Developing a System Architecture for Integrating Patient Data Analytics into PICU Capacity Management

MOT2910: Master Thesis Project

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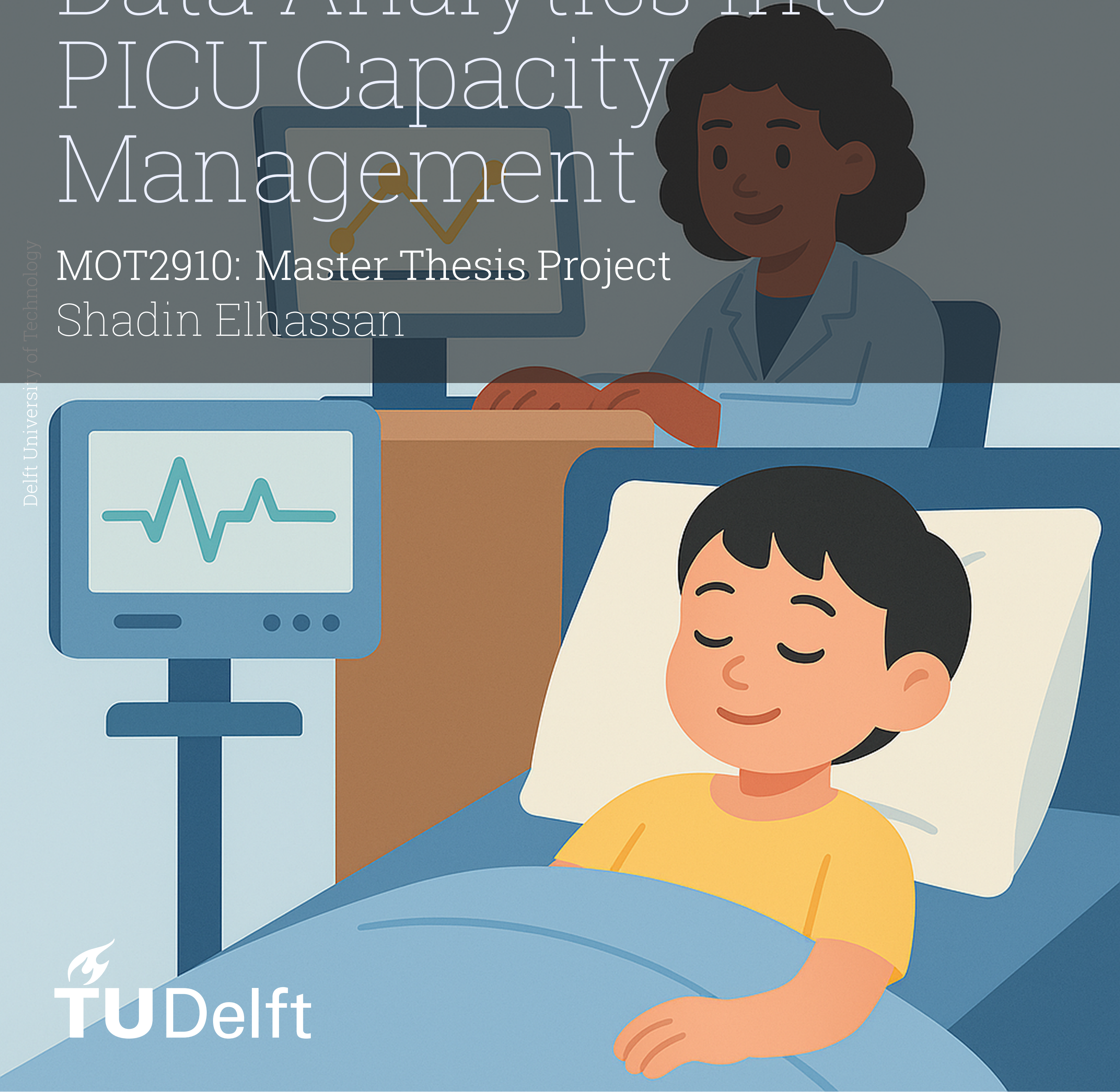

TU Delft

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by

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The efficient management of Pediatric Intensive Care Units (PICUs) is of critical importance, as timely decision-making can significantly impact patient outcomes in situations where every minute—or even every second—matters. This research explores the potential of developing a system architecture that enables the sharing of privacy-preserving patient data, and the use of data analytics, aimed at optimizing PICU management. The insights and findings presented in this thesis are the results of academic literature review and interviews, and I hope they will contribute to advancements in healthcare management.

My master thesis aligns with the TU Delft MOT program by addressing the strategic integration of technology and management in healthcare.

I would like to express my deepest gratitude to my supervisors, Dr. Saba Hinrichs-Krapels and Dr. Marcela Tuler de Oliveira, for their invaluable guidance and support throughout this project. Their expertise and encouragement were instrumental in shaping the direction and depth of this research.

Finally, I would like to thank my family and friends for their unwavering support and understanding during the course of my studies.

Shadin Elhassan
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Executive Summary

PICU capacity planning plays a vital role in healthcare systems. However, current planning approaches are based on static models and retrospective hospital data, which are fundamentally limited in their ability to deal with dynamic and sudden changes in demand. These systems largely depend on historical patient flow and length of stay predictions that are internal to the hospital and do not consider external influences or real-time developments. As a result, they often fail to adapt when capacity is most under pressure, leading to delayed responses and inefficient resource allocation.

This research investigates how new approaches to patient data analytics can improve PICU utilization planning and what system architecture could enable that shift. By examining how capacity planners currently use data, what legal and technical constraints exist, and what new data sources could be relevant, this study addresses the disconnect between available information and its practical application in planning. One of the main findings is that while a variety of data is already being generated—such as from wearable devices, remote monitoring systems, and external hospital departments—this information remains fragmented and unintegrated in current PICU planning systems. This fragmentation limits forecasting capability and responsiveness.

Legal frameworks such as GDPR and the EU AI Act introduce additional complexity by restricting how data can be exchanged and processed. However, these same frameworks also provide structure for designing compliant systems. This study proposes a new system architecture that integrates diverse data sources in a legally responsible way to improve forecasting accuracy and operational decision-making in PICUs. This architecture allows predictive models to function with a wider and more timely dataset, making planning more responsive to real-world developments. Involving specialists in the data collection process ensures that the data included supports decision-making in practice and meets actual clinical needs.

The research contributes to PICU capacity management by bringing together data analytics and automation while taking into account legal constraints. Furthermore, a genuine scientific contribution lies in how predictive modeling from different data sources is brought together within the system architecture while considering legal constraints for capacity management—an approach not previously explored in the general capacity management literature. A third scientific contribution lies in addressing the challenge of fragmented data by exploring how different data sources can be effectively brought together for PICU capacity management.

The results from this study may offer useful insights for future improvements in PICU capacity planning, as well as capacity management in other areas where similar challenges arise.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
AI	Artificial Intelligence
COVID-19	Coronavirus Disease 2019
EHR	Electronic Health Record
EPD	Elektronisch Patiëntendossier (Electronic Patient Record)
EU	European Union
FHIR	Fast Healthcare Interoperability Resources
GDPR	General Data Protection Regulation
GP	General Practitioner
HDP	Health Data Platform
HiX	Health information eXchange platform (by ChipSoft)
HL7	Health Level 7 (set of international standards for transfer of clinical and administrative data)
ICU	Intensive Care Unit
LBTC	Landelijke Beraadsgroep Traumachirurgen (National Council of Trauma Surgeons)
LIS	Letsel Informatie Systeem (Injury Information System)
LNAZ	Landelijk Netwerk Acute Zorg (National Acute Care Network)
LCPS	Landelijk Coördinatiecentrum Patiëntenspreiding (National Coordination Center for Patient Distribution)
LoS	Length of Stay
LTR	Landelijke Traumaregistratie (National Trauma Registry)
MDR	Medical Device Regulation
NIS Directive	Network and Information Systems Directive
OR	Operating Room
PICU	Pediatric Intensive Care Unit
SEH	Spoedeisende Hulp (Emergency Department)
WGBO	Wet op de Geneeskundige Behandelingsovereenkomst (Medical Treatment Agreement Act)
Wabvpz	Wet aanvullende bepalingen verwerking persoonsgegevens in de zorg (Supplementary Provisions on the Processing of Personal Data in Healthcare Act)
ZIS and HIS	Ziekenhuis Informatie Systeem (Hospital Information System)

1
Introduction

1.1. Problem background

Challenges in Pediatric Intensive Care Unit (PICU) capacity planning

Patients arriving at an Pediatric intensive care unit (PICU) are in need of timely and adequate care, the efficiency of the PICU management plays a critical role in this (Biagas and Hardart, 2013) . However, difficulties in maximizing PICU management efficiency arise because of the complicated relations between PICU capacity management such as the high patient demand, the variations of patients, the regulatory requirements, and technology limitations. Dutch hospitals have a difficult time improving capacity planning , while there is an increasing demand for intensive care services.

Intensive Care Units (ICUs) capacity planning in the Netherlands faces challenges, often falling short of optimal efficiency due to the unpredictable nature of patient flow and emergencies. Despite the use of data from Electronic Health Records (EHRs) and Hospital Information Systems (HIS) to monitor bed occupancy and predict demand, current methods frequently struggle with accurately forecasting and managing surges in ICU needs (Kuntz et al., 2007). This can lead to bed shortages, delayed admissions, and inefficient resource allocation, highlighting the need for improved planning techniques (Pinsky et al., 2024).

In clinical practice, challenges related to patient flow management, the use of predictive methods, and the coordination of PICU capacity are frequently observed. Healthcare professionals report recurring difficulties in ensuring timely access to intensive care beds, particularly during periods of fluctuating or unexpectedly high patient admissions. These capacity issues are observed across multiple hospital settings and can result in critically ill children remaining in emergency departments or general wards longer than medically desirable. Such delays place considerable logistical pressure on clinical teams and contribute to an increased workload among professionals responsible for triage and resource allocation (Radboud University Medical Center, 2021).

Efficient healthcare processes are crucial for reducing overcrowding of patients and providing timely care. Using patient data could increase this efficiency by planning the required capacity ahead. Using this data can lead to predictions of patient flow. (Garcia-Vicuña et al., 2023). Potential tools that could streamline PICU operations consist of efficient electronic health records, real-time monitoring systems, and predictive analytics/Artificial Intelligence (AI). However, on first sight , current regulations such as the General Data Protection Regulation (GDPR), prohibit sharing or using patient data for anything other than the treatment of the patient unless the patient gives consent (Ministerie van Algemene Zaken, 2023). This complicates and constraints the improvement of PICU efficiency using data analytics. Additionally, integrating the data analytical methods into the current technical platforms such as HIX (used in Dutch hospitals), complicates the issue even further. It remains unclear which data can be used to address these constraints, as legal frameworks that allow for easy data sharing between parties are limited.

The growing complexity of managing PICU capacity highlights a persistent mismatch between the unpredictable nature of critical care demand and the static retrospective tools currently used for planning. Existing systems are often unable to respond swiftly to surges in admissions, which may lead to delays in care, inefficient bed usage, and increased pressure on healthcare staff. While data is routinely collected across healthcare institutions, its use for prospective, system-wide coordination remains limited (Garcia-Vicuña et al., 2023). Current approaches to patient flow planning are frequently fragmented and reactive rather than anticipatory, which undermines the potential for optimal resource allocation. Moreover, healthcare professionals encounter legal and technical constraints in accessing and sharing patient data across institutions, limiting opportunities to implement more dynamic, data-driven planning strategies. These limitations have been widely observed in clinical practice (Radboud, 2021) and are echoed in recent literature, which underscores the potential of data analytics to enhance operational efficiency in critical care (Garcia-Vicuña et al., 2023). Therefore, before considering technical innovations or architectural redesigns, a deeper understanding is needed of how PICU capacity is currently managed, what role data plays in that process, and which barriers prevent more proactive and integrated planning. Having a more in depth analysis of how current intensive care capacity planners use data to manage and predict patient flow and analysis on legal constraints, can provide more insight to improve patient flow predictions and resource allocation, using existing data-driven strategies and thus, which according to research, could enhance operational efficiency significantly (Garcia-Vicuña et al., 2023).

Research Gap

Current literature on PICU management and privacy-preserving data sharing reveals several significant gaps. The literature search for finding the gap can be found in Appendix A.1. While there are established systems for using patient flow data to reduce pressure on intensive care and create predictions, the integration of these systems with privacy-preserving techniques is lacking. Furthermore, it is unclear how more patient health data can be securely shared and used for predicting PICU demands under current legal and technical constraints and what data would be beneficial to tackle the constraints.

Existing studies have primarily focused on either reducing ICU pressure using data analytics or preserving patient data during sharing, but not both. This separation fails to address the practical realities faced by healthcare providers who must balance the need for data-driven insights with stringent privacy requirements. Additionally, much of the research has been conducted in contexts that do not reflect the unique system limitations and legal constraints present in Dutch hospitals.

Another gap in the literature is the lack of clarity regarding which specific types of data need to be gathered to improve PICU overcrowding predictions. While general patient flow data can provide some insights, more granular data, such as real-time health metrics and demographic information, may be necessary to create accurate predictive models. However, the process of identifying and collecting this data must be carefully managed to ensure compliance with privacy laws.

Moreover, the existing body of research often overlooks the potential benefits of integrating data from multiple data sources, such as general practitioners and other hospitals. This integration could provide a more comprehensive view of patient needs and improve the accuracy of PICU demand predictions. However, it also introduces additional challenges related to data compatibility and privacy preservation.

In the Netherlands, the legal framework surrounding patient data sharing is restrictive, further complicating efforts to implement data-driven PICU management strategies. The General Data Protection Regulation (GDPR) imposes strict requirements on how patient data can be collected, stored, and shared. These regulations are essential for protecting patient privacy, but they also create significant barriers to the seamless flow of information needed for effective PICU management.

Conducting a literature review and researching online will also show that it is not clear what current practices are for predicting PICU capacity in Dutch hospitals. There is not a clear system architecture in place of how this is done.

Lastly, there is a need for more research focused on the practical application of theoretical models in real-world settings. Many studies propose frameworks or algorithms for improving PICU management, but few have been tested and integrated in actual hospital environments. This gap highlights the need for a research approach that not only develops new models but also evaluates their feasibility and effectiveness in practice.

1.2. Research Objective

The primary objective of this research is to explore how patient data analytics can enhance planning and resource utilization in PICUs by conceptualizing and developing a novel system architecture. This study aims to address the legal constraints and system limitations that currently hinder effective data sharing and management and ways to tackle the constraints. By developing a new system architecture, the research seeks to guide the use of privacy-preserving patient data to improve management processes in the PICUs. This new system architecture will be instrumental in enhancing the operational efficiency of PICUs, ensuring better patient flow, and preventing overcrowding, all while strictly adhering to privacy regulations.

The development of this system architecture involves several key steps. First, the study will identify and evaluate current data management practices within PICU settings. This includes a comprehensive analysis of existing technological infrastructures and their ability to support data integration and sharing. The research will also investigate the legal frameworks governing patient data sharing in the Netherlands in the healthcare setting, with a particular focus on GDPR compliance. Understanding these constraints is crucial for developing a system architecture that is both practical and legally sound.

In addition to evaluating current practices, the research will explore innovative methods for anonymizing and encrypting patient data and predictive models. These techniques are essential for ensuring that patient data can be used effectively for predictive analytics without violating privacy laws. The study will also consider the potential for integrating new data sources, such as wearable devices and remote monitoring systems, into existing healthcare infrastructures. These new data sources could provide valuable insights into patient health and help improve the accuracy of PICU demand predictions.

The ultimate goal of this research is to provide healthcare professionals with a practical tool that can be implemented within existing systems to improve patient outcomes and operational efficiency of the PICU.

1.3. Research Scope

This research will focus on hospitals in the Netherlands, specifically their PICUs. The scope includes:

- Current Practices in Data Management: Examining how patient data is currently managed, shared, and utilized within PICU settings. This includes a detailed analysis of the existing technological infrastructure and the extent to which it supports data integration and sharing. Understanding these practices will provide a baseline for identifying areas where improvements can be made. The literature will focus on the overall ICU since research focused in PICU is limited, but comparable.
- Legal Constraints: Investigating the legal framework governing patient data sharing in the Netherlands, with a particular focus on GDPR compliance. The study will assess how these regulations impact the ability to share and utilize patient data for ICU management. This assessment will include a review of relevant legal documents and guidelines, as well as interviews with data protection officers and legal experts.
- System Limitations: Identifying the technical and organizational barriers that hinder effective data sharing and management in ICUs. This includes exploring the compatibility of different hospital information systems and the challenges of integrating data from multiple sources. The research will also consider the potential for developing new technological solutions to address these limitations.
- New Data Possibilities and analytical methods: Exploring potential new sources of data that could enhance PICU management, such as data from wearable devices, remote monitoring systems, and electronic health records. As well as data analytical methods that could be employed for this goal. The study will evaluate the feasibility of integrating these data sources and analytical models within the current legal and technical framework. This evaluation will include a review of

existing literature on these technologies, as well as interviews with healthcare professionals and technology experts.

- Stakeholder Perspectives: interviews with key stakeholders, including PICU planners, data protection officers, and data security chiefs. These interviews will provide insights into the practical challenges and opportunities associated with implementing privacy-preserving data management strategies in PICUs. The perspectives of these stakeholders are crucial for ensuring that the proposed new system architecture is both practical and acceptable to those who will be using it.

By focusing on these areas, the research aims to develop a comprehensive understanding of the factors influencing data sharing and management in PICUs and provide actionable recommendations for improvement.

1.4. Research Questions

The central research question guiding this study is: *How can new approaches to patient data analytics improve planning for PICU utilization?*

To address this overarching question, the following sub-questions will be explored:

Research sub-question 1

How do current PICU capacity planners use data to manage and predict patient flow?

This question will be addressed through both a literature review and interviews to understand the existing practices and their effectiveness. The goal is to identify the strengths and weaknesses of current data management strategies and how they can be improved. This sub-question will provide a detailed understanding of the current system and legal contraints within the architcture.

Research sub-question 2

What are current system and legal constraints to manage and predict patient flow?

The second question will provide an exploration, derived from the literature review, of what data could be beneficial to tackle the current system and legal constraints present within the architecture.

Research sub-question 3

What data could be beneficial to tackle these system and legal constraints?

This question will explore potential new data sources and patient data analytics and evaluate their feasibility within the existing legal and technical frameworks through literature review and interviews. The study will investigate innovative data sources such as wearable devices, remote monitoring systems, and other digital health technologies as well as data analytical methods for PICU capacity prediction. This sub-question aims to identify new opportunities for enhancing the predictive capabilities of PICU management systems.

Research sub-question 4

What new system architecture could be used for improving intensive care facility management, considering current systems and legal constraints?

By synthesizing insights from literature and interviews, this question aims to identify best practices that can be adapted and incorporated into the new system architecture. The goal is to create an architecture as an information source that could provide insights for the potential more efficient architecture for PICUs in the Netherlands .

These questions are designed to provide a comprehensive understanding of the current state of data management in ICUs and identify opportunities for improvement. The answers to these questions will inform the development of the new system architecture, ensuring that it is grounded in real-world practices and challenges.

1.5. Research Relevance

This section highlights the scientific relevance of addressing gaps in PICU data sharing and forecasting under legal constraints, and the societal relevance of improving PICU capacity planning by addressing current data-sharing limitations in Dutch hospitals.

