Buck, R. K., Wallace, T. J., Bondurant, P. G., & Faster, N. E. (2023). Standards for Levels of Neonatal Care: II, III, and IV. *Pediatrics*, *151*(6), e2023061957. https://doi.org/10.1542/peds.2023-061957

Strauss, A., & Corbin, J. (1998). *Basics of qualitative research: Techniques and procedures for developing grounded theory, 2nd ed.* (pp. xiii, 312). Sage Publications, Inc.

Sullivan, B. A., Kausch, S. L., & Fairchild, K. D. (2023). Artificial and human intelligence for early identification of neonatal sepsis. *Pediatric Research*, *93*(2), 350–356. https://doi.org/10.1038/s41390-022-02274-7

Taha, S., Simpson, R. B., & Sharkey, D. (2023). The critical role of technologies in neonatal care. *Early Human Development*, *187*, 105898. https://doi.org/10.1016/j.earlhumdev.2023.105898

Tan, K., & Lai, N. M. (2012). Telemedicine for the support of parents of high-risk newborn infants. *Cochrane Database of Systematic Reviews*, *2012*(6). https://doi.org/10.1002/14651858.CD006818.pub2

Thébaud, B., Goss, K. N., Laughon, M., Whitsett, J. A., Abman, S. H., Steinhorn, R. H., Aschner, J. L., Davis, P. G., McGrath-Morrow, S. A., Soll, R. F., & Jobe, A. H. (2019). Bronchopulmonary dysplasia. *Nature Reviews Disease Primers*, *5*(1), 78. https://doi.org/10.1038/s41572-019-0127-7

Tobias, J. (2010). Conventional mechanical ventilation. *Saudi Journal of Anaesthesia*, *4*(2), 86. https://doi.org/10.4103/1658-354X.65128

Topalidou, A., Ali, N., Sekulic, S., & Downe, S. (2019). Thermal imaging applications in neonatal care: A scoping review. *BMC Pregnancy and Childbirth*, *19*(1), 381. https://doi.org/10.1186/s12884-019-2533-y

Traumacentrum Zuidwest-Nederland. (2023). *ROAZ Regiobeeld Geboortezorg ZWN versie 2*.

UNICEF. (2023). *Levels & trends in child mortality: Report 2022*.

United Nations. (2015). *Transforming our world: The 2030 Agenda for Sustainable Development* (A/RES/70/1). https://www.refworld.org/docid/57b6e3e44.html

Valeri, B. O., Holsti, L., & Linhares, M. B. M. (2015). Neonatal Pain and Developmental Outcomes in Children Born Preterm: A Systematic Review. *The Clinical Journal of Pain*, *31*(4), 355–362. https://doi.org/10.1097/AJP.0000000000000114

Van De Schoot, R., De Bruin, J., Schram, R., Zahedi, P., De Boer, J., Weijdema, F., Kramer, B., Huijts, M., Hoogerwerf, M., Ferdinands, G., Harkema, A., Willemsen, J., Ma, Y., Fang, Q., Hindriks, S., Tummers, L., & Oberski, D. L. (2021). An open source machine learning framework for efficient and transparent systematic reviews. *Nature Machine Intelligence*, *3*(2), 125–133. https://doi.org/10.1038/s42256-020-00287-7

Variane, G. F. T., Camargo, J. P. V., Rodrigues, D. P., Magalhães, M., & Mimica, M. J. (2022). Current Status and Future Directions of Neuromonitoring With Emerging Technologies in Neonatal Care. *Frontiers in Pediatrics*, *9*, 755144. https://doi.org/10.3389/fped.2021.755144

Westenberg, L. E. H., Van Der Geest, B. A. M., Lingsma, H. F., Nieboer, D., Groen, H., Vis, J. Y., Ista, E., Poley, M. J., Dijk, P. H., Steegers, E. A. P., Reiss, I. K. M., Hulzebos, C. V., & Been, J. V. (2022). Better assessment of neonatal jaundice at home (BEAT Jaundice @home): Protocol for a prospective, multicentre diagnostic study. *BMJ Open*, *12*(11), e061897. https://doi.org/10.1136/bmjopen-2022-061897

Wilson, E., Zeitlin, J., Piedvache, A., Misselwitz, B., Christensson, K., Maier, R. F., Norman, M., Edstedt Bonamy, A., & the EPICE Research Group. (2018). Cohort study from 11 European countries highlighted differences in the use and efficacy of hypothermia prevention strategies after very preterm birth. *Acta Paediatrica*, *107*(6), 958–966. https://doi.org/10.1111/apa.14230

Yalçın, N., Kaşıkcı, M., Çelik, H. T., Allegaert, K., Demirkan, K., Yiğit, Ş., & Yurdakök, M. (2023). Development and validation of a machine learning-based detection system to improve precision screening for medication errors in the neonatal intensive care unit. *Frontiers in Pharmacology*, *14*, 1151560. https://doi.org/10.3389/fphar.2023.1151560

Zamboni, K., Schellenberg, J., Hanson, C., Betran, A. P., & Dumont, A. (2019). Assessing scalability of an intervention: Why, how and who? *Health Policy and Planning*, *34*(7), 544–552. https://doi.org/10.1093/heapol/czz068

Appendix

A1. Ethics Application and Approval

This study was approved by the Human Research and Ethics Committee of TU Delft. Below you can find the approval.

Date 23-May-2024
Correspondence hrec@tudelft.nl

Human Research Ethics
Committee TU Delft
(http://hrec.tudelft.nl)

Visiting address
Jaffalaan 5 (building 31)
2628 BX Delft

Postal address
P.O. Box 5015 2600 GA Delft
The Netherlands

Ethics Approval Application: Capacity shortages in neonatal care systems
Applicant: Dietz, Alexander

Dear Alexander Dietz,

It is a pleasure to inform you that your application mentioned above has been approved.

Thanks very much for your submission to the HREC which has been approved. We do additionally note/advise the following:

Please make sure to strictly follow the proposed mitigation approach of letting participants review transcripts.

In addition to any specific conditions or notes, the HREC provides the following standard advice to all applicants:
• In light of recent tax changes, we advise that you confirm any proposed remuneration of research subjects with your faculty contract manager before going ahead.
• Please make sure when you carry out your research that you confirm contemporary covid protocols with your faculty HSE advisor, and that ongoing covid risks and precautions are flagged in the informed consent - with particular attention to this where there are physically vulnerable (eg: elderly or with underlying conditions) participants involved.
• Our default advice is not to publish transcripts or transcript summaries, but to retain these privately for specific purposes/checking; and if they are to be made public then only if fully anonymised and the transcript/summary itself approved by participants for specific purpose.
• Where there are collaborating (including funding) partners, appropriate formal agreements including clarity on responsibilities, including data ownership, responsibilities and access, should be in place and that relevant aspects of such agreements (such as access to raw or other data) are clear in the Informed Consent.

Good luck with your research!

Sincerely,