1.5.1. Scientific Relevance

Current research on PICU capacity planning tends to focus either on reducing pressure on the unit through retrospective data analysis or on preserving patient privacy during data sharing. However, the combination of these two dimensions is largely absent. It remains unclear how patient health data can be securely shared and used for forecasting PICU demand, and how this is currently approached in practice. Moreover, there is little clarity in the literature about which specific patient data should be collected to improve forecasting and reduce PICU overcrowding. Existing research rarely addresses how these processes can be aligned with legal requirements such as GDPR and the EU AI Act. Additionally, most studies have not investigated how these challenges play out within the Dutch healthcare system.

This research addresses these gaps by exploring how new patient data sources —such as wearable devices, remote monitoring, and cross-departmental flows — can be integrated for predictive PICU planning. It also examines how legal constraints shape what is possible in practice. Through the development of a new system architecture, this study shows how fragmented data sources can be brought together in a way that enables automation, supports predictive analytics, and remains compliant with data protection regulations. The research contributes to the scientific literature in three ways: by bringing together data analytics and automation while taking into account legal constraints; by integrating predictive modeling from diverse data sources into a system architecture under these constraints; and by addressing how to technically and legally bring together fragmented data sources for capacity management.

1.5.2. Societal Relevance

During the COVID-19 pandemic, it became evident that the Netherlands lacked sufficient preparedness for the strain on its ICUs. This led to patients experiencing delays in receiving assistance due to inadequate bed availability. Additionally, the situation placed significant stress on healthcare professionals. Now, with an even smaller pool of healthcare providers, the capacity to admit patients is limited (Radboud University Medical Center, 2021). This pressure on the PICU could be reduced by more efficient healthcare processes. Healthcare processes in the Netherlands are not as evolved as expected with the current technological evolvement. This is related to the fact that in Dutch hospitals the sharing of patient data is prohibited. The only exception is when explicit permission is given by the patient, and the data is only used for the treatment of the patient (Ministerie van Algemene Zaken, 2023). Another reason is that hospitals work with different systems which makes the sharing of data even harder (Chipsoft, n.d.). However, the integration of technology and data-driven strategies could reshape how medical services are delivered in intensive care. Therefore it is important that intensive care facilities can achieve patient data which can help streamline processes in the intensive care, such as severe medical conditions, demanding a nuanced approach to facility management (Garcia-Vicuña et al., 2023). The urgency and sensitivity inherent in these specialised settings amplify the importance of leveraging data for operational efficiency. However, the path to optimization is riddled with the need to navigate patient privacy concerns. General Practitioner (GP) data, electronic health records, real-time monitoring systems, predictive analytics and maybe even more could help streamline intensive care operations. Yet, this potential is accompanied by the challenge of safeguarding patient data and the laws that come with this. There is a societal need to find an approach to plan the PICU capacity more efficiently and improve patient outcomes by using data and prediction methods.

1.6. Reading Guide

This section provides an overview of the structure and progression of the thesis. It outlines the broader research context, details the development process of the proposed model, and introduces the framework through which its validity and applicability will be assessed.

The current chapter introduces the background and scope of the the research, along with the central research questions derived from the literature. These questions form the conceptual basis of the study and are aimed to be answered throughout the upcoming chapters.

Chapter 2 presents the research design, outlining the qualitative methodology employed to explore the complexities of PICU management. It describes the coding process used in data analysis and explains the iterative development of a layered architecture model that conceptualizes PICU structures and workflows.

Chapter 3 provides the literature review and shifts the focus to the contextual landscape of the Dutch ICU system. It examines current management practices, analytical approaches, relevant data sources, and existing systemic limitations. Additionally, it outlines the legal and regulatory frameworks that influence ICU policy and operations in the Netherlands. Moreover, it provides an overview of the legal and regulatory constraints that must be considered in the design of any future system architecture. The final section of Chapter 3 turns to innovative opportunities in ICU management, with an emphasis on novel data applications and predictive methods aimed at enhancing capacity efficiency. It discusses the potential of early warning systems, real-time dashboards, and advanced analytics to support proactive and adaptive resource allocation. *Note that this chapter focusses on ICU as a whole, since PICU literature information is more limited.

Chapter 4 addresses the gap between theoretical possibilities found in the literature and their practical implementation in PICU settings. It highlights the limited insight into how clinical and planning staff engage with data in everyday decision-making. To address this, the chapter incorporates a series of interview quotes from professionals involved in ICU planning and data governance, bridging the gap between academic knowledge and real-world practice.

Chapter 5 explores the legal and ethical considerations relevant to the development of a new PICU system architecture, drawing directly from the insights shared during the interviews. Participants emphasized the importance of compliance with privacy legislation, consent procedures, access governance, and cybersecurity protocols particularly in light of the increasing use of real-time monitoring and predictive technologies. Regulations such as the General Data Protection Regulation (GDPR) and national healthcare frameworks were consistently identified as both enablers and constraints for data use in clinical settings. This chapter synthesizes these findings and highlights the implications of regulatory frameworks for system design and implementation.

Chapter 6 investigates the crucial role of collaboration in the effective management of PICU capacity. Drawing on the results of the interviews, it highlights the importance of coordination within the hospital — between the PICU, the emergency department, the general wards — as well as with external partners such as regional hospitals and home care providers. Despite its significance, several barriers to effective communication and collaboration are identified.

Chapter 7 introduces the current architecture models developed from the interview data. These models reflect the structure and workflows of the existing PICU system and provide a visual and conceptual basis for understanding its layered complexity. This also sets the stage for comparison with the future system model presented in Chapter 9.

Chapter 8 builds on these insights by exploring emerging forms of beneficial data and forecasting methods that could enable more responsive and efficient PICU management. The findings derived from interviews offer practical recommendations for integration into a redesigned, future-oriented system architecture.

Chapter 9 presents the proposed future system architecture. This model incorporates the identified improvements and aims to create a more adaptable, data-driven structure that is aligned with the evolving demands of critical care.

Chapter 10 evaluates the proposed system design based on expert feedback obtained through reflective interviews. In light of this feedback, two revised system architectures are presented.

Chapter 11 critically reflects on the research findings. It discusses the practical feasibility, contextual alignment, and implementation challenges of the proposed model, while also acknowledging the limitations of the study.

Finally, Chapter 12 concludes the thesis by synthesizing the key insights and proposing directions for future research, with particular emphasis on long-term applicability and opportunities for further development. Furthermore, the conclusion consists of a personal reflection.

1.7. Conclusion

In this chapter, the focus has been placed on defining the central research question that guides this study: How can new approaches to patient data analytics improve planning for PICU utilization? The research aims to address a critical gap in the literature concerning data-informed capacity management within pediatric intensive care settings. While data is increasingly available, its effective integration into PICU planning and decision-making remains limited due to systemic, legal, and architectural constraints.

2

Research Approach

This research aims to optimize the utilization intensive care facilities by leveraging patient data. To achieve this, the study will develop a new system architecture to guide the use of such data and data analytics approaches while addressing legal constraints and working within current system limitations. The central research question is: How can new approaches to patient data analytics improve planning for PICU utilization?

The research will be conducted through a combination of design thinking, and thematic analysis. The approach is designed to ensure a comprehensive understanding of current practices, challenges, and opportunities for using patient data in PICU management.

2.1. Research methodology

The main research method which is used for this research is thematic analysis (TA). However, often times the diversity in TA leads to a lack in design coherence in research (Braun and Clarke, 2022). Therefore, TA comes closer to a method than a methodology (Braun and Clarke, 2022). This amplifies the need for careful conceptualisation and design thinking when using TA.

The integration of TA within the Double Diamond method gives more of a methodology. The Double Diamond is a design process method of design thinking, which gives a structured approach for solving complex problems through the phases: discovering, defining, developing and delivering (Tschimmel, 2012). This process matches the aim of the research to develop a new conceptual framework. The process is visualized in Figure 1.

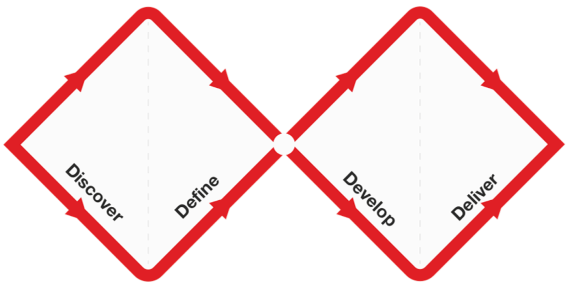

Figure 1: Double Diamond model. Source: (Design Council, 2024) .

The TA gives a structured approach as to how to interpret, analyze and understand data from interviews and literature. The Double Diamond model enhances the application of TA by providing a structured and systematic approach for navigating the research process. The stages of discovery, definition, development, and delivery, of this model help ensure that the research remains focused and coherent, even when dealing with the complexity and variability inherent in thematic analysis (Tschimmel, 2012).

In the discovery phase, the model allows for the exploration of all possible insights and perspectives on the problem as well as new information and insights, gathering a comprehensive understanding of the research problem. Following this, the definition phase narrows down these insights to define the core issues clearly, aligning them with the research objectives. During the development phase, potential solutions or concepts are created, reflecting on how best to integrate existing data analytics practices into PICU capacity planning. Finally, the delivery phase focuses on finalizing, testing and presenting the conceptual system architecture, ensuring that it is ready for practical application or further research (Tschimmel, 2012). However, due to time constraints, the system won't be tested.

2.2. Research Phases

This section will break down the phases of the Double Diamond model as applied in this research.

2.2.1. Research Phase 1: Discover

In this initial phase, the study began by identifying a current pressing problem related to PICU capacity and the integration of data analytics practices. This phase ensured that the problem addressed was not only relevant to the healthcare field but also aligned with the overall goals of improving PICU management and patient care. During this phase, the study highlighted a significant gap: the challenge of effectively integrating data analytics into PICU capacity planning while complying with privacy regulations and overcoming technological limitations. This discovery guided the subsequent phases of the research, focusing efforts on addressing these key challenges and providing valuable insights into how data-driven approaches can optimize PICU operations.

The main research question formulated based on this identified gap is:

> ***How can new approaches to patient data analytics improve planning for PICU utilization?***

The focus in this phase lies in gathering information to understand the current state of PICU planning, the challenges involved, and the role of data analytics. Furthermore, in this phase, new data sources as well as legal constraints are identified. The information is gathered through a literature review and interviews.

Research Questions Addressed:

- Sub-question 1: How do current PICU capacity planners use data to manage and predict patient flow?
- Sub-question 2: What are current system and legal constraints to manage and predict patient flow?

2.2.2. Research Phase 2: Define

In the second phase of the research, the focus shifted from broad exploration to a more precise definition of the problem. Building on the insights gathered during the Discover phase, this phase aimed to synthesize the information collected from the literature review and stakeholder interviews into a clear understanding of the core challenges in PICU capacity planning. This phase was crucial for narrowing down the research scope and identifying specific, actionable problem areas that would guide the development of conceptual new system architecture.

During the Define phase, thematic analysis was applied to analyze the qualitative data obtained from the initial research activities. This analysis involved systematically coding the data to identify recurring patterns and themes related to data usage, privacy concerns, and technological limitations in PICU management. Key themes that emerged included the necessity for real-time data integration to enhance patient flow predictions, the critical need for compliance with privacy regulations such as GDPR, and the constraints posed by existing hospital information systems. These themes provided a focused understanding of the underlying issues affecting PICU capacity planning and highlighted specific areas for improvement.

This phase also involved defining the research objectives based on the themes identified. The objectives included exploring strategies for securely integrating predictive analytics into existing systems, identifying potential new data sources for improving patient flow predictions and conceptualizing a system architecture that supports these advancements while ensuring data privacy and security.

Research Questions Addressed:

- Sub-question 3: What data could be beneficial to tackle these system and legal constraints?

2.2.3. Research Phase 3: Develop

In the third phase of the research, the focus moved from defining the problem to developing potential solutions. Building on the clear understanding and objectives established in the Define phase, this Develop phase aimed to explore and conceptualize innovative ways to integrate data analytics into PICU capacity planning. The goal was to generate and refine a range of possible solutions that address the identified challenges while ensuring compliance with privacy regulations and technological feasibility.

During the Develop phase, all the information acquired from the literature review and interviews was employed to generate possible new system architectures for enhancing PICU management. These models considered various aspects, including data sources, predictive analytics, data privacy, and the adaptability of existing hospital information systems. The emphasis was on creating solutions that not only improve patient flow predictions and resource allocation but also align with the legal and technical constraints identified in the previous phases.

Due to time constraints, the model could not be iteratively tested. However, the new system architectures were created to visualize how data analytics tools could be integrated into the existing PICU management systems. These visualizations provided a concrete representation of the proposed changes, allowing for a better understanding of their potential impact and feasibility. Feedback loops were established, wherein preliminary solutions were evaluated based on their practicality, scalability, and alignment with the defined research objectives.

Research Questions Addressed:

- Sub-question 4: What new system architecture could be used for improving intensive care facility management, considering current systems and legal constraints?

2.2.4. Research Phase 4: Deliver

In the final phase of the research, the focus shifted to refining and presenting the conceptual solutions developed in the previous phase. The Deliver phase aimed to finalize the conceptual system architecture for integrating data analytics into PICU capacity planning, ensuring that it effectively addresses the identified challenges while remaining practical and feasible within the existing healthcare framework. Although direct testing and implementation were beyond the scope of this research, this phase emphasized the importance of creating a clear, detailed, and well-documented conceptual framework that can guide future research and practical applications.

The Deliver phase involved a thorough review and refinement of the conceptual solutions generated during the Develop phase. The feedback and insights gathered from stakeholders and experts during earlier phases were revisited to ensure that the final conceptual models aligned with real-world needs and constraints. Special attention was given to aspects such as data privacy compliance, technological compatibility, and the scalability of the proposed solutions. These considerations were crucial for ensuring that the conceptual architecture would be adaptable to different PICU environments and capable of supporting enhanced patient care and efficient resource management.

Given the limitations in directly testing or implementing the system architecture, the focus of this phase was on creating comprehensive documentation and visual representations of the proposed solutions. These visualizations and descriptive frameworks are designed to communicate the conceptual architecture effectively, making it accessible to healthcare professionals, IT specialists, and policymakers who might be involved in future implementation efforts.

Research Questions Addressed:

- Sub-question 4: What new system architecture could be used for improving intensive care facility management, considering current systems and legal constraints?

2.3. Literature review

The literature review was conducted by identifying and analyzing relevant publications through a structured literature search, the details of which are provided in Appendix A.2.

2.4. Interview Approach

To gain a comprehensive understanding of current data sources, potential data sources, system and legal challenges, existing system architectures, prediction methods, and current capacity planning system architectures, a series of six interviews were conducted, where one interview consisted of two people. Purposeful sampling ensured that a diverse range of professionals with relevant experience in ICU capacity management and patient data analytics participated in the study, enriching the research with a variety of perspectives. To ensure the workload is manageable and the number of interviews is not excessive, the study carefully selected participants who could provide the most relevant and comprehensive insights. This focused approach ensured depth and quality in the data collected within the time constraints.

These interviews were held with specialists in data analytics, an admission coordinator, consultants/advisors in healthcare and capacity management and a PICU residents (AIOS) from hospitals in Rotterdam and Delft. Most interviewees were from the PICU.
Another two validation interviews were conducted with data analytic/capacity management specialists.

The interviews followed a structured open-ended format, ensuring consistency across participants while allowing for in-depth exploration of key themes. This approach enabled the identification of current practices, challenges, and opportunities in PICU capacity planning and predictive modeling. The full list of interview questions is provided in Appendix C.

Prior to participation, all respondents were required to provide informed consent, confirming their understanding of the study's objectives, their rights as participants, and the measures in place to ensure data confidentiality. Additionally, to comply with ethical and data security regulations, the research was reviewed and approved by the Human Research Ethics Committee (HREC).

2.5. Coding Approach

The focus of this research is on exploring the current system architecture for planning PICU capacity, its limitations, and the integration of predictive analytical methods within the constraints of the law. Using ATLAS.ti software, the interview transcripts were analyzed using thematic analysis approach. The interviews covered a range of topics, including the current system's design and functionality, limitations in data sharing and utilization, potential for predictive analytics, legal constraints such as GDPR compliance, and the integration of new methods and technologies.

These interviews provided comprehensive insight into the practical challenges and opportunities in PICU management, offering technical and operational perspectives. By thematically analyzing the interview data, recurring themes and patterns were identified, which form the basis for understanding the key areas that require improvement and innovation in PICU capacity planning.

The coding process involved labeling the quotes with descriptive codes and grouping those codes into broader themes, which ultimately led to a synthesis of the findings to address the research objectives.

Open Coding

In the initial phase, sentences and phrases from the interview transcripts were individually coded, focusing on capturing the key topics discussed. Each code represented a specific concept or issue mentioned by the interviewees, such as *"data privacy," "predictive modeling,"* or *"integration challenges."* This phase generated a large number of preliminary codes, providing a granular view of the data.

Axial Coding

To refine the understanding of the data, the codes were grouped into broader categories based on shared characteristics or underlying concepts. For example, codes such as*"Data sharing challenges"* and *"GDPR Compliance"* were grouped under the theme **"Legislation,"** while *"Flexible PICU Clustering"* and *"Optimalising PICU Utilisation"* were categorized under **"Possible PICU-management**

improvements.” This step helped to structure the data and highlight connections between different codes.

Thematic coding

In the final phase, the themes were further analyzed to identify their significance and relationships to the research questions. Key themes, such as **”Possible PICU-management improvements,” ”Desired Prediction Methods,”** and **”Legislation,”** emerged as central to the research focus. Themes that were frequently mentioned or had significant implications for PICU capacity planning were classified as higher-level themes, while others were identified as lower-level themes.

Example of the Coding Process

> *”I think in order to build confidence it is very important to view the predictive models as a support or position them as a support and not something that makes a decision.”*

- **Initial Code:** *”Supportive Role Models”*
- **Topic:** *”Model Acceptance and Understanding”*
- **Selective Theme:** *”Management and Context”*

Summary of Themes

Table 2 presents the identified themes and their descriptions.

Table 2: Identified topics during Coding Process

	Topic	Description
Current System Overview	*Current Prediction Method*	Description of how predictions are currently performed within the system, including methodologies and tools used.
	Current System Architecture	Overview of the structural and operational components of the current system.
	PICU Structure	Description of the PICU structure and how it is equipped.
Data, Challenges and Limitations	*Data Analysis Process*	Overview of the process of data collection and data analysis methods.
	Missing Data	Specific examples and consequences of unavailable or missing data points.
	Personalized Medicine	Description of feasibility, benefits, and barriers regarding personalized medicine.
	Use of Social Determinants	Perspectives on the inclusion of social determinants in data collection, highlighting both benefits and challenges.
	Legislation	Discussion of laws and regulations that impact system design and implementation.
	Data Models Integration	Challenges involved in integrating data models in the PICU .
	Implementation of Data Sharing	Description of challenges and considerations in implementing data sharing, including technical interoperability, standardization, and collaboration between hospitals.
Management and Context	*PICU Management Approaches*	Overview of management styles and decision-making processes affecting system evolution.
	Decision-Making in Pandemics	Impact of the COVID pandemic on system priorities, challenges, and developments.
	Internal and External Collaboration Systems	Collaboration between internal hospital departments, including the PICU, and external organizations for coordinated patient care.
	Hospital System Influence	Impact of hospital systems on decision-making, including the influence of hospital culture, healthcare policies, and insurance structures.
	Models Acceptance and Understanding	Necessity of acceptance and understanding of models for successful integration, including factors influencing trust, usability, and adoption within healthcare settings.
Future Systems	*New System Architecture*	Conceptualization of the proposed new system architecture integrating predictive analytics.
	Desired Prediction Methods	Suggestions for prediction methods and models.
	Possible PICU Improvements	Suggested improvements to PICU processes through the integration of predictive analytics.

This coding process provided a structured framework for analyzing the interview data, identifying critical areas for improvement, and guiding the development of the conceptual system architecture.

2.6. Layered Architecture Model Approach

A layered design is often used to enhance data flow management (Decruyenaere et al., 2003) and facilitate data collection (Nasiri et al., 2021). The selected layered model was established after thematic analysis had been performed and allows certain units to depend on other layers, which presents a key advantage. This dependency contributes to a well-structured system, promoting both flexibility and scalability. This architectural approach enables higher layers to utilize the services provided by lower layers without compromising system stability. Consequently, improvements or expansions can be implemented in specific layers without necessitating modifications to the entire system. This characteristic makes it particularly suitable for describing processes within healthcare, especially regarding data management (Pourmirza et al., 2017). The model for the system architectures that will be designed will consist of five layers aligned with principles of layered system architecture, tailored to the IC management context. The Data Source Layer maps to internal and external information flows. The Data Processing & Integration Layer reflects the traditional Data Layer, where data is transformed and consolidated. The Decision Support & Analytics Layer corresponds to the Persistance Layer, focusing on tools that enable data-driven decision-making. The Operational Management and Collaboration Layers together extend the concept of the Presentation Layer, encompassing both the interface through which information is accessed and the organizational processes through which it is applied and shared to the various end-users. At the top of the architecture, the request originates from users or organizational needs, flowing downward through the layers as information is retrieved, processed, and contextualized to support decision-making and collaboration. At the bottom, services interact directly with data sources, enabling the extraction and delivery of raw data that feeds into the system's higher layers for further processing and analysis to higher in the organization (Rana and Saleh, 2022)

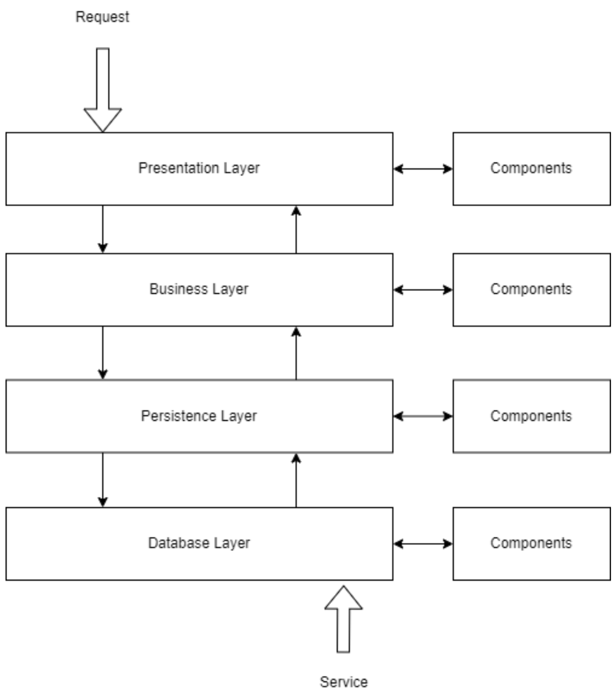

Figure 2: Example of Layered Architecture Design ((Rana and Saleh, 2022)

2.7. Validation

After the initial set of interviews, the research questions were addressed based on the results derived from the participants' input. In order to validate these findings and assess the applicability of the developed model, two additional interviews were conducted. These follow-up interviews are intended to critically reflect on the model using the following two guiding questions:
1) *'In what ways does the current model reflect (or not reflect) the actual situation?'*
2) *'How attainable do you see the proposed future model, and what changes would make it more feasible in practice?'*
The insights gained from these reflective interviews served as a guideline to test and refine the model. Based on the feedback, necessary adjustments were made to ensure that the final version is both practically relevant and implementable in the clinical setting.

2.8. Flow diagram

A Flow Diagram provides a comprehensive overview of the input of information used to answer each sub-question, the chapters that will address the related sub-question and the output of information for each of the phases of the research. The Flow Diagram is visualized in Table 3.

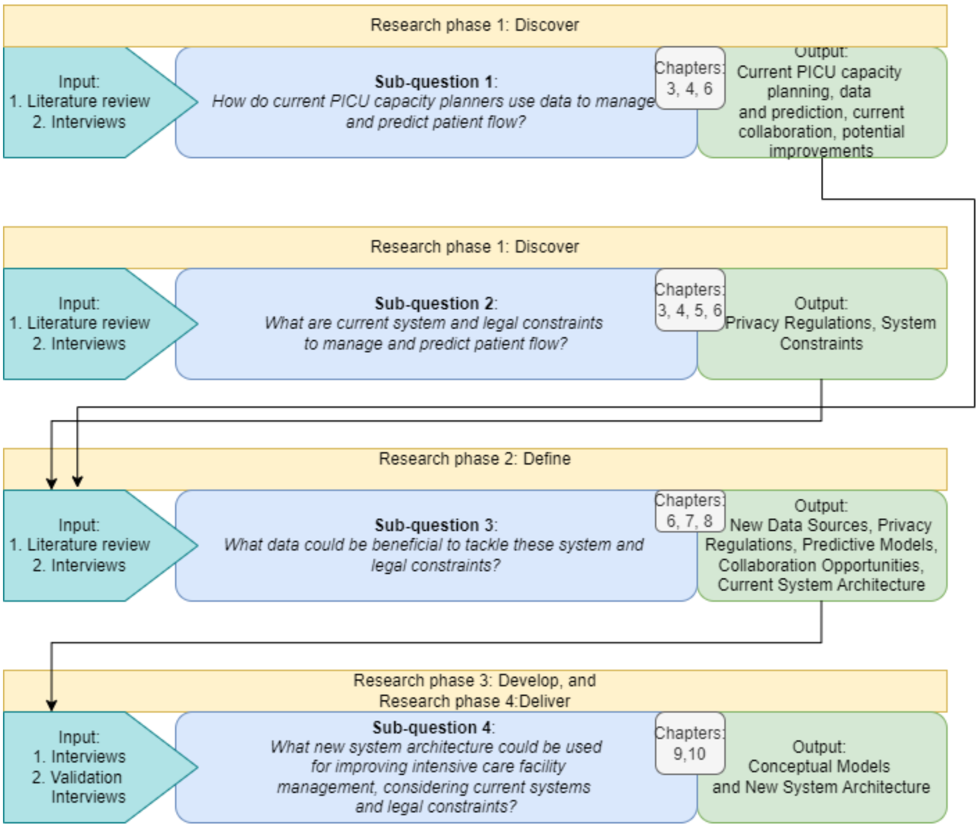

Figure 3: Research Flow Diagram

2.9. Reporting Standards

This study used the Consolidated Criteria for Reporting Qualitative Research (COREQ) (Tong et al., 2007) as a checklist for reporting important aspects of the research team, study methods, context of the study, findings, analysis and interpretations. The checklist consists of 32-items and covers three domains: (1) Research team and reflexivity, (2) Study design, and (3) Data-analysis and reporting. A completed version of the checklist is provided in Appendix D.

2.10. Use of AI Tooling

Throughout the development of this thesis, the AI language model ChatGPT (developed by OpenAI) was used as a writing assistant. Its primary role was to support grammar correction, sentence refinement, and to help ensure that the academic language met the standard expected of a master's-level thesis.

Example prompt used with ChatGPT:

> *"Can you please review the following paragraph for grammar, clarity, and academic tone at the level of a master's thesis? Rewrite it if necessary, but preserve the original meaning."*

If the answer of the prompt did not match the original statement, it was changed manually to match the original thought.

ChatGPT was also used to cross-check the accuracy and completeness of data-related legislative acts identified through manual web searches focused on regulations in the Netherlands in Chapter 2.

The AI tool was not used to generate original content, research results, or analytical insights, but rather to aid in improving clarity, coherence, and stylistic quality of the text. Lastly, ChatGPT was used to generate the cover page image.

2.11. Conclusion

To contribute to filling this gap, the study will explore how patient data can support more responsive and efficient management of PICU resources. This involves investigating current data usage practices, identifying constraints in existing systems, assessing which additional data may be beneficial, and proposing a system architecture that aligns with both operational realities and legal frameworks. The research adopts a qualitative approach, informed by design thinking and coding analysis, to generate insights grounded in both empirical findings and existing theoretical frameworks. Through this approach, the study seeks to develop a conceptual solution and future system architecture, using an layered architecture model, that advance the understanding and application of data-driven capacity planning in intensive care environments.

3

Literature Review

Understanding the current practices, challenges, and opportunities in ICU capacity management is essential for developing an effective new system architecture. This literature review critically examines existing data management strategies, operational practices, and technological tools used within ICUs. It further explores emerging data sources, predictive models, and legal frameworks that govern healthcare data usage.

By synthesizing insights from academic research, national guidelines, and technical documentation, this chapter aims to provide a comprehensive foundation for identifying gaps in current practices and informing the design of improved data-driven solutions.

This stage of the research aligns with the "Discover" phase of the Double Diamond model, which focuses on gathering insights, defining the problem space, and exploring existing systems. The findings presented here help to contextualize the design challenges and opportunities that will be addressed in the later stages of the model — particularly during the "Define" and "Develop" phases.

**Note that this chapter focusses on ICU as a whole, since PICU literature information is more limited.*

3.1. Current ICU Management

This chapter explores these existing limitations and examines how data is currently used in ICU capacity planning. By examining existing practices, we can identify the strengths and limitations of current data management strategies within ICUs as part of the resources. These practices encompass a wide range of activities, including patient admission and discharge processes, staff scheduling, resource allocation, and the use of advanced technologies to monitor and manage patient care.

A key aspect of ICU management is capacity planning, which involves forecasting patient admissions and managing bed occupancy. This is particularly important in the Netherlands, where healthcare facilities must balance high demand with limited resources. ICU managers use historical data and predictive analytics to anticipate patient flow and make informed decisions about resource allocation for the long-term (Kwaliteitsstandaard Organisatie van Intensive Care, 2016).

Long-term planning helps ensure that ICU resources align with projected patient care needs while accommodating variations in demand. Another critical component of ICU management is staffing. Adequate staffing levels are essential for providing high-quality care, and this involves not only ensuring that there are enough healthcare professionals available but also that they are appropriately trained and supported. In the Netherlands, ICU staffing is managed through a combination of fixed schedules and flexible staffing models that allow for adjustments based on patient demand (Kwaliteitsstandaard Organisatie van Intensive Care, 2016). It is important as it influences efficiency and patient outcomes. Currently, nurse-to-patient ratios fluctuate based on patient acuity, but forecasting staffing needs remains a challenge.

Recent implementation research in hospital scheduling highlights the importance of distinguishing between different planning levels: strategic, tactical and operational, in order to optimise resource use and coordinate hospital operations effectively (Vosa et al., 2024).

Hospitals struggle to align staffing levels with predicted ICU demand, manage seasonal variations such as flu seasons and pandemics, and ensure that ICU teams are neither overworked nor underutilized. Integrating staff scheduling systems with ICU demand prediction models could help address these imbalances by ensuring that sufficient personnel are available during peak demand periods, without unnecessary overstaffing during quieter times. To structure these efforts effectively, it is useful to distinguish between different planning levels. Strategic planning involves long-term decisions such as investments in workforce capacity, training programs, and ICU infrastructure. Tactical planning refers to medium-term adjustments, including setting staff rosters and planning shift flexibility in anticipation of seasonal fluctuations. Operational planning, finally, concerns short-term decisions that need to be made on a daily basis, such as reallocating staff in response to real-time changes in patient acuity and admission rates. These distinctions mirror the implementation considerations identified in hospital scheduling literature, where blueprint schedules for operating theatres are positioned between tactical and operational levels, requiring adaptability while maintaining centralised efficiency. Recognizing and integrating these planning levels can help hospitals respond more effectively to fluctuating ICU demands while safeguarding staff well-being and care quality (Vosa et al., 2024).

Key Components of Effective ICU Management

Resource allocation is another crucial element of ICU management. This includes the availability of medical equipment, such as ventilators and monitors, as well as essential supplies like medications and personal protective equipment. Effective resource allocation requires close coordination between different hospital departments and continuous monitoring of inventory levels (Kwaliteitsstandaard Organisatie van Intensive Care, 2016).

Technology plays a significant role in modern ICU management. Electronic Health Records (EHRs) are used to maintain comprehensive and up-to-date patient information, which can be accessed by authorized healthcare professionals. Real-time monitoring systems track vital signs and other critical health metrics, enabling prompt interventions when necessary.

Collaboration and communication are also vital for effective ICU management. In the Netherlands, multidisciplinary teams work together to develop and implement care plans for each patient. Regular meetings and communication channels ensure that all team members are informed about patient status and any changes in care requirements. This collaborative approach helps to ensure that patients receive coordinated and comprehensive care.

Overall, ICU management practices in the Netherlands are characterized by a data-driven approach, the aim to use advanced technologies, and a strong emphasis on collaboration and communication. These practices are essential for managing the complex and dynamic environment of the ICU and ensuring that patients receive the highest standard of care (Kwaliteitsstandaard Organisatie van Intensive Care, 2016).

3.1.1. National and Regional Coordination of ICU Capacity Planning

Since July 1, 2023, the duties of the Landelijk Coördinatiecentrum Patiëntenspreiding (LCPS) have been incorporated into the Landelijk Netwerk Acute Zorg (LNAZ). The LCPS plays a key role in coordinating patient distribution when ICU capacity is strained. Its main focus areas include managing information—such as gathering and analyzing data—and coordinating efforts to distribute patients across different regions, especially when capacity issues arise (Landelijk Coördinatiecentrum Patiëntenspreiding, n.d.).

Data is crucial for LCPS's role. It gains insights from the Landelijke Traumaregistratie (LTR), which includes details about trauma patients like their demographics, types of injuries, and treatment outcomes. This information helps healthcare providers understand the demand on ICU resources and improve how these resources are allocated. By integrating trauma data with real-time monitoring systems, LNAZ can make better decisions about patient transfers and emergency responses (Landelijke Beraadsgroep Traumachirurgen (LBTC) and Landelijk Netwerk Acute Zorg (LNAZ), 2023).

The Regional Consultation Acute Care Chains (ROAZ) is essential in coordinating and managing acute care within different regions in the Netherlands. While it may appear that this does not directly involve the ICU, in reality, the ICU is highly dependent on the functioning and coordination of acute care services. Participants include general hospitals, specialized hospitals, academic medical centers, mental health crisis units, ambulance services, and general practitioner posts. These organizations collaborate to ensure effective acute care delivery based on the agreements made during ROAZ meetings (ROAZ | Acute Zorg Euregio, n.d.). The key responsibilities of ROAZ are (ROAZ | Acute Zorg Euregio, n.d.):

- **Mapping Acute Care Services:** ROAZ maps out the acute care services available in the region by collecting and analyzing data on which providers deliver specific types of care, their treatment capacities, and existing agreements. This information is crucial for understanding the regional acute care landscape and ensuring that resources are allocated effectively.
- **Addressing Gaps in Care ('Witte Vlekken'):** ROAZ uses data to identify and address gaps in care availability, known as "witte vlekken". If a provider plans changes that could lead to such gaps, it must be reported to ROAZ beforehand. Data-driven assessments are conducted to understand the impact of these changes and to develop solutions to maintain access to care.
- **Coordinating Care Providers:** ROAZ coordinates the activities of different care providers using data to ensure efficient delivery of acute care. This includes planning for emergency and disaster response, ensuring that accurate data informs preparedness and capacity management.
- **Monitoring and Reporting:** ROAZ continuously monitors the regional accessibility and capacity of acute care services, using data to generate annual reports. These reports provide insights into the care delivered and help track key indicators to improve the quality and readiness of acute care services.

In the Dutch healthcare system, individual hospitals are responsible for managing their ICU capacity. They use internal systems to monitor real-time data such as bed occupancy, patient admissions, and resource availability. For example, many hospitals employ Electronic Health Records (EHR) systems that integrate patient data, allowing staff to track how many ICU beds are currently occupied and predict when beds will become available based on patient discharge schedules. Additionally, these systems often include dashboards that provide a live overview of patient conditions and resource needs, such as the availability of ventilators or specialized medical staff.

3.1.2. Data Sources and Technical tools for ICU capacity management in the Netherlands

ICU capacity management in the Netherlands relies on a diverse array of data sources that provide comprehensive information about the patient. This section describes the different type of data sources often times used in the Netherlands.

Electronic Health Records (EHRs)

EHRs are the cornerstone of ICU data management. EHRs contain detailed patient information, including medical histories, treatment plans, laboratory results, and imaging studies. This information is continuously updated and accessible to authorized healthcare professionals, ensuring that all relevant data is available when making clinical decisions. EHRs also support interoperability, allowing data to be shared seamlessly across different healthcare settings, which is crucial for coordinated care (Kwaliteitsstandaard Organisatie van Intensive Care, 2016).

Healthcare Information eXchange (HiX) and Epic

HiX and Epic, Elektronisch Patiëntendossiers (EPD's), play a vital role in managing (P)ICU capacity by streamlining data access and supporting efficient decision-making in hospitals. They provide healthcare professionals with real-time visibility into both current and historical patient information, which is critical for effectively managing ICU resources. Both Epic and HiX are continuously innovating, with the hopes to provide better healthcare. Sharing the data between the two systems is also possible due to standardization (ChipSoft, n.d.-a).

Data Management and Analytics with HiX or Epic:

- **Real-Time Data Access:** The software enables healthcare staff to access real-time data on patient conditions, bed availability, and care needs directly from the emergency department. The use of dynamic maps provides a visual overview of patient locations and statuses, allowing quick decisions about (P)ICU admissions and patient flow. This capability is essential for optimizing (P)ICU capacity, especially during high-demand situations (ChipSoft, n.d.-b).
- **Streamlined Data Entry and Structured Order Sets:** The administrative workload is minimized by using standardized templates for procedures like lab tests and imaging. This structured approach ensures consistent data entry, which is crucial for maintaining high-quality data for analysis. By simplifying these processes, HiX helps speed up patient admissions and transfers, which is vital for managing ICU space efficiently (ChipSoft, n.d.-b).
- **Integration with External Systems:** Ambulance services is integrated into the software, allowing emergency department teams to receive real-time data about incoming patients before they arrive. This integration ensures that care teams can prepare appropriately. Such seamless data flow supports better coordination and improves patient outcomes by providing a comprehensive view of patient needs (ChipSoft, n.d.-b).
- **Challenges in Expanding Data Analytics:** While the softwares are effective in managing and displaying data from within the hospital, incorporating more advanced data analytics or integrating data from additional external sources could present challenges. The system is primarily designed for internal use and specific integrations, meaning that expanding capabilities to include predictive analytics for (P)ICU demand or integrating data from wearable devices might require significant adjustments. Ensuring compatibility, maintaining data quality, and adhering to strict privacy regulations would be critical considerations for any such expansions (ChipSoft, n.d.-b).

The Nationale Intensive Care Evaluatie (NICE)

One of the most relevant databasources for ICUs is The Nationale Intensive Care Evaluatie (NICE) is a national registry in the Netherlands that collects and publishes data from intensive care units to monitor care quality and outcomes (NICE, n.d.).

Letsel Informatie Systeem (LIS)

The Letsel Informatie Systeem (LIS) is a key system in the Netherlands that collects detailed data on injuries and accidents treated at emergency departments across various hospitals. Established by VeiligheidNL, LIS plays a crucial role in understanding injury trends and informing prevention strategies. The data collected through LIS helps to identify risk groups and factors, allowing for targeted interventions to reduce injury-related healthcare demands. Some properties of LIS are:

- **Data Collection and Usage in LIS** LIS gathers data from 14 ED locations in 12 hospitals, which form a representative sample of emergency departments in the Netherlands. The data collected includes both basic patient information (such as arrival and discharge times) and details about the cause and nature of injuries. This information is crucial for understanding the broader landscape of injury-related healthcare needs. The uniform collection method ensures that data is comparable across hospitals, which is essential for accurate national extrapolations (VeiligheidNL, 2023).
- **Importance for Capacity Planning** LIS data is used to monitor trends in emergency visits, which can indirectly impact ICU capacity plan- ning. By identifying shifts in injury patterns, hospitals can better anticipate demand for ICU beds and other critical resources. For example, if LIS data indicates an increase in severe traffic accidents, hospitals can prepare by ensuring adequate ICU staff and equipment are available. Moreover, regular reporting and feedback mechanisms with participating hospitals help to maintain high data quality, enabling reliable analytics for capacity planning (VeiligheidNL, 2023).
- **Data Integration into Hospital Information Systems** The integration of LIS data into hospital information systems allows for near-automatic extraction and submission of injury data to VeiligheidNL. This integration reduces the administrative burden on healthcare providers and enhances

the reliability of data. However, the system's reliance on uniform data formats and specific variables can pose challenges when attempting to integrate more advanced data analytics or incorporating external data sources. Expanding data types or integrating real-time analytics would require significant adjustments to the existing LIS framework (VeiligheidNL, 2023).

Administrative and operational data

Administrative and operational data is also be important for ICU management. This includes data on bed occupancy, staffing levels, resource availability, and hospital throughput. Analyzing this data helps ICU managers optimize resource allocation, plan staffing schedules, and ensure that the ICU operates efficiently.

3.1.3. Data Sources and Technical Tools in place, but not yet (frequently) used for ICU Capacity Management

Although several data sources and technological tools are available within the healthcare system, many are not yet applied to ICU capacity management. Some of which will be mentioned in this subsection.

Real-time monitoring systems

Real-time monitoring systems are essential for tracking patient vital signs and other critical health metrics in the ICU. These systems use sensors and devices to collect data on parameters such as heart rate, blood pressure, oxygen saturation, and respiratory rate. The data is transmitted in real-time to central monitoring stations, where ICU staff can monitor patient status continuously. This immediate access to patient data allows for rapid identification of changes in condition and timely interventions.

External health data platforms

Large External health data platforms with other institutions such as other hospitals, social determinants and healthcare providers is also integral to ICU management. This data includes information about a patient's recent healthcare visits, medications, social environment, and chronic conditions, providing a comprehensive view of their health.(Kwaliteitsstandaard Organisatie van Intensive Care, 2016). These large inter hospital platforms are not used/available on a large scale.

Wearable devices and remote monitoring technologies

Wearable devices and (remote) monitoring technologies are emerging valuable sources of health data. These devices can track a range of health metrics, including physical activity, sleep patterns, and specific biomarkers. The data collected by wearable devices can provide insights into a patient's overall health and recovery progress, which can be particularly useful for monitoring patients after discharge from the ICU. While the integration of wearable data into ICU management is still evolving, it holds significant potential for enhancing patient care.

Environmental and Contextual Data/ Social Determinants

Data on environmental factors such as air quality, weather conditions, and even social determinants of health (e.g., housing stability, access to care) can influence patient health and ICU demand. Integrating this data can help create more comprehensive predictive models that account for a wider range of factors affecting patient flow (Zhang & Li, 2024).

3.1.4. Data Security Storage

Secure data storage in the current system architecture is vital for protecting sensitive patient information from unauthorized access and data breaches. These solutions include encryption technologies, access control mechanisms, and regular security audits. In compliance with the General Data Protection Regulation (GDPR), Dutch hospitals implement stringent data protection measures to ensure that patient data is stored securely and can only be accessed by authorized personnel. These measures are essential for maintaining patient trust and avoiding legal repercussions associated with data breaches (Kwaliteitsstandaard Organisatie van Intensive Care, 2016).

3.1.5. Current Prediction Method: Analytical Calculations

In the Netherlands often times the analytical methods used in hospitals are not automated and rely on manual input of data. The analytic is often times Descriptive and Predictive. Descriptive analytics suggest that analytics using patient data are used to identify patterns in the ICU utilization, plotting historical data, average ICU occupancy rates and demographic numbers. This is for example done in Excel using information that can be extracted from HiX. An example of calculating Bed Capacity in German hospitals is using the following formula (Kuntz et al., 2007) :

$$\text{Bed capacity} = \frac{\text{population} \times \text{hospital-admissions-frequency} \times \text{length-of-stay}}{\text{occupancy-rate} \times 365 \text{ days}}$$

And,

$$\text{Occupancy rate} = \frac{\text{cases-per-year} \times \text{length-of-stay}}{\text{number-of-beds} \times 365 \text{ days}}$$

As can be seen in the formula above, the calculations are made on a yearly basis. The issue that can arise from this method is that this can lead to non-productive usage of bed capacity, since the ICU will be designed according to these numbers, which might change during the year. In turn this method can lead to excessive operational costs, since cost per case is not involved. Furthermore, the system is very prone to missing data or data inaccuracies (Kuntz et al., 2007) .

Scenario Modelling is often times done for seasonal flu outbreaks or during pandemics. In such urgent matters ICU capacity is adjusted according to predictions. These models are often times used on regional levels, for hospitals to not become overcrowded. Often times multiple hospitals work together in this case.

Decision support systems are not yet widely used for managing ICU capacity efficiency. It is true that HiX and Epic give possibilities for patient triage recommendations, and viewing discharge planning and bed allocation. However the system itself does not provide predictive measures.

Historical Data Analysis

The method described before is based on historical data. Examining the data such as past admission rates, discharge patterns, and length of stay statistics, ICU planners can identify trends and anticipate future demand, with the use of basic mathematical models. Historical data provides valuable insights when it comes to emergency cases and seasonal variations. This data can be extracted from for example HiX or Epic or national databases such as the RIVM.

3.1.6. Challenges and Limitations in Current Data Management Practices

While the Netherlands has made significant strides in leveraging data for ICU management, several challenges and limitations persist in current data management practices. These obstacles can hinder the effective utilization of data, impacting patient care and operational efficiency. This section explores the key challenges and limitations when it comes to ICU capacity planning using patient data, which are described in the literature (see Table 3).

Table 3: Literature Review Articles highlighting current ICU Capacity Planning

Author(s)	Year	Title
Hardenberg, Jan-Hendrik B.	2024)	Data-driven intensive care: a lack of comprehensive datasets
Kuntz, Ludwig et al.	2007)	Incorporating efficiency in hospital-capacity planning in Germany
Pinsky, Michael R. et al	2024)	Use of artificial intelligence in critical care: opportunities and obstacles

Data Silos and Interoperability Issues

One of the most significant challenges in ICU data management is the existence of data silos. The models based on generated data sets are often restricted to the individual hospital. As a result the datasets are small and do not show variety, Furthermore this leads to less generalizability and utility for the daily practice. (Pinksy 2024, Hardenberg et al., 2024 and Kuntz et al., 2007). There is also a lack of binding semantic definitions, established by the hospital industry, used within these datasets (Hardenberg et al., 2024). Consequently, ICU managers may not have a comprehensive view of a patient's medical history, which can impede clinical decision-making and coordination of care.

Efforts to integrate these systems are ongoing, but achieving full interoperability remains a complex and resource-intensive task. The need for standardization of data formats and communication protocols is critical to overcoming this challenge and ensuring that data can be shared more easily between systems.

Data Privacy and Compliance with GDPR

Compliance with the GDPR which will be explored more in chapters 3.3 and 5, presents another significant challenge for ICU data management. GDPR imposes strict requirements on how patient data is collected, stored, and shared. While these regulations are essential for protecting patient privacy, they can also create barriers to effective data utilization. However there are examples, where datasets are available for public, such as the University Medical Center of Amsterdam which is valuable. As a result of de-identification, it is the case that other important information cannot be-shared such as anamnestic information (Hardenberg, 2024). Pinsky et al., 2024 adresses the importance of sharing data and models between hospitals, where adequate cyber security of the algorithims should be secured.

Technical Limitations and Data Infrastructure

The technical infrastructure required for advanced data management and analytics can be a limiting factor. Not all healthcare facilities have access to the latest technologies and tools needed for predictive analytics, and machine learning. Investing in technical solutions and development can tackle technical issues (Hardenberg et al., 2024 and Pinsky et al., 2024).

Data Quality and Accuracy

Ensuring the quality and accuracy of data is another critical challenge. Inaccurate or incomplete data can lead to incorrect predictions and poor clinical decisions. Data quality issues can arise from various sources, including manual data entry errors, outdated information, and inconsistencies between different data systems and having enough space to save the obtained data (Hardenberg, 2024). Moreover, data is not always timely accesible, which would be valuable to have in a clinical setting. (Kuntz et al., 2007 and Pinsky et al., 2024).

Staff Training

In order to adapt new data management practices and technologies staff needs to be adequately trained. Effective change management strategies and comprehensive staff training are crucial for development of example AI models and data and privacy management. Furthermore, this enhances more sharing of perspectives amongst employee and facilitates an innovating work enviroment (Pinsky et al., 2024).

3.1.7. Conclusion

This section has explored the current state of ICU management, with a particular focus on capacity planning. Despite the growing availability of data through systems such as EHRs, ICU resource management continues to face substantial operational and structural challenges. Bed occupancy decisions for example can be actively, hindered by limited integration between departments, delays in discharge, and insufficient predictive capabilities, issues that contribute to inefficiencies in patient flow and resource use.

At the national and regional levels, coordination remains fragmented, with organizations like ROAZ offering some structure, but with limited overarching strategic planning. While technical tools such as HiX and EPIC provide valuable data, their potential for capacity management is not yet fully realized, especially when it comes to integrating less commonly used sources like wearables, telemedicine, or social determinants of health.

Furthermore, significant barriers persist around data privacy, infrastructure, staff training and interoperability. The reliance on ad hoc decision-making during recent crises underscores the urgent need for more robust, real-time decision support systems. These findings confirm a gap between available data and its effective application in ICU planning—highlighting the importance of developing a new, integrated system architecture. This deeper understanding of existing practices and limitations forms the foundation for the following phases of the research, particularly within the 'discover' stage of the double diamond model and in order to create a future architecture model.

3.2. New beneficial Data and Prediction methods for ICU Capacity efficiency

This subchapter aims to show that there are many suggestive analytical methods which could be used for ICU predictions. Incorporating one or more of these methods into the current systems—while keeping legal constraints in mind—could lead to a new system architecture that enables more efficient ICU capacity management.

In this subchapter data analytical methods regarding mathematical and simulation models, machine learning, telemedicine, wearables and medical devices will be mentioned, as well as an overview of integration of these into a current system architecture. In the following paragraphs, an overview is given regarding the main adressed topics in the chapter with a list of the mentioned literature.

3.2.1. Prediction methods

The prediction methods will be described here together with relevant constraints and advantages.

Simulation models

In the literature the use of simulation modelling/predictive modelling has often been mentioned as can be seen in the following tables:

Table 4: Literature Review Articles on Predictive methods such as Predictive Modelling and Simulation Models

Author(s)	Year	Title
Friedrichson, Benjamin et al.	2024	Web-based Dashboard on ECMO Utilization in Germany: An Interactive Visualization, Analyses, and Prediction Based on Real-life Data
Stahel, Philip F. et al	2024	The Rothman Index predicts unplanned readmissions to intensive care associated with increased mortality and hospital length of stay
Keim-Malpass, Jessica et al	2024	Prospective validation of clinical deterioration predictive models prior to intensive care unit transfer among patients admitted to acute care cardiology wards
Zhang, W., Li, X.	2024	A data-driven combined prediction method for the demand for intensive care unit healthcare resources in public health emergencies
Rooney, S.R., Clermont, G	2023	Forecasting algorithms in the ICU
Antmen, Z.F., Oğu-lata, S.N	2023	The capacity planning of intensive care units via simulation: A case study in university hospital
Murray, L.L., Wilson, J.G., Ro-drigues, F.F., Zaric,G.	2023	Forecasting ICU Census by Combining Time Series and Survival Models
Alkhachroum, A., Kromm, J., De Georgia, M.A	2022	Big data and predictive analytics in neurocritical care
Bleibtreu, Elena et Al.	2022	Service-, needs-, and quality-based hospital capacity planning – The evolution of a revolution in Switzerland
Ghorbani, R., Ghousi, R., Makui, A., Atashi, A	2020	A New Hybrid Predictive Model to Predict the Early Mortality Risk in Intensive Care Units on a Highly Imbalanced Dataset
Assaf, R., Jayousi, R	2020	30-day Hospital Readmission Prediction using MIMIC Data
Keim-Malpass, J., Clark, M.T., Lake, D.E., Moorman, J.R.	2020	Towards development of alert thresholds for clinical deterioration using continuous predictive analytics monitoring
Michard, F., Teboul, J.L	2019	Predictive analytics: beyond the buzz
Krishnan, G.S.,Sowmya Kamath,S.	2019	A Supervised Approach for Patient-Specific ICU Mortality Prediction Using Feature Modeling
Zaleski, J	2019	Big Data for Predictive Analytics in High Acuity Health Settings
Inan, T.T., Samia, M.B.R., Tamanna, I., Islam, M.N.	2018	A decision support model to predict ICU readmission through data mining approach
Angelo, S.A., Arruda, E.F., Gold-wasser, R., Salles,A., e Silva, J.R.L.	2017	Demand forecast and optimal planning of intensive care unit (ICU) capacity
Patrick J. et al.	2015	A simulation model for capacity planning in community care
Mathews, K.S., Long, E.	2015	A conceptual framework for improving critical care patient flow and bed use
Fernandes, M.P.B., Silva, C.F., Vieira, S.M., Sousa, J.M.C	2014	Multimodeling for the prediction of patient readmissions in Intensive Care Units
Asaduzzaman, Md	2014	Capacity planning of a perinatal network with generalised loss network model with overflow
Cismondi, F., Fialho, A.S., Vieira, S.M., Sousa, J.M.C., Finkelstein, S.N	2013	Missing data in medical databases: Impute, delete or classify?
Azcárate, Cristina et al	2012	Sensitivity analysis in bed capacity studies including the medical staff's decision making
Campbell, Christiana	2010	The benefits of designing a stratification system for New York City pediatric intensive care units for use in regional surge capacity planning and management
Kuntz, Ludwig et al.	2007	Incorporating efficiency in hospital-capacity planning in Germany
Nguyen, Jean- Michel et al.	2007	An objective method for bed capacity planning in a hospital department: A comparison with target ratio methods

Table 5: Literature Review Articles on healthcare capacity planning, specifically addressing critical care resources, ICU capacity forecasting, and community health service networks

Author(s)	Year	Title
McManus, M.L., Long, M.C.,Cooper, A., Lit vak, E	2004	Queuing Theory Accurately Models the Need for Critical Care Resources
Angelo, S.A., Arruda, E.F., Goldwasser, R., Salles, A., e Silva, J.R.L.	2017	Demand forecast and optimal planning of intensive care unit (ICU) capacity
Mohammadi Bidhandi, Hadi et al.	2019	Capacity planning for a network of community health services

Table 6: Literature Review Articles of Simulation Models for ICU Capacity Planning

Author(s)	Year	Title
Sent, Danielle et al.	2024	A quality improvement study on how a simulation model can help decision making on organization of ICU wards
Patrick J. et al.	2015	A simulation model for capacity planning in community care
Sarac Guleryuz S. et al.	2023	Simulation of intensive care bed capacity based on mixture distribution
Antmen Z.F., & Oğulata S.N.	2013	The capacity planning of intensive care units via simulation: A case study in university hospital
Mathews, K.S., Long, E.	2015	A conceptual framework for improving critical care patient flow and bed use

Modelling in ICU Capacity Management

Simulation models are vital for ICU capacity management, enabling data ministrators to assess resource requirements and optimize patient care. Through modeling real-world scenarios, such as patient admissions, discharges, and bed availability, these simulations provide valuable insights into resource demands. Discrete event simulation (DES) is especially effective, as it examines ICU operations at the event level, tracking factors like patient arrivals and departures in real time. This technique is particularly useful for predicting the ICU response during patient surges, allowing planners to prepare for varying demand levels (Antmen & Ogulata, 2013; Guleryuz & Koyuncu, 2023; Sent et al., 2024). Simulation models also allow for comparisons between different ICU configurations and illustrate how these organizational differences influence capacity performance (Sent et al., 2024).

Additionally, mixture distribution models enhance accuracy in simulation by accounting for the variability in patient interarrival times (IAT) and lengths of stay (LOS). Traditional statistical distributions may not effectively capture ICU data's high variability and outliers. Mixture distributions provide flexibility by accommodating skewed and long-tailed data distributions, allowing for simulations that more closely represent actual ICU conditions (Guleryuz and Koyuncu, 2023; Sent et al., 2024).

Important Data

Accurate ICU simulation models rely on a comprehensive dataset, including metrics such as IAT, LOS, and bed occupancy rates. By collecting data on both planned and emergency admissions, these models can differentiate between scheduled and urgent patient flows, helping to develop precise performance metrics. Key data points involve admission sources (e.g., emergency room or operating room), arrival times, and discharge patterns (Antmen and Oğulata, 2013; Sent et al., 2024).

Descriptive statistics—mean, median, skewness, and kurtosis—are essential for understanding data distributions and fitting parameters in mixture distribution models, which are used to represent ICU demand accurately (Guleryuz & Koyuncu, 2023). Multi-year data provide the added benefit of preparing the model to account for seasonal trends or unexpected demand surges, as seen during the COVID-19 pandemic (Sent et al., 2024).

Legal Constraints regarding Simulation Models

ICU simulations must adhere to data privacy laws, particularly the General Data Protection Regulation (GDPR), which mandates that patient data remain anonymous. This topic is more enlightend in the chapters 3.3 and 5. In the Netherlands, such compliance is crucial, requiring that all simulation inputs be stripped of identifiable patient information (Antmen & Ogulata, 2013; Sent et al., 2024).

Beyond data privacy, ethical guidelines ensure equitable allocation of critical resources within simulations. Bed allocation policies that prioritize critically ill patients must be mirrored within simulation models to prevent potential biases. Strict adherence to these policies aligns simulation outcomes with national health guidelines, supporting a fair and realistic approach to resource management (Sent et al., 2024).

Technical Constrains regarding Simulation Models

The technical demands of simulation models, particularly those using mixture distributions, can be significant. Models that simulate ICU capacity require extensive computational resources to process the complex calculations involved in parameter estimation for IAT and LOS. Specific software, like R for statistical analysis or ARENA for process simulations, is often necessary, as is hardware capable of managing large data volumes (Guleryuz & Koyuncu, 2023; Sent et al., 2024).

Precise calibration of ICU simulation models is also critical, as minor data input inaccuracies can lead to less effective resource forecasts. Calibrating these models demands a high level of technical expertise, and ongoing updates are required to ensure that the models accurately reflect real-time changes in ICU staffing and bed availability (Guleryuz & Koyuncu, 2023).

Implementation of simulation models

To integrate ICU simulation models into existing healthcare frameworks in the Netherlands, compatibility with electronic health record (EHR) systems is essential. Such integration allows real-time data access, supporting dynamic resource adjustments (Sent et al., 2024). Additionally, a cloud-based framework could facilitate access for ICU administrators across different hospitals, adhering to local data-sharing guidelines (Antmen & Ogulata, 2013; Guleryuz & Koyuncu, 2023).

A layered architecture is recommended, with separate data, processing, decision-support and managerial layers. The data layer would gather patient and operational data, the processing layer would manage simulations, and the decision-support layer would offer actionable insights. This setup enables ICU administrators to monitor metrics like bed occupancy in real time and receive recommendations for managing resources, such as rescheduling elective procedures to prioritize emergency cases (Sent et al., 2024). This proposed architecture can enhance ICU management across Dutch hospitals, supporting ethical and legally compliant resource allocation.

Advantages and Disadvantages of Simulation Modelling in ICU

Simulation models offer several key advantages for ICU management. They provide a controlled environment where administrators can test the effects of various scenarios, such as unexpected patient surges or bed shortages, allowing hospitals to plan proactively and avoid overextension of resources (Antmen & Ogulata, 2013). Additionally, they help to improve efficiency by identifying optimal bed occupancy rates and rescheduling strategies, which can be tailored to specific hospital needs. This customization capability is a significant benefit, as models can incorporate unique patient flow data and ICU characteristics to produce highly relevant projections (Sent et al., 2024).

Another advantage is the flexibility to simulate different ICU designs, such as dedicated versus non-dedicated ICUs. This helps hospitals make informed decisions about ICU configuration, as the model results can illustrate trade-offs in resource utilization, patient outcomes, and staff satisfaction (Sent et al., 2024).

However, simulation models also have limitations. One major drawback is the high computational and technical demand required to develop, run, and maintain these models. The reliance on advanced software and hardware can pose a barrier for some healthcare facilities, particularly smaller hospitals with limited technical resources (Guleryuz & Koyuncu, 2023). Furthermore, these models require precise calibration and validation with real patient data, which can be a time-intensive process. Minor inaccuracies in input data can significantly impact predictions, potentially leading to misinformed decisions (Sent et al., 2024).

Another disadvantage relates to the ethical and legal constraints. Although simulation models can incorporate anonymized data to comply with GDPR, there remain concerns about the extent to which patient privacy can be fully protected, especially when data from multiple sources are combined. Adhering to these legal requirements can complicate model implementation and may limit the depth of data that can be used (Sent et al., 2024).

In conclusion, simulation-based models, when embedded within ICU systems, support data-driven, dynamic decision-making to meet capacity challenges effectively. While they offer clear advantages in managing ICU resources and planning for demand variability, these models must be developed and applied carefully to address their technical, ethical, and operational limitations.

Machine Learning Practices

Predicting ICU admissions and effectively managing resources is a critical component of healthcare, especially during health crises such as the COVID-19 pandemic. Machine learning (ML) and deep learning (DL) models have significantly advanced ICU prediction systems, providing healthcare providers with tools to anticipate patient deterioration, optimize ICU admissions, and allocate resources more efficiently.

Table 7: Literature Review Articles on Machine Learning for ICU Capacity Planning

Author(s)	Year	Title
Prithula, Johayra et al	2024	Improved pediatric ICU mortality prediction for respiratory diseases: machine learning and data subdivision insights
Hardenberg, Jan- Hendrik B	2024	Data-driven intensive care: a lack of comprehensive datasets
Wu, Jacky Chung- Hao et al	2024	Deep-Learning-Based Automated Anomaly Detection of EEGs in Intensive Care Units
Ahmad, F., Ayub,H., Liaqat, R.,Nawaz, A., Younis, B.	2021	Mortality Prediction in ICU Patients Using Machine Learning Models
Goic, Marcel et al.	2021	COVID-19: Short-term forecast of ICU beds in times of crisis
Ozyurt, Y., Kraus,M., Hatt, T., Feuerriegel, S.	2021	AttDMM: An Attentive Deep Markov Model for Risk Scoring in Intensive Care Units
Guerra, D., Gawlick, U.,Bizarro, P.,Gawlick, D.	2011	An integrated data management approach to manage health care data
Machine learning specifically AI:		
Pinsky, Michael R. et al.	2024	Use of artificial intelligence in critical care: opportunities and obstacles

Machine Learning Practices in ICU Capacity Management

Predictive models for ICU capacity management leverage machine learning algorithms, which are integrated into hospital data infrastructures. These models process information from multiple clinical data sources. Deep learning architectures are commonly used for such predictions. These techniques enable the automated detection of patient deterioration, allowing timely clinical interventions and more efficient resource allocation (Ahmad et al., 2021; Wu et al., 2024).

For instance, GRU-based models have been applied to real-time EEG monitoring to detect non-convulsive seizures by analyzing spikes in brain activity. This approach reduces the workload of ICU staff and provides early warnings for life-threatening events, potentially allowing for quicker interventions (Wu et al., 2024). Additionally, mortality prediction models based on clinical data, including demographics, vital signs, and laboratory results, support decision-making regarding patient discharge and ICU admission prioritization. These models are often trained on large datasets such as MIMIC-III, which provides comprehensive ICU patient data (Ahmad et al., 2021; Prithula et al., 2024).

However, one of the key challenges is that many of these models are trained on single-center datasets, limiting their generalizability to other hospitals. While multicenter datasets such as ICU-CRD offer a broader scope, they often lack granularity, making them less applicable across diverse clinical settings (Hardenberg, 2024).

Machine learning models, especially those based on deep learning architectures, have proven highly effective in predicting ICU admissions and mortality. These models often combine multiple data types, including physiological data, lab results, and clinical histories, to enhance prediction accuracy.

In their study on COVID-19-related ICU admissions, Goic et al., 2021 demonstrated the power of ensemble forecasting models. By combining autoregressive, ML, and epidemiological approaches, they achieved highly accurate short-term forecasts of ICU demand, allowing healthcare providers to manage resources effectively during surges. This forecasting system delivered prediction errors as low as 4% for one-week predictions, making it a crucial tool for resource management during the pandemic.

Deep learning models, such as the Attentive Deep Markov Model (AttDMM) proposed by Özyurt et al. (2021), have taken this a step further. AttDMM combines deep probabilistic models with attention mechanisms to predict mortality risk in ICU settings. It captures long-term disease dynamics and latent disease states, outperforming traditional models like GRU-D by a significant margin. The model achieved an AUROC of 0.876 in tests on the MIMIC-III dataset, improving by 2.2% over previous state-of-the-art methods. AttDMM's ability to provide earlier warnings, often by several hours, allows healthcare providers to intervene sooner, potentially saving lives (Özyurt et al., 2021).

Similarly, Ahmad et al. (2021) reported on the efficacy of machine learning models for mortality prediction in ICU settings, emphasizing the importance of continuous monitoring of patient data. These models integrate real-time data streams from vital signs, lab tests, and EEG recordings to predict patient deterioration, enabling more dynamic resource management in ICUs.

Important Data

The data required for ICU capacity management and risk prediction models are diverse and cover several domains. Successful implementation of these models depends on the availability and integration of multiple types of data, including clinical data such as psychological data (Ahmad et al., 2021), biochemical markers (Prithula et al., 2024) and imaging such as EEG data (Wu et al., 2024), which can all influence patient's health and can predict adverse outcomes. Clinical history and demographics such as a patient's age, gender, medical history, and ICD-10 diagnoses are essential components of many mortality prediction models. These data points contribute to the personalization and accuracy of predictions (Ahmad et al., 2021; Prithula et al., 2024). Moreover data on environmental factors such as air quality, weather conditions, and even social determinants of health (e.g., housing stability, access to care) can influence patient health and ICU demand. Integrating this data can help create more comprehensive predictive models that account for a wider range of factors affecting patient flow (Zhang and Li, 2024). Datasets like MIMIC-III and AmsterdamUMCdb are valuable for accessing this necessary data. However, due to privacy concerns, such datasets are often de-identified, which may limit their granularity, particularly when sensitive clinical information like free-text notes and medical images are removed (Hardenberg, 2024).

Legal constraints regarding Machine Learning

The use of sensitive patient data for predictive modeling in ICU settings is subject to strict legal frameworks that aim to protect patient privacy while allowing for in novative healthcare solutions.

In Europe, the General Data Protection Regulation (GDPR) imposes stringent requirements for the protection of personal data. Datasets used in predictive modeling, such as AmsterdamUMCdb, must apply techniques like k-anonymity and L-diversity to prevent the re-identification of individuals. However, this often results in the removal of key clinical data, such as free-text records and medical images, which can limit model performance (Hardenberg, 2024).

In the United States, the Health Insurance Portability and Accountability Act (HIPAA) governs the use of healthcare data. Compared to GDPR, HIPAA is less restrictive, allowing datasets like MIMIC-IV to include medical images and other sensitive data, without requiring explicit patient consent. This richer dataset enables the development of more robust machine learning models and less loss of value of the data itself. However, these differences in legal frameworks create inconsistencies between the datasets used in European and U.S.-based models, leading to challenges in global model implementation (Hardenberg, 2024).

Technical constrains regarding Machine Learning

Despite the success of predictive models in ICU settings, several technical challenges still need to be addressed for widespread adoption.

- Data heterogeneity: ICU data is collected from various sources, including monitoring devices, lab tests, and clinical notes, each with different formats and standards. The lack of standardization across hospitals makes it difficult to integrate these data streams into a cohesive system for real-time prediction (Hardenberg, 2024; Prithula et al., 2024).
- Model generalizability: Models trained on single-center datasets often fail to generalize across different hospitals or regions. This is a significant limitation, especially in cases where external validation is required to implement the model effectively in new clinical environments (Ahmad et al., 2021; Hardenberg, 2024).
- Class imbalance: ICU datasets often have an imbalance in the number of positive outcomes (e.g., mortality) versus normal outcomes. This class imbalance skews the model predictions towards the majority class. Techniques like Synthetic Minority Over-sampling Technique (SMOTE) are used to address this issue, but they can introduce other biases (Ahmad et al., 2021 and Prithula et al., 2024).
- Computational demands: Real-time models, especially those based on continuous data like EEG, require substantial computational resources. GRU-based models used for EEG anomaly detection, for example, need to balance accuracy with real-time processing constraints, which can be resource-intensive (Wu et al., 2024).

Future developments in ICU predictive modeling will focus on overcoming the limitations mentioned above. One promising direction is the use of ensemble models, which combine multiple predictive techniques to improve accuracy. Goic et al. (2021) demonstrated that ensemble models combining compartmental, autoregressive, and machine learning approaches can significantly reduce prediction errors. Additionally, real-time model updating is an important area for future research, as continuously learning models that adapt to new data could offer more accurate predictions during health crises (Hurley et al., 2021).

Telemedicine

Telemedicine allows healthcare providers to deliver healthcare remotely (see Table 8. This is also done in the ICU as will be mentioned in the following paragraphs.

Table 8: Literature Review Articles of Telemedicine for ICU Capacity Planning

Author(s)	Year	Title
Weiss, B., Paul, N., Balzer, F., Noritomi, D.T., Spies, C.D.	2019	Telemedicine in the intensive care unit: A vehicle to improve quality of care?

Telemdicine in ICU Capacity Management

The rise of personalized medicine is transforming the way healthcare is delivered, including in ICU management. With the integration of wearable technologies, remote monitoring, and AI-driven analytics, hospitals are exploring new ways to optimize patient care and resource allocation. While some personalized medicine applications are already being implemented, their widespread adoption in ICU settings remains a work in progress due to technological, ethical, and operational challenges.

The tele-ICU system typically consists of a centralized ”telemedical cockpit” and remote sites, where critically ill patients are being cared for. The cockpit is staffed by experienced intensivists, ICU nurses, and additional personnel, such as administrative staff. The cockpit is connected to the remote ICUs through an audiovisual system that allows real-time monitoring and consultation. Key features of this system include (Weiss et al., 2021):

- Telemedical Cockpit: The cockpit serves as the hub for remote monitoring, where intensivists oversee ICU patients at various hospitals. The cockpit can monitor real-time patient data, including vital signs, ventilator settings, patient records, and imaging (X-rays, echocardiograms). The connection between the tele-ICU cockpit and remote ICU sites is established via cameras and communication technology, allowing remote doctors to observe, assess, and consult on patient care (Weiss et al., 2021).
- Remote Sites: Hospitals that participate in tele-ICU programs are equipped with audiovisual technology, such as camera-equipped carts or robots. This technology facilitates a real-time, two-way audiovisual connection between the telemedical cockpit and the local ICU team. Depending on the setup, the tele-ICU staff may review patient records, assist in care planning, and make decisions in critical situations (Weiss et al., 2021).
- Data Integration: Tele-ICU intensivists have access to a wide array of patient data, including vital signs, laboratory results, medication records, and imaging. The cockpit can also use decision-support tools, alerts, and real-time notifications to assist in making timely and informed clinical decisions. This constant data flow allows remote intensivists to support bedside teams in critical care management (Weiss et al., 2021).
- Operational Flexibility: Tele-ICU programs can vary in terms of the responsibilities and autonomy granted to the remote intensivists. In some models, remote intensivists have full authority to make care decisions, while in others, their role is limited to advice or assistance in emergencies. Some programs offer 24/7 coverage, while others may only operate during off-hours (e.g., night shifts or weekends) Weiss et al., 2021.

Important Data

The tele-ICU system relies on several data streams to function effectively according to (Weiss et al., 2021). The data streams consist of: real-time vital signs (heart rate, oxygen levels, blood pressure), patient medical records, other medical equipment settings, automated alerts for critical events (e.g., abnormal vital signs) and decision-support tools to assist in clinical management.

Legal constraints regarding Tele-Medicine

While the paper does not directly address specific legal constraints, it implies the need for clear role definitions between on-site and tele-ICU teams. There must be established protocols regarding the decision-making authority of the remote intensivists, especially in life-threatening situations. This is crucial to prevent conflicts between on-site and remote care teams, ensuring that both teams can work together smoothly without misunderstandings (Weiss et al., 2021). Data privacy regulations (e.g., GDPR) complicate the use of continuous monitoring devices in hospitals. Also, accountability in remote monitoring remains unclear: Who is responsible for interpreting the data?

Technical constrains regarding Tele-Medicine

The implementation of telemedicine in ICUs comes with multiple technical challenges (Weiss et al., 2021):

- Technology Reliability: The effectiveness of a tele-ICU system depends on a stable and secure audiovisual connection between the tele-ICU cockpit and the remote hospitals. Any technical failure, such as video system malfunction or network issues, can disrupt care.

- Data Integration: The system requires real-time data access, which means the tele-ICU must be integrated with the hospital's existing medical record systems and other technology, like ventilators and monitoring devices. The paper highlights that the variation in technology and competencies across different tele-ICU programs can affect the success of telemedicine interventions.
- Staffing Models: The level of involvement by remote intensivists can vary. Some programs allow for full autonomy, while others limit their role to emergency interventions or oversight. This variability means that tele-ICU systems need to be flexible and adaptable based on local hospital needs.
- Acceptance by Staff: The success of tele-ICU programs often hinges on the acceptance of the remote intensivist by the local ICU team. Staff resistance, concerns over additional workload, or fear of being scrutinized can pose barriers to successful telemedicine implementation.
- AI-based predictions require large, high-quality datasets, but hospital data is often fragmented. The lack of standardized machine learning models makes it difficult to create reliable, generalizable AI tools.

Advantages and Disadvantages of Tele-Medicine Use

Tele-medicine can give many advantages as summed up in Table 9.

Table 9: Advantages of Telemedicine in ICU Care, Inspired by (Weiss et al., 2021)

Advantage	**Description**
Improved Adherence to Best Practices	Telemedicine interventions enhance adherence to clinical guidelines and best practices. Studies indicate that tele-ICU systems prompt physicians and nurses to follow protocols more consistently, leading to improved patient outcomes (e.g., deep vein thrombosis and stress ulcer prevention).
Reduction in Mortality and Complications	Some studies report that telemedicine reduces ICU and hospital mortality, lowers preventable complications, and shortens the length of stay (LoS).
Increased Efficiency	Provides continuous intensivist coverage, particularly during off-hours (nights and weekends), addressing staffing shortages and ensuring that critically ill patients receive timely care.
Cost Savings	Remote ICU interventions can reduce the need for physical staffing of intensivists, prevent complications, and decrease extended hospital stays, leading to cost savings.
Access to Specialized Care	Enables hospitals, especially in rural or under-resourced areas, to access specialized critical care expertise remotely, improving the quality of care.
Enhanced Patient Monitoring	Tele-ICU systems allow real-time monitoring of vital signs, lab results, and imaging, ensuring continuous patient assessment and enabling faster interventions in critical situations.

However, Many disadvantages are also involved as summed up in Table 10.

Furthermore, in pediatric ICUs, patients range from premature newborns to 18-year-olds, making it difficult to apply a one-size-fits-all predictive model and some conditions require continuous bedside observation, rather than relying solely on wearables or remote monitoring.

Table 10: Disadvantages of Telemedicine in ICU Care, Inspired by (Weiss et al., 2021)

Disadvantage	Description
Mixed Evidence on Outcome Improvements	The effectiveness of telemedicine in improving outcomes is not universally agreed upon. Some studies report improvements in mortality and length of stay (LOS), while others find no significant differences, particularly in well-functioning ICUs.
Technological Limitations	The success of telemedicine relies on stable technology. Technical failures, such as camera malfunctions and network outages, can disrupt communication between the tele-ICU cockpit and on-site teams, reducing effectiveness.
Staff Acceptance Issues	Gaining acceptance from on-site ICU staff can be challenging. Some staff members perceive telemedicine as increasing workload or interfering with their workflow. Additionally, concerns about being monitored by remote physicians may create resistance.
Communication Barriers	The lack of physical presence of remote intensivists can create challenges in communication. Differing medical opinions between on-site and tele-ICU physicians may lead to tension and hinder effective care coordination.
Limited Impact on Well-Functioning ICUs	In hospitals that are already well-staffed and adhere to best practices, telemedicine may not provide substantial benefits. Its advantages are more apparent in under-resourced settings with staff shortages.
Lack of Long-Term Outcome Data	Research on telemedicine has mainly focused on short-term outcomes like mortality and LOS. There is limited data on long-term patient recovery, quality of life, and functional outcomes after ICU discharge.

Wearables and Medical Devices Usage in the ICU

Table 11: Literature Review Articles on Wearables and Medical Devices for ICU Capacity Planning

Author(s)	Year	Title
Sloane, E.B., Gehlot, V.	2007)	Use of Coloured Petri Net models in planning, design, and simulation of intelligent wireless medical device networks for safe and flexible hospital capacity management

Adaption of Wearables and Medical Devices in the ICU

Wearable and remote monitoring systems work by continuously collecting, transmitting, and analyzing data from ICU patients. In the case of CoCross, this is done via wireless medical devices that communicate with mobile applications. For example, a Bluetooth-enabled stethoscope records lung and heart sounds, which are then transmitted to a tablet running the CoCross4Pros app (Kilintzis et al., 2022). The app manages the recording session, linking the collected data to specific patients and ensuring that all relevant information (such as location of the auscultation or ventilator settings) is included. Once the data is collected, it is uploaded to a secure cloud-based server, where it is stored alongside other patient data, such as diagnostic images and biosignals.

For ICU clinicians, this means that they can review data almost instantaneously through the CoCross web application. The web interface allows authorized healthcare professionals to listen to lung or heart sounds, view ultrasound images, and analyze vital signs remotely, providing them with a more comprehensive picture of the patient's condition (Kilintzis et al., 2022). This capability is especially important for predictive models that rely on real-time data to forecast ICU demand or patient outcomes.

The remote surveillance systems described by Safavi et al., 2019 extend this concept by collecting physiological data not only in the ICU but also in other care settings, such as general wards and patient homes. These systems utilize wearable devices like biosensors and patches to track continuous physiological data, which is fed into a central data repository. Prediction algorithms analyze the data to identify patterns that may indicate clinical deterioration, alerting clinicians to intervene before adverse events occur.

Important Data

For predictive models to be effective, all earlier mentioned data must be collected continuously and integrated into a common database in real time, ensuring that the most up-to-date information is always available for analysis. To make use of this real-time sensor data, ICU prediction models need to:

- Standardize data collection across different hospital systems.
- Develop interoperability protocols with electronic health records (EHRs) like HiX.
- Utilize AI-driven algorithms to identify subtle trends and anomalies in patient data.

Legal constraints regarding Wearables and Medical Devices in the ICU

In the context of the Netherlands, where data privacy regulations are stringent, the use of wearable and remote monitoring devices faces significant legal challenges. The General Data Protection Regulation (GDPR) governs how personal health information (PHI) can be collected, stored, and shared, and it requires that patients give explicit consent for their data to be used in any way that goes beyond direct treatment (Kilintzis et al., 2022).

For ICU predictive models that rely on data from multiple sources, ensuring compliance with GDPR is a major concern. To address this, systems like CoCross employ data anonymization and encryption techniques to ensure that sensitive patient information is protected throughout the data collection, transmission, and storage processes (Kilintzis et al., 2022). Anonymization removes personally identifiable information (PII) from the data, making it difficult to trace back to a specific individual, while encryption secures the data during transmission to prevent unauthorized access.

In addition to anonymization and encryption, the use of patient data must adhere to strict access control measures. Only authorized personnel, such as ICU planners and clinicians, should have access to this data, and role-based permissions must be enforced to ensure that data is only available to those who absolutely need it (Kilintzis et al., 2022).

Furthermore, patients must be informed about how their data will be used, and they must provide informed consent before their data can be shared between hospitals or used in predictive models. This presents a challenge, particularly in emergency situations where obtaining explicit consent may not be feasible.

Technical constrains regarding Wearables and Medical Devices in the ICU

There are several technical challenges involved in the integration of wearable devices and remote monitoring systems into ICU predictive models:

- Data Compatibility and Interoperability: Hospitals use a variety of medical devices and IT systems that may not always be compatible with each other. For example, a pulse oximeter from one manufacturer might store data differently than a blood pressure monitor from another manufacturer. Systems like CoCross use HL7 FHIR to standardize how data is exchanged between devices and the hospital's central database, but interoperability issues can still arise when different vendors use slightly different implementations from the standard (Kilintzis et al., 2022).
- Latency and Data Transmission: Predictive models for ICU capacity rely on real-time data to be effective. Any delays in data transmission can hinder the ability to intervene early in critical

situations. Systems like CoCross mitigate this by transmitting data almost instantaneously, but any technical issues—such as network outages or bandwidth limitations—could cause delays that compromise patient safety (Safavi et al., 2019).

- Device Reliability and Durability: The wearable devices used in ICU settings must be reliable, durable, and capable of operating continuously without requiring frequent maintenance or replacement. Battery life is a common concern, especially for devices that are meant to be worn for extended periods. If a device fails or its battery runs out unexpectedly, it could result in missed opportunities to detect critical changes in a patient's condition (Safavi et al., 2019).
- Scalability: While systems like CoCross have been deployed successfully in a few hospitals, scaling these systems to larger networks of hospitals or across entire healthcare systems poses additional technical challenges. More devices, more data, and more users mean greater strain on the system's cloud infrastructure and data storage capabilities. Ensuring that the system remains responsive under heavier loads requires robust scalability planning (Kilintzis et al., 2022).

Integration of Data-Analytical Methods for ICU Capacity Prediction

Implementing the earlier mentioned wearable and remote monitoring devices into the existing ICU infrastructure requires an architectural update that facilitates real-time data integration, processing, and storage. Platforms like CoCross have already demonstrated how to integrate such devices effectively. CoCross combines medical devices, cloud services, and web-based applications to create a system where ICU data is collected, analyzed, and stored in a unified format (Kilintzis et al., 2022). The system has three key components:

CoCross4Pros Application: This mobile application for example manages communication between wearable medical devices (such as digital stethoscopes, pulse oximeters, and ultrasound probes) and the CoCross system. Data from these devices are transmitted wirelessly to the hospital's cloud infrastructure. Cloud-Based Data Management Services: Data collected from ICU patients is stored and processed on secure cloud servers. The system uses HL7 FHIR (Fast Healthcare Interoperability Resources), a healthcare data standard that ensures compatibility across devices and systems, enabling seamless integration into existing hospital infrastructure (Kilintzis et al., 2022). Real-Time Web-Based Application for Clinicians: The platform allows intensivists to access patient data in real time through a web-based interface, regardless of their physical location. This capability enhances decision-making by providing continuous access to vital information, which is crucial for predictive modeling and capacity management. Similarly, remote monitoring technologies, such as those described by Safavi et al. (2019), offer real-time surveillance of patients across different stages of care—preoperative, intraoperative, and postoperative. These systems rely on wearable devices that continuously collect data on vital signs. By transmitting this data to a centralized database, the system enables predictive models to operate in real time, identifying early signs of deterioration and helping optimize ICU capacity. Integrating new data sources with existing ICU management systems involves several technical and organizational challenges. To maximize the benefits of new data while maintaining efficient operations and compliance with legal standards, a structured approach to data integration is necessary. Here diverse aspects of the integration are listed:

- Technical Integration: One of the primary challenges is ensuring compatibility between new data sources and existing hospital information systems. This requires the development of robust data integration platforms that can aggregate and harmonize data from diverse sources. Interoperability standards and protocols must be established to facilitate seamless data exchange and integration. For example, implementing APIs (Application Programming Interfaces) that allow wearable devices to communicate with EHR systems can enable real-time data sharing and analysis (Sent et al., 2024).
- Data Standardization: To ensure that data from different sources can be effectively combined and analyzed, it is essential to standardize data formats and terminologies. This involves creating common data models and definitions that all systems adhere to, reducing the risk of data discrepancies and improving the accuracy of predictive models. Standardization efforts may involve collaboration with device manufacturers, software developers, and healthcare providers (Zhang & Li, 2024).
- Data Security and Privacy: Integrating new data sources also raises concerns about data security

and patient privacy. Compliance with GDPR and other data protection regulations is critical. Measures such as data encryption, access controls, and regular security audits must be implemented to protect sensitive patient information. Additionally, de-identifying data where possible can help mitigate privacy risks while still enabling valuable insights (Kwaliteitsstandaard Organisatie van Intensive Care, 2016).

- Workflow Integration: Successfully integrating new data sources into ICU management also requires adapting clinical workflows to incorporate new data inputs. This may involve training staff to use new technologies and interpret new types of data. Workflow integration should aim to enhance clinical decision-making without adding undue complexity or burden to healthcare professionals (Sent et al., 2024).
- Collaborative Efforts: Effective integration often requires collaboration between various stakeholders, including IT professionals, clinicians, administrators, and external partners such as technology vendors. Establishing clear communication channels and governance structures can help coordinate efforts and ensure that integration projects align with organizational goals and regulatory requirements (Zhang & Li, 2024).

By addressing these technical and organizational challenges, healthcare providers can successfully integrate new data sources with existing systems, enhancing the predictive capabilities of ICU management and improving patient outcomes.

Legal and Ethical Considerations

The integration of new data sources into ICU management raises important legal and ethical considerations, particularly regarding patient privacy and data protection. Compliance with the General Data Protection Regulation (GDPR) and other relevant laws is essential to ensure that patient data is handled responsibly and securely.

- Data Privacy: Protecting patient privacy is a fundamental ethical obligation. The GDPR requires healthcare providers to obtain explicit consent from patients before collecting and using their data. This consent must be informed, meaning that patients should understand what data is being collected, how it will be used, and their rights regarding their data. Healthcare providers must implement robust processes for obtaining and documenting patient consent (Sent et al., 2024).
- Data Security: Ensuring the security of patient data is crucial to prevent unauthorized access and data breaches. This involves implementing technical measures such as encryption, access controls, and secure data storage. Regular security audits and risk assessments can help identify vulnerabilities and ensure that security measures are effective. Healthcare providers must also establish protocols for responding to data breaches, including notifying affected patients and relevant authorities (Kwaliteitsstandaard Organisatie van Intensive Care, 2016).
- Anonymization and De-identification: Where possible, data should be anonymized or de-identified to protect patient privacy while still enabling valuable insights. Anonymization involves removing personally identifiable information (PII) so that individuals cannot be re-identified. De-identification involves altering data in a way that reduces the risk of re-identification. Both approaches can help mitigate privacy risks while allowing for the analysis and sharing of health data (Zhang & Li, 2024).
- Ethical Use of Data: Beyond legal compliance, ethical considerations include ensuring that data is used in ways that benefit patients and do not cause harm. This involves being transparent about data practices, respecting patient autonomy, and considering the potential impacts of data use on individuals and communities. Healthcare providers should establish ethical guidelines for data use and involve patients and other stakeholders in decision-making processes (Sent et al., 2024).
- Equity and Access: Integrating new data sources can also raise issues of equity and access.

By addressing these legal and ethical considerations which are even more highlighted and elaborated on in the chapters 3.3 and 5, healthcare providers can ensure that the integration of new data sources into (P)ICU management is conducted responsibly and in ways that respect patient rights and enhance patient care. This approach helps build trust with patients and the broader public, ensuring the sustainable and ethical use of health data.

3.2.2. Conclusion

The exploration of data-driven methodologies for ICU capacity prediction highlights the growing role of predictive analytics, real-time monitoring, and advanced modeling in optimizing patient care and resource allocation. Each method presents unique advantages, but also technical, legal, and operational challenges that must be addressed for successful implementation.

Predictive mathematical models offer a structured approach to estimating ICU demand, yet lack real-time adaptability. Simulation models provide flexibility in scenario testing, assisting hospitals in crisis planning and optimizing resource use. Machine learning techniques leverage vast datasets for high-accuracy predictions but require substantial computational power and robust data integration. Telemedicine expands ICU monitoring capabilities beyond physical constraints, yet faces challenges in staff acceptance and technological reliability. Wearable devices and remote monitoring introduce continuous, real-time patient data into predictive models. Furthermore, patient-reported outcomes and environmental & contextual data, could offer data for these prediction models. However the use of the necessary data must overcome interoperability and privacy concerns. The integration of these methodologies requires a multi-layered approach that balances technological feasibility, ethical considerations, and clinical applicability.

Table 12: Summary of Data Analytical Methods for ICU Capacity Prediction

Method	**Advantages**	**Challenges**
Predictive Mathematical Models	Structured approach for ICU demand forecasting	Limited real-time adaptability, relies on historical data
Simulation Models	Scenario testing for crisis planning and resource optimization	High computational demands, requires extensive calibration
Machine Learning	High accuracy predictions leveraging vast datasets	Computationally intensive, data standardization and privacy issues
Telemedicine	Expands ICU monitoring beyond physical constraints	Staff acceptance, technological reliability, and communication barriers
Wearable Devices and Remote Monitoring	Real-time patient data for early deterioration detection	Interoperability issues, data privacy, and security concerns

3.3. Legislation

The legislative framework surrounding healthcare data and the use of artificial intelligence (AI) in healthcare is critical for ensuring compliance, protecting patient privacy, and fostering innovation (“Regulation - EU - 2024/1689 - EN - EUR-LEX”, 2024) and to create an innovative system architectue. Legislative acts were identified by conducting a Google search using the query ”ICU data related acts in the Netherlands”, and by reviewing as many relevant websites as possible within the available timeframe. To validate the findings, results were cross-checked using ChatGPT to confirm consistency. Therefore it is possible that not all laws have been taken into account.

3.3.1. General Data Protection Regulation (GDPR)

Introduction

The General Data Protection Regulation (GDPR) is a comprehensive data protection law that governs the handling of personal data within the European Union (EU). It aims to protect the privacy and personal data of individuals and imposes strict requirements on organizations that process personal data.

Key Provisions

Key principles: The GDPR states in Article 9 (2016) that personal data can only be stored and processed if the patient has given their consent for this (“Art. 9 GDPR – Processing of special categories of personal data - General Data Protection Regulation (GDPR)”, 2016). In some circumstances, explicit consent is not needed. For example, when processing is needed for preventive or occupational medicine, medical diagnoses, provision of healthcare, or treatment, based on EU or member state law (“Art. 9 GDPR – Processing of special categories of personal data - General Data Protection Regulation (GDPR)”, 2016).

In the context of ICU Capacity planning this could imply that data processing may be justified for the sake of public health and in order to provide high-quality care, with the most efficient distribution of resources. Especially in cases such as the COVID-19 pandemic (European Data Protection Board, 2020). Since data can be used for the provision of healthcare this could apply to ICU capacity planning, for the sake of improving outcomes as well.

Furthermore, Articles 12-23 of the GDPR give patients more rights when it comes to controlling their personal data. Patients have the right to access their personal data in a structured format and know if their data is being processed, they have the right to rectify their personal data as well as the right to request erasure when the data is not needed anymore for their original purposes. Additionally, patients can object to the processing of data if it is used for profiling or marketing purposes (“Art. 21 GDPR – Right to object - General Data Protection Regulation (GDPR)”, 2018). In the case of capacity planning this means that patients should be able to access their data used in capacity planning analytical models, and give patients the possibility to correct the data as well, which is important for the accuracy of the data. Since patients can ask for the deletion of data, hospitals should have clear guidelines as to how to handle these requests, this is also the case if a patient objects to the use of their personal data. Article 22 also gives patients the right to request human intervention and it states that healthcare workers should be able to be transparent when automated decisions are made (“Art. 22 GDPR – Automated individual decision-making, including profiling - General Data Protection Regulation (GDPR)”, 2018).

Additionally, articles 5(1)(b) and 5(1)(c) of the GDPR (2021) describe regulations of purpose limitation and data minimization subsequently. In the case of this research, this implies that data collected for the purpose of ICU capacity planning should not be used for other purposes such as marketing if there is no explicit consent or lawful basis for it (“Art. 21 GDPR – Right to object - General Data Protection Regulation (GDPR)”, 2018). This is necessary to make sure that the purpose stays in the context of improving healthcare and patient care. The patient data collected should be limited to only what is necessary for the prediction of patient flow or managing ICU capacity (“Art. 5 GDPR – Principles relating to processing of personal data - General Data Protection Regulation (GDPR)”, 2021).

Article 5(2) of the GDPR (2021) states that accountability should be carried by hospital organizations. In the case of ICU capacity planning, this implies that hospitals must implement and document the Data Protection Impact Assessments (DPIAs) to assess the impact data analytical tools could have on patient privacy and risks(“Art. 5 GDPR – Principles relating to processing of personal data - General Data Protection Regulation (GDPR)”, 2021). Furthermore, the records of the data processing should be maintained, according to Articles 30 and 35 of the GDPR (2018). For this, it is important to detail the descriptions of which data is collected, such as how this data is processed, who is allowed to access the data and which security measures are in place(“Art. 30 GDPR – Records of processing activities - General Data Protection Regulation (GDPR)”, 2018)(“Art. 35 GDPR – Data protection impact assessment - General Data Protection Regulation (GDPR)”, 2018).

Article 32 mentions the importance of implementing measures that ensure a high level of security (“Art. 32 GDPR – Security of processing - General Data Protection Regulation (GDPR)”, 2016). Examples include encryption, pseudonymization of patient data and consistent security assessments. Access to the patient data should be limited to authorized personnel. In the case of a patient data breach, the supervisory authority should be notified within 72 hours, if the breach creates a risk to the rights and freedoms of the patient. If the risk is high, the patient should also be informed. For efficiency, a hospital should have a clear response plan.

As stated by Articles 28 and 19, data that is shared with third parties should always comply with the GDPR requirements, Data Processing Agreements (DPAs) is often the way to do this (“Art. 28 GDPR – Processor - General Data Protection Regulation (GDPR)”, 2018)(“Art. 19 GDPR – Notification obligation regarding rectification or erasure of personal data or restriction of processing - General Data Protection Regulation (GDPR)”, 2018). In these agreements, it should be mapped out what the outline of the scope, purpose and security measures are. Sensitive health data transferred internationally should also ensure continuous compliance with the GDPR and safeguards must be in place, as mentioned in Chapter 3.

3.3.2. Medical Treatment Agreement Act (WGBO)

Another agreement involving the use of patient data is the Medical Treatment Agreement Act (WGBO). In the WGBO (2006) it is described which rights and obligations both healthcare and patients have. Here it is stated that healthcare providers should keep a medical dossier for all patients and which information about the patient is confidential .

This act states that accurate records of treatments and care provided to the patient should be maintained(“wetten.nl - Regeling - Wijzigingswet Burgerlijk Wetboek, enz. (geneeskundige behandelingsovereenkomst) - BWBR0007021”, 2006). In the case of ICU capacity management, this would mean that up-to-date data could be used for predictive analytics. If the predictive analytics influence the care provided to the patient, this should be recorded as well. This information can oftentimes be found in either HiX or Epic.

The WGBO (2006) furthermore states that explicit consent is needed for sharing patient data with third parties unless it is directly needed for their treatment. In the case of research obtaining patient consent is needed, or the data needs to be anonymised.

3.3.3. Additional regulations

Additional Provisions for Processing Personal Data in Healthcare Act (Wabvpz)

This law Wabvpz, as an addition to GDPR is specifically focused on healthcare. This act focuses on patient data protection and security in the context of electronic health records and managing data breaches (“wetten.nl - Regeling - Wet aanvullende bepalingen verwerking persoonsgegevens in de zorg - BWBR0023864”, 2023) .

For this research, this means that potential data analytics tools should meet security standards and enforce strict security measures for not only storing but also processing patient data. BSN should be used by healthcare providers for the identification of patients in EHR. This can be important for maintaining consistency and accuracy in data analytics.

AI Act (Proposed EU AI Regulation)

In order to ensure that Artificial Intelligence (AI) is used safely, while also adhering to fundamental rights, the European Commission proposed a regulation on AI (“Regulation - EU - 2024/1689 - EN - EUR-LEX”, 2024). This means that this act is also important in healthcare, where AI systems are starting to get more popular.

One important factor of these regulations, that could be applicable when using data analytics for ICU capacity management is that if AI systems are used, they should be graded on their level of risk. The risk can either be inapplicable, high, limited or minimal. The healthcare sector has access to very sensitive information. Therefore regulations are important in AI-use, due to the self-learning character. It is very important to first test and validate the system before using it. Another factor is that it should be very clear what the capabilities and limitations of the AI systems are. These systems should also be checked upon, enduring human oversight and accountability.

EU Directive on Security of Network and Information Systems (NIS Directive)

This directive has the goal to enhance the cybersecurity capabilities in the EU. This directive applies to the healthcare sector as well. In the healthcare sector this means that the operators should implement security measures to prevent incidents and manage risks. Hospitals should be sure to have secure IT systems installed. As stated previously in the GDPR this directive also requires the monitoring and reporting of cybersecurity-related incidents .

Medical Device Regulation (MDR)

Medical devices have the potential to be a helping asset in ICU capacity management. The Medical Device Regulation (MDR) is there to ensure that medical devices are safe and perform well as needed. To test this performance regular clinical evaluations should be in place and there should be evidence that the system is safe and efficient. The continuous monitoring is also mandatory after the device is sold to another party (“Regulation - 2017/745 - EN - Medical Device Regulation - EUR-LEX”, 2017).

EU Data Governance Act

The EU Data Governance Act is there to empower safe data sharing and data availability, by eliminating technical obstacles for data sharing (Ministerie van Economische Zaken en Klimaat, 2023). This act encourages organisations (in this case hospitals) to make data available, which could be used for the common good. This act also stimulates the re-use of health data, if this can be done securely. It is therefore important to have an intermediate to share the data through.

Overview

Table 3, gives an overview of the important legislation involving data usage in the (P)ICU.

3.3.4. Data Anonymization and Privacy

To comply with privacy regulations, ICU data systems must incorporate robust anonymization and pseudonymization measures. The distinction between these two techniques is crucial:

- Anonymization ensures that all personal identifiers are removed, making it impossible to trace data back to an individual.
- Pseudonymization replaces personal identifiers with unique codes, allowing controlled re-identification under strict conditions.

For ICU system development, data minimalization is another crucial factor. Hospitals implement strict data governance frameworks to ensure that only the necessary information is collected and processed for ICU operations. Before any data is used for research or system optimization, a data steward evaluates whether the request aligns with legal and ethical requirements.

3.3.5. Access Control and Cybersecurity

Access to ICU patient data must be strictly regulated to prevent unauthorized use while allowing medical teams to retrieve real-time information when needed. Healthcare institutions enforce role-based access controls (RBAC), ensuring that only authorized personnel can access specific patient records. This differentiation is crucial for ICU operations, where doctors, nurses, and administrators require different levels of access.

Furthermore, cybersecurity is a growing concern, particularly in ICU environments where system downtime can have life-threatening consequences. Hospitals must store sensitive ICU data on secure servers located within compliant jurisdictions. Storing healthcare data on non-EU servers (e.g., in the US or China) is legally restricted due to data protection laws.

Data breaches and cyberattacks pose an additional risk. Past incidents, such as cyberattacks on Maastricht University, illustrate how vulnerable healthcare institutions can be to ransomware and hack-

Table 13: Summary of Legislative Acts Relevant to ICU Data and AI Implementation

Regulation	**Key Provisions**	**Implications for ICU Capacity Management**
GDPR	Patient consent, data security, processing limitations	ICU data use must comply with strict privacy laws, requiring anonymization and accountability measures
WGBO	Medical record-keeping, patient rights	Ensures availability of up-to-date patient data for predictive models and capacity planning
Wabvpz	Secure healthcare data processing	Hospitals must enforce strict security measures in data analytics and electronic records
AI Act	AI risk classification, human oversight	ICU AI tools must undergo rigorous validation and ensure transparency
NIS Directive	Cybersecurity measures, incident reporting	Hospitals must strengthen IT security to protect patient data from cyber threats
Medical Device Regulation (MDR)	Safety and performance validation	AI-based ICU tools and medical devices require continuous monitoring and compliance checks
EU Data Governance Act	Secure data sharing	Promotes ethical data reuse and encourages hospitals to contribute anonymized data for medical research

ing attempts. Therefore, ICU system architectures must include multi-layered security measures, such as:

- Encrypted data transmission to prevent interception.
- Authentication protocols (e.g., two-factor authentication) for access control.
- Automated log-out mechanisms to secure unattended workstations.

3.3.6. Conclusion

This section outlines the legal framework relevant to the collection and use of patient data within the ICU, particularly in the context of data-driven system design. Central to this framework is the General Data Protection Regulation (GDPR), which establishes principles such as data minimization, transparency, and accountability. National legislation, including the WGBO and the Wabvpz, further specifies the obligations of healthcare providers regarding patient rights and data security. Additional European regulations, such as the proposed AI Regulation, the NIS Directive, and the Data Governance Act, provide further guidance on risk classification, cybersecurity, and responsible data sharing. These laws collectively underscore the importance of secure data processing, explicit consent procedures, and robust access control. Their implementation is essential for ensuring that ICU data systems align with ethical and legal standards while supporting clinical and operational decision-making.

3.4. Conclusion Literature Review

This chapter has provided an overview of the current state of ICU capacity management, the legal frameworks governing healthcare data, and the potential of new data sources and predictive methods to enhance planning efficiency. Existing ICU planning approaches are predominantly retrospective and limited in responsiveness, particularly within the context of paediatric intensive care. Legal regulations, while posing necessary restrictions on data handling, also offer a structural foundation for responsible system design.

However, the literature reveals a gap between theoretical possibilities and their practical implementation in hospital settings for the PICU. There is limited insight into how capacity planners and clinical staff actually engage with data in day-to-day decision-making. To address this gap, this research includes a series of interviews with professionals involved in ICU planning and data governance. These interviews aim to bridge between existing academic knowledge and real-world practices, providing essential context for the development of an effective and compliant system architecture.

4 Current PICU management

The next chapters will aim to provide the insights gained from the interviews. The aim of this chapter is to identify the structure of the current PICU capacity planning and identify certain barriers and proposed solutions and answers regarding the research question. This deeper understanding of current PICU management practices aligns with the 'discover' phase of the double diamond model. Key insights from all main topics have been derived, which will be added as an improvement to the current system architecture, in Chapter 9.

**Note that the following chapters (unlike chapter 3) are focused on the PICU since most interviews were held with professionals in the PICU department.*

4.1. PICU Unit Composition

PICUs are typically divided into multiple units, each containing a designated number of beds. These units are structured to optimize patient monitoring and staff efficiency. As described by one interviewee:

> **Quotation**
>
> "...the PICU department consists of multiple different units, and in this case, a unit consists of a room with a certain number of beds..."

Additionally, PICUs may include cluster departments, where capacity is planned based on maximum occupancy rather than a fixed number of available staff members. This approach allows for operational flexibility and ensures efficient patient care, even when unexpected admissions arise (Interview, 2024).

It requires a careful balance between available resources and unpredictable patient demand. One challenge is the pre-assignment of beds, which leaves little room for short-term adjustments. Strategic capacity planning also involves long-term assessments of required bed numbers. Historical data and predictive models are used to estimate the demand for PICU beds in future (Interview, 2024):

> **Quotation**
>
> "...At what we call a strategic level, you look ahead for a longer period to determine, for example, how many beds we will actually need in a new construction situation, how many beds we will need for the coming year..."

Hospitals struggle with:

- Aligning staffing levels with predicted (P)ICU demand.
- Managing seasonal variations (e.g., flu season, pandemics)
- Ensuring that (P)ICU teams are neither overworked nor underutilized.

Integrating staff scheduling systems with PICU demand prediction models could help address these imbalances, ensuring that enough personnel are available during peak demand periods without unnecessary overstaffing during quiet periods (Interview, 2024).

(P)ICUs often operate under a structured scheduling system, where operations are planned using fixed scheduling blocks (so-called ”straatjes”). This approach allows for a predictable allocation of PICU beds post-surgery, minimizing fluctuations in daily PICU occupancy. One interviewee described the data-driven adaptation of these planning blocks (Interview, 2024):

> **Quotation**
>
> ”...IC-streets are based on data, so at some point, they look back and say, okay, neurosurgery already had a bed reserved until Monday, but in 80% of cases, that bed was not used, and those departments really want a bed on Monday. So, based on that data, those IC-streets are possibly adjusted...”

However, one of the main challenges in PICU management is handling unplanned admissions, such as emergency cases from operating rooms (OR), emergency departments, or hospital wards. The lack of comprehensive integration between different hospital departments complicates real-time bed allocation and requires improved coordination across units (Interview, 2024).

Technology plays a pivotal role in contemporary (P)ICU management. EHRs facilitate the maintenance of comprehensive and continuously updated patient data, which is accessible to authorized medical personnel. Real-time monitoring systems enable the continuous assessment of vital signs and other critical physiological parameters, thereby allowing for timely and appropriate clinical interventions. Furthermore, advanced data analytics and machine learning algorithms are increasingly employed to forecast patient outcomes and enhance the efficiency and effectiveness of care delivery (Interview, 2024).

4.2. Social Determinants in PICU Planning

At present, PICU planning is based mainly on clinical indicators and expert judgment, rather than predictive models incorporating social and demographic data. During the interviews, the topic of social determinants of health arose organically. Several interviewees reflected on the potential influence of demographic and socioeconomic factors on PICU admissions and capacity planning. However, the general consensus was that social determinants are primarily used for long-term trend analysis rather than for immediate operational decisions in PICU management and come with ethical issues too (Interview, 2024).

Long-term, social determinants are sometimes considered in healthcare forecasting but are not systematically integrated into ICU planning models. The used type of data for the PICU is mainly regarding bed-allocation rather than incorporation with demographics (Interview, 2024).

> **Quotation**
>
> “...Actually, what is being used now is just, in the long term, a bit to see how the beds and such are being allocated...”

While there is potential value in using public health databases or regional patient data to anticipate shifts in ICU demand, its current application is limited to retrospective analysis rather than real-time decision-making. One interviewee mentioned that certain social determinants, such as socioeconomic background, are analyzed in specific studies, but their predictive use remains underdeveloped (Interview, 2024).

Challenges and Ethical Considerations

Even if social determinants were to be integrated into predictive models, challenges remain regarding practical implementation and ethical concerns. Interviewees expressed skepticism about using social or economic status to predict PICU occupancy, as this could lead to generalizations that do not apply at the individual level (Interview, 2024).

Furthermore, certain demographic indicators, such as lifestyle factors, are seen as more relevant for public health policy rather than ICU-specific decision-making. Some interviewees pointed out that variables like education level or financial status are difficult to quantify in a way that meaningfully contributes to PICU planning (Interview, 2024).

Additionally, privacy regulations limit the use of personally identifiable social data in hospital settings, making it difficult to integrate such data into capacity management models (Interview, 2024).

4.3. Current Prediction Method

The largest data-source is the EHR, such as HIX or EPIC.

> **Quotation**
>
> ”The data in HiX forms the backbone of capacity planning, capturing when a patient is admitted, how long they stay, and when they are discharged. This information is crucial for making day-to-day planning decisions.”

Complementing HiX, data from other sources such as regional databases, Excel sheets, and specialized tools is sometimes combined to provide a more comprehensive picture. These additional datasets often include specific patient metrics, departmental reports, or even regional health statistics.

Prediction methods primarily focus on bed occupancy analysis, which depends on factors such as emergency department pressure and surgical department demands. Important parameters include the length of stay for specific patient groups, but it can change depentently on the other departments. One interviewee illustrated this (Interview, 2024):

> **Quotation**
>
> ”...we have, for example, a cardiology ward where actually all cardiology children are supposed to be, we have a neurology and congenital anomalies ward, but at the moment that the cardiology ward is full and the other ward has a spot, then we look within those cardiology children which of those children can then be placed in that other ward, so that the bed can still be optimally utilized...”

According to the interviews the knowledge on the possibilities and integration of prediction methods is still limited.

> **Quotation**
>
> ”...we can have 10 beds at one time, and now for example it is completely full.. I am also curious whether there will ever be a model that could predict this or predict it better...”

Moreover, while some prediction models exist, they are not widely implemented in PICU planning (Interview, 2024).

PICU data is recorded at multiple levels, ranging from general patient information to detailed records of bed utilization, patient admission reasons, and length of stay. Data structuring often involves categorization and labeling to improve usability. A key aspect of this process includes (Interview, 2024):

- Bed occupancy monitoring (frequency, duration, and efficiency of usage)
- Patient flow tracking (admission source, length of stay, and discharge timing)
- Data extraction from electronic patient records (EPR), primarily using systems such as HiX, ChipSoft, and Epic
- The application of data processing tools like Excel, SPSS, and Python for statistical analysis

However, data accuracy remains an issue. Incomplete or imprecise documentation regarding expected patient discharge dates leads to inconsistencies in bed availability forecasts. A patient may be expected to stay for a week but is discharged earlier, affecting predictive accuracy. Data collected from EPDs and monitoring systems are integrated into a data warehouse, forming the basis for predictive modeling. The Business Intelligence (BI) department plays a crucial role in building these models, which rely heavily on historical data rather than real-time forecasting. To improve capacity planning, seasonal patterns are applied to data analysis. Due to disruptions like COVID-19, the chosen seasonal pattern must be carefully selected to ensure it reflects realistic expectations. PICU bed planning also considers occupancy rates and rejection probabilities, adjusting margins depending on department-specific requirements (Interview, 2024).

Comparisons with other ICUs through NICE provide additional benchmarking data, but these reports are based solely on historical data without predictive capabilities.

- Patient flow tracking (admission source, length of stay, and discharge timing)
- Data extraction from electronic patient records (EPR), primarily using systems such as HiX, ChipSoft, and Epic
- The application of data processing tools like Excel, SPSS, and Python for statistical analysis

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> **Quotation**
>
> ”...For ICU management, this process is particularly critical because occupancy rates and the likelihood of rejecting patients play a significant role. While departments with planned care can maintain a certain degree of flexibility, it is essential for the ICU to keep the rejection rate as close to zero as possible...”

4.4. Data Validation and Optimization

A major component of the PICU data analysis process is validation. Before calculations proceed, data undergoes a multi-step verification (Interview, 2024):

- Initial validation ensures completeness and correctness of occupancy rates, admission records, and other key metrics.
- The BI department constructs the calculation model in Structured Query Language (SQL), but the final adjustments and validations are often done in Excel due to its flexibility.

> **Quotation**
>
> ”...We apply data minimization. So we carefully inquire about the purpose of the research and what exactly is needed...”

Strategic proposals and policy decisions sometimes involve the use of five-variant calculations to assess different scenarios, further supporting robust decision-making (Interview, 2024).

4.5. Missing Data

The availability and quality of data play a crucial role in the development of predictive models for ICU capacity management. While it is rare for data to be completely unavailable, inconsistencies, missing fields, and limitations in accessible variables can impact the reliability of these models. Interviewees noted that when certain data points are missing, alternative approaches are often employed rather than discarding the entire dataset (Interview, 2024). One interviewee highlighted the importance of adaptation in the face of missing data:

> **Quotation**
>
> ”... If the data is not available, we do not fill it in. I must say that these types of issues are related to data quality. So, it is actually not that the data does not exist, but rather that it is either incomplete, in the wrong place, or incorrectly entered. However, regarding predictive models, we actually have so much data that you can always choose to use a different dataset or another cohort. So, I have not really experienced data availability as a major problem concerning predictive planning questions. It does happen that we are sometimes not allowed to use the data.”

Despite these adaptive approaches, missing data can still reduce the overall quality of predictive models. One limitation is the reliance on historical data, which may not fully reflect real-time dynamics. This is particularly evident in emergency department (ED) and surgical department predictions, where literature suggests that incorporating additional variables could improve model accuracy. However, as one interviewee explained, models are often designed to function effectively with only a subset of available parameters (Interview, 2024):

> **Quotation**
>
> ”... If ten fields are mentioned in the literature, but we only have eight of them, we do not look for those two additional data points. Instead, we examine whether we can create a valuable predictive model with the eight we do have. Then, we apply a form of deduction...”

Another challenge lies in integrating missing data into predictive frameworks. Some ICU departments, particularly those working with advanced machine learning techniques, are exploring methods to impute missing values rather than disregarding incomplete datasets. This approach is particularly relevant when missing data itself conveys valuable clinical insights, such as in cases where the absence of a specific measurement may indicate patient stability (Interview, 2024):

> **Quotation**
>
> ”...sometimes the absence of data also indicates something about the patient. So, for example, if a patient does not receive a certain measurement, it can sometimes mean that they are actually quite stable, because otherwise, they would have received that measurement...”

To mitigate the risks associated with missing data, PICU management teams employ validation checks at multiple levels. Manual cross-referencing, integration with external databases, and consultations with medical staff are common practices to ensure data accuracy. Despite these efforts, complete data integration remains a challenge due to system fragmentation and differing data structures. Ensuring that missing data does not compromise PICU planning remains an ongoing priority for capacity management teams (Interview, 2024).

Data Models Integration Barriers

During the interviews, the topic of data integration in the PICU emerged as a crucial factor in improving patient monitoring, predictive modeling, and capacity planning. The ability to seamlessly integrate different data sources into a centralized Electronic Patient Record (EPR), such as HiX, is essential for enhancing real-time decision-making, predictive analytics, and resource allocation in the ICU (Interview, 2024).

However, several technical, organizational, and practical challenges hinder full integration of ICU data, including real-time monitoring data, AI-driven predictions, and wearable technology inputs. Interviewees emphasized that while some progress has been made, true integration remains a work in progress.

One of the key technical barriers to PICU data integration is ensuring that monitoring data, AI-driven insights, and capacity planning information can be combined into a single platform, while maintaining data security and system compatibility. Although hospitals are already working on integrating monitoring data, full integration with personalized medicine technologies is still in development (Interview, 2024). However, the practical implementation of this integration is complex. It is not just about extracting data, but also ensuring that it is usable and accessible within the existing hospital infrastructure:

> Quotation
>
> "...We first have to look at whether we can even make that kind of data available in the EHR, or at least in some kind of layer around the EHR. So that doctors can see what a smartwatch or another wearable provides in terms of information, so that they can include that in an analysis. But to immediately push through and build all kinds of AI on top of that, that seems to me — for healthcare — still a few steps too far in the short term..."

This highlights an important tension in PICU data integration—while technical feasibility exists, practical implementation and usability for clinicians remain challenges.

Barriers to Integrating PICU Data with Hospital-Wide Systems

Hospitals rely on large-scale EPR systems like HiX, which are designed for standardized medical data storage. However, deviating from these standards to integrate new types of PICU data, such as real-time patient monitoring or AI-generated predictions, is difficult (Interview, 2024):

> Quotation
>
> "...That is the disadvantage with HiX indeed. It is a system that is used worldwide, with standards, but if you want to deviate from those standards, then many people have to agree to deviate from that standard before it can be integrated. So that is still a hurdle...."

Additionally, adding external applications to complement HiX does not necessarily simplify the proces. Beyond technical restrictions, hospital workflows also create barriers. Different types of ICU data serve different purposes, making full integration complex, Instead of full integration, a more layered approach might be necessary, where different ICU data streams interact without forcing them into a single rigid system (Interview, 2024).

4.6. Decision-making in Pandemics

During the interviews, the topic of pandemic decision-making naturally emerged, particularly in relation to (P)ICU capacity planning, data collection, and forecasting models. The COVID-19 crisis highlighted both the potential and limitations of predictive models in emergency situations. While forecasting tools were developed to predict (P)ICU demand, real-time crisis management often overruled data-driven decision-making, as hospitals had to act swiftly under rapidly changing conditions. Several respondents noted that the (P)ICU had to be rapidly scaled up within a matter of days, highlighting the inflexibility of pre-existing planning models and the need for more dynamic, data-driven approaches (Interview, 2024).

4.6.1. The Role of Predictive Models in Crisis Situations

The COVID-19 pandemic led to an increased focus on ICU forecasting models, as hospitals sought to predict surges in patient admissions. However, despite their potential, these models were not widely utilized in real-time crisis decision-making, as urgency often took precedence over long-term projections. One interviewee described how predictive modeling was considered but not fully integrated during the pandemic response (Interview, 2024):

> Quotation
>
> "During COVID, I wasn't working there at the time, but I know that they were asked to help with predictive models, because it had such a large impact."

One of the main challenges in pandemic forecasting is the unpredictability of novel viruses. While seasonal influenza waves can be anticipated based on historical patterns, the exact timing and severity remain uncertain, making preemptive scaling of ICU capacity difficult (Interview, 2024):

One interviewee emphasized the unpredictability of the influenza season, explaining that although it is typically expected to start in late October, actual peaks may occur much later, as seen last year when the wave only intensified in January. Hospitals are therefore required to maintain maximum ICU capacity for extended periods, without clear indications of when a surge will occur. This uncertainty complicates decision-making, as hospitals must balance surge preparedness with the continuation of routine care (Interview, 2024).

4.6.2. Limitations of (P)ICU Forecasting During Pandemics

One of the biggest lessons from the COVID-19 crisis was that decision-making in a pandemic is highly dynamic and often overrides pre-existing models. While ICU demand predictions were attempted, the immediate nature of the crisis meant that hospitals relied more on ad-hoc responses than on pre-calculated forecasts. An interviewee reflected on why predictive models were not widely used during the peak of the pandemic (Interview, 2024):

> **Quotation**
>
> “...they thought, well, maybe we can help with predicting how the impact will be if there’s a new wave of the pandemic. But what I know from my colleagues is that at the time of the crisis, the feeling of crisis and decision making was so high and everything had to be decided so fast that there was no time to look at these models...”

Another major issue in pandemic forecasting is the lack of comparable historical data. While previous outbreaks such as SARS or the Spanish flu provide some insights, each pandemic behaves differently, making it difficult to generalize predictions. One interviewee reflected on the limitations of predictive modelling in the context of pandemics, emphasizing that responses are often ad-hoc due to the unpredictability of emerging threats. Relying solely on the COVID-19 pandemic as a reference point was considered insufficient, as future pandemics may follow entirely different patterns. The interviewee noted that meaningful forecasting would require data from multiple past pandemics, which is currently lacking (Interview, 2024).

This highlights a fundamental limitation in pandemic modeling—without sufficient historical cases, reliable prediction models are difficult to develop.

4.6.3. Lessons from COVID-19

Despite these challenges, some useful patterns were identified during COVID-19 that helped guide decision-making. Comparing real-time data from other countries enabled hospitals to anticipate the next phase of the pandemic and take preemptive measures: One interviewee pointed out the value of international comparisons during the COVID-19 pandemic, noting that observing developments in other countries, particularly when not being the first affected — provided useful insights. Similar epidemiological patterns across countries allowed for short-term anticipation of national trends, such as predicting when a peak would occur based on others’ experiences. This suggests that international data-sharing and real-time monitoring may offer more practical value in future pandemics than relying solely on historical predictive models. Furthermore, hospitals are now exploring long-term ICU crisis management strategies, including (Interview, 2024):

- Surge capacity planning: Preparing for pandemics or mass casualty incidents.
- Flexible staffing models: Allowing ICU personnel to be redeployed quickly.
- Inter-hospital coordination: Ensuring better regional ICU patient distribution and improving general wards.

4.7. Dashboarding

Hospitals are developing predictive and integrated dashboard tools to estimate ICU demand and discharge timelines, but real-time implementation remains a challenge (Interview, 2024).

> **Quotation**
>
> "I think we need a dashboard that is linked to HiX, the patient system, which displays a predicted discharge date for each patient and the hospital they are being transferred to. And that updates in real time."

A well-integrated model should be able to link PICU planning to hospital-wide patient flows, ensuring that critical care units are neither overwhelmed nor underutilized. Improved real-time forecasting would not only assist in bed allocation but also help optimize staff deployment, ensuring that nursing and medical teams are appropriately assigned based on projected patient acuity. It is important to analyse strategies to have enough data available in shared data set, while de-identifying the data at the same time. Also within the hospital, in order to properly make use of the models and secure technical efficiency, staff training and a learning environment should be encouraged. Moreover, to ensure optimal data quality, management should invest in the development of tools to create accurate models and timely access to data. On an managerial industrial level, it is important to create binding regulations on sharing datasets and on semantic definitions within datasets (Interview, 2024).

4.8. Capacity Planning and Real-Time PICU Data Use

From a capacity planning perspective, data integration could improve ICU efficiency by providing real-time insights into bed availability and patient needs. However, interviewees noted that current PICU data systems still lack predictive tools for real-time capacity forecasting and that it would be useful to integrate prediction models in the EPD. One proposed solution is to develop a dynamic dashboard linked to the ICU's EPR and patient management system, which would track patient status, predict discharge times, and update in real-time (Interview, 2024):

> **Quotation**
>
> "We need to have a dashboard that is linked to HiX, to the patient system, which displays a predicted discharge date per patient and the hospital it will go to. And that updates in real time."

However, integrating wearable technology and AI-driven predictive analytics into ICU workflows would require a significant expansion of computing infrastructure:

> **Quotations**
>
> "So then you're assuming that we're going to use those wearables and all those technical gadgets. There would have to be a really big computer for that."
>
> "Also that data—managing it and being able to find it back in the right place—is a thing. But I think that, especially when it comes to wearables, you would want to act on that directly. You would want to see that data directly in your file. Well, then your integration with your EHR, with a party like HiX, is definitely a challenge, because they are, first of all, not very keen on it. Secondly, yes, you know, there are so many different wearables, systems, integrations, that it becomes very challenging for such a vendor....."

4.8.1. Broader hospital resource management

Ensuring PICU availability requires a combination of historical data analysis and dynamic forecasting models. One crucial aspect is maintaining a buffer of available PICU beds to accommodate critical cases. Additionally, tactical planning meetings help assess upcoming staffing and resource needs (Interview, 2024):

> **Quotation**
>
> ”...If you look ahead, how will you manage with your staff? Will you even be able to keep those beds open? For us, it’s manageable, but if you look nationwide at the staff shortage in healthcare… So, you do try to consider that. Will we be able to keep those beds open? If not, where can we make the best choices? How can we adjust for that? This is done in the tactical planning meeting, where the supply side is considered, looking at what actions need to be taken...”

Moreover, PICU capacity cannot be considered in isolation from the hospital’s total care capacity. A holistic approach, integrating ICU planning with broader hospital resource management, is essential for optimizing patient flow and minimizing strain on the healthcare system.

By refining bed allocation strategies, improving coordination between hospital departments, and leveraging data-driven scheduling adjustments, PICUs can enhance their ability to manage patient demand while maintaining high-quality care (Interview, 2024).

4.8.2. Enhancing PICU Capacity Utilization through Real-Time Monitoring

One of the most critical areas for PICU improvement is ensuring that beds and resources are used as efficiently as possible. Currently, PICU beds are often occupied for longer than necessary due to delays in discharge or lack of visibility into patient flow. A centralized monitoring system, similar to an air traffic control tower for patient movement, could help manage PICU resources more effectively (Interview, 2024).

> **Quotation**
>
> “Such a “capacity cockpit”—which is already in use in some U.S. hospitals—could provide real-time visibility into where each patient is, what procedures are pending, and what steps need to be taken to facilitate faster transitions to other departments. This would reduce unnecessary ICU occupancy and allow for more efficient use of resources.”

This type of system could allow nursing teams to coordinate with pharmacy, radiology, and hospital administration to ensure that patients are transferred as soon as possible, freeing up PICU beds for those in critical need (Interview, 2024).

4.9. Financial and Structural Barriers to PICU Improvement

While technological advancements and process optimizations could greatly enhance PICU efficiency, financial constraints remain a significant barrier. Many improvements require upfront investments, which may not always align with hospital financial priorities.

Potential solutions to overcome financial barriers which came forward from the interviews include (Interview, 2024):

- Government or insurance incentives for ICU optimization projects.
- Collaborative funding models that allow hospitals to share resources.
- Investment in AI-driven automation, reducing manual administrative workload and improving efficiency.

4.10. Reducing Delays in Patient Transfer and Discharge

Another mentioned recurring issue from the interviews in (P)ICU efficiency is the delay between when a patient is ready for transfer and when they actually leave the ICU. Data analysis has shown that many patients remain in the ICU for days longer than necessary due to administrative and logistical barriers (Interview, 2024).

Reducing these delays requires:

- Better coordination with downstream hospital departments to ensure bed availability.

- Streamlining discharge procedures to avoid unnecessary administrative bottlenecks.
- Developing predictive tools that flag patients who are likely to be ready for transfer soon, allowing proactive discharge planning.

By improving PICU outflow, hospitals can increase the number of patients who receive critical care without needing to expand physical capacity.

4.11. Positive directions for PICU management

Despise the growing enthusiasm for predictive models in ICU management, several barriers remain (Interview, 2024):

1. **Limited interoperability** – PICU models must integrate seamlessly with existing hospital IT infrastructures, particularly EHR systems like HiX.
2. **Resistance to change** – Many PICU staff are accustomed to experience-based decision-making, making it essential for predictive models to be intuitive and clinician-friendly.
3. **Uncertainty in predictive modeling** – While AI can estimate patient trajectories, it cannot replace clinical judgment, and unexpected complications can alter patient courses.
4. **Data privacy and security** – Integrating real-time ICU data with external predictive systems must adhere to strict security regulations to protect patient confidentiality.

Future improvements could involve better integration of predictive algorithms and data analytics to refine capacity planning, since the current system remains reliant on historical data and manual adjustments, limiting its forecasting accuracy. To ensure successful implementation, future predictive models should:

- Incorporate real-time clinical data rather than rely solely on historical trends.
- Allow dynamic adjustments to adapt to unexpected patient changes.
- Present insights in a way that is intuitive for medical professionals.

In order to facilitate development it is important to enhance data-sharing, so that multi-center datasets can be set up for daily clinical use. This can enhance the generalization of the datasets and derived models. Furthermore, predictive analytics can optimize patient care and resource management. Currently, decision-making is often reactive, based on experience and intuition rather than real-time data as said in the interviews. This section will go more in depth in possible future adjustments.

Predictive Models

Predictive models could help ICU teams anticipate changes in patient conditions, optimize bed usage, and allocate staff more effectively. However, adoption remains slow due to concerns about trust and interpretability. To ensure widespread acceptance, predictive models must be (Interview, 2024):

- Clinician-friendly, providing clear, actionable insights.
- Continuously updated with real-time patient data.
- Integrated into ICU workflows without adding administrative burden.

Hospitals that have implemented predictive analytics in ICU management can analyse bed turnover rates, length of stay, and staff allocation more precise.

ICU capacity planning is a cornerstone of effective management, ensuring that resources align with patient needs. Key considerations include:

- Strategic (long-term) predictions: Estimating yearly demand based on population health trends, surgical scheduling, and epidemiological data.
- Tactical (mid-term) predictions: Forecasting weekly ICU admissions, factoring in seasonal variations, emergency admissions, and planned procedures.
- Operational (real-time) predictions: Providing daily or hourly insights into ICU occupancy levels, allowing managers to dynamically adjust resources.

4.12. Conclusion

This chapter examined the current state of I(P)ICU capacity management based on insights from interviews with professionals involved in clinical planning, data governance, and hospital operations. The findings reveal that current systems pronamely rely on manual processes, fragmented data sources, and retrospective models, which limit responsiveness and predictive accuracy. While Electronic Health Records (EHRs) like HiX and Epic form the backbone of data collection, integration with real-time monitoring, wearable technology, and predictive analytics remains limited.

Capacity planning is largely structured around historical trends and static scheduling blocks, with limited use of dynamic forecasting. Challenges include inconsistent data quality, limited interoperability, and delays in patient discharge, all of which hinder optimal PICU bed utilization. Financial constraints and structural barriers further complicate system innovation. Nonetheless, there is a growing recognition of the need for real-time dashboards, federated data-sharing models, and integrated decision-support tools to enhance PICU efficiency. These insights provide a crucial foundation for developing a future-oriented, data-driven system architecture, discussed in the following chapters.

5 Legislation

The development of a new PICU system architecture requires a deep understanding of legal and ethical regulations surrounding patient data. Given the complexity of intensive care monitoring, the integration of real-time analytics, and predictive modelling, compliance with privacy laws, consent requirements, access controls, and cybersecurity protocols is crucial. Regulations such as the General Data Protection Regulation (GDPR) and national healthcare policies impose strict guidelines to protect patient privacy while ensuring data availability for medical decision-making and research.

5.1. Ethical Oversight and Compliance Frameworks

All PICU system architectures must comply with institutional and national regulations. Before any new system can be deployed, ethical review boards (such as the Medical Ethics Review Committee (METC)) evaluate its alignment with GDPR and healthcare privacy standards (Interview, 2024).

Hospitals also have dedicated legal and privacy officers who assist in ensuring compliance. In institutions like Erasmus MC, a data board is responsible for reviewing system policies and updating them when necessary. If an existing policy is insufficient for a new (P)ICU data management system, new legal frameworks are developed to ensure compliance (Interview, 2024).

5.2. Implementation of Data Sharing

Data sharing is a critical component of modern PICU management, enabling hospitals to collaborate on patient care, optimize resource allocation, and advance medical research. However, implementing efficient data-sharing strategies is fraught with technical, ethical, and regulatory challenges. The interviews revealed that while progress has been made in interoperability, data security, and international collaboration, significant barriers remain, particularly regarding insurance constraints, regulatory compliance, and technological limitations (Interview, 2024).

5.2.1. The Necessity of Data Sharing in PICU Environments

External health data from other institutions such as other hospitals, social determinants and healthcare providers is also integral to (P)ICU management. This data includes information about a patient's recent healthcare visits, medications, social environment, and chronic conditions, providing a comprehensive view of their health (Kwaliteitsstandaard Organisatie van Intensive Care, 2016). Sharing PICU data across hospitals and healthcare systems has the potential to improve clinical outcomes, enhance predictive modeling, and streamline capacity planning. However, hospitals must navigate conflicting priorities between patient care, financial sustainability, and privacy regulations. One interviewee expressed concern about the implications of being funded by health insurers. They noted that while insurers are invested in maintaining population health, they are equally interested in obtaining information about individuals' health conditions. According to the interviewee, this necessitates careful consideration of what information is disclosed and what remains confidential. They concluded by stating that, in their view, this balance is currently being managed well (Interview, 2024).

5.2.2. Benefits of PICU Data Sharing:

PICU data sharing comes with the following benefits (Interview, 2024):

- Optimized resource allocation: Hospitals can balance patient load across PICUs by identifying real-time capacity.
- Enhanced predictive analytics: Shared data improves AI-driven models that forecast PICU demand and patient outcomes.
- Benchmarking and quality improvement: Hospitals can compare PICU performance metrics, such as length of stay and mortality rates, with peer institutions.
- Facilitating research and innovation: Shared datasets accelerate clinical research and drug development.

Despite these benefits, interoperability remains a significant challenge in PICU data-sharing initiatives as mentioned by different interviewees due to certain data standards. According to insights from the interviews, data privacy and access control are actively enforced within the hospital's digital infrastructure. Access to patient data is role-dependent, with each staff member operating under a unique identification number that restricts the scope of information they can view. For example, administrative personnel such as secretaries have access to different sets of information compared to medical coordinators or clinical staff. This hierarchical structure ensures that sensitive patient data is only visible to individuals directly involved in clinical decision-making or patient care, in line with privacy regulations and institutional policy (Interview, 2024).

5.2.3. Implication for Data Collection PICU System Architecture

One of the key legal requirements in the PICU is obtaining explicit parental/guardian consent before collecting and utilizing personal health data. The specificity of consent in medical settings presents a major challenge, particularly in the PICU where patients often require continuous monitoring and dynamic treatment plans. Currently, patient data usage is treatment-specific, meaning each new medical condition or research purpose requires separate approval (Interview, 2024).

This case-by-case approach to consent complicates the implementation of an integrated ICU system, as real-time monitoring technologies generate continuous streams of patient data that might require retrospective approval for extended usage. A more centralized consent system, allowing ICU patients (or their representatives) to grant broader data permissions at the beginning of their admission, could enhance system functionality. However, this requires alignment with ethical standards and legal regulations governing informed consent (Interview, 2024).

5.2.4. Technical and Organizational Barriers to Data Sharing

PICU data management faces several key challenges (Interview, 2024):

1. **Data Security and Compliance Concerns:** Ensuring secure and ethical data exchange is a priority in (P)ICU settings, especially given the sensitivity of patient information. Strict privacy regulations limit how PICU data can be shared.

   Key security barriers include:

   - **General Data Protection Regulation (GDPR)** in Europe, which restricts sharing personal health data.
   - **Institutional policies** that limit data sharing beyond hospital networks.
   - **Concerns over data misuse** by commercial entities or insurance providers.

2. **Regulatory Restrictions and Insurance Barriers:** Hospitals operate in a fragmented regulatory environment, making it difficult to standardize in (P)ICU data sharing.

> **Quotation**
>
> ..."we're struggling with that in Brabant in the project that I'm working on, we trying to collaborate through the whole healthcare chain, but the hospital is not allowed to provide patient data, only to a nurse/doctor, they have a relation to the patient. But on large scale you're not allowed to share personal data."

Moreover, insurance companies play a role in shaping (P)ICU data-sharing policies, as financial incentives often dictate whether hospitals prioritize collaboration.

> **Quotation**
>
> "...as soon as you start using it as steering information for your operations, of course, your agreements with health insurers are also linked to it...'

These restrictions hinder hospitals from collaborating on predictive modeling and capacity planning, as sharing real-time PICU data with external parties is often prohibited.

3. **Lack of Standardized Data-Sharing Platforms:** The absence of a centralized, standardized system makes PICU data exchange fragmented and inefficient.

> **Quotation**
>
> "'...I think it is very important to also move towards a regional and national data exchange platform, yes, because right now it is still very much like: I send something to Maastricht. But actually, you want an amazon.com for research data, where everyone can access what they are allowed to have. Without us having a one-on-one relationship every time, like: okay, I am sending it to the line now. Have you received it on the other side? So, much more can be automated..."

Existing initiatives, such as Healthery, have attempted to streamline ICU data sharing, but adoption remains slow due to bureaucratic and logistical hurdles. Challenges are found in establishing large data sharing structured platforms in the Netherlands. The platforms would be useable as they could easy datasharing adequately, as also an automated-solution is valuable (Interview, 2024).

5.2.5. European and International ICU Data-Sharing Models

Some European ICUs are participating in a secure federated data-sharing model, where hospitals retain local data while contributing to a centralized analysis system (Interview, 2024).

> **Quotation**
>
> "The children's ICU here is involved in a large European collaboration. Where they have a kind of structure in place. That everyone keeps their data locally, and that there is then a server with a kind of codebook that knows exactly: How does everyone's data look, and which data is collected everywhere? Without actually having patient data, but literally just the code of the data. And that if you want to perform an analysis on all that data, you then send a request to the central code. That translates it into all local datasets. That then sends back: this is the analysis you need to perform. Then they run it locally and return the results. So that you don't have to work with the data itself, but only with your analysis plan and your results.."

This approach protects patient privacy while allowing large-scale PICU data analysis. Within the Netherlands, regional ICU benchmarking is becoming more common, but hospitals remain cautious about sharing real-time operational data (Interview, 2024).

5.2.6. Future Directions: Overcoming PICU Data-Sharing Barriers

Despite the challenges, there is a growing recognition that more effective PICU data sharing is essential for capacity management, research, and quality improvement (Interview, 2024):

> **Quotation**
>
> "Everyone is realizing that AI and advanced analytics require more data. The medical field is actively seeking ways to relax some of the barriers while ensuring security."

5.2.7. Strategies for Improving PICU Data Sharing

The interviews showed that certain strategies could improve ICU settings' data sharing (Interview, 2024):

- Developing secure federated data-sharing models: Similar to the European children's ICU initiative, enabling hospitals to run local analyses while maintaining data privacy.
- Creating a national data-sharing infrastructure: A standardized PICU data exchange platform across Dutch hospitals would reduce inefficiencies.
- Aligning financial incentives: Hospitals require clear funding structures to prioritize data-sharing initiatives.
- Improving interoperability: Standardized healthcare data formats and API-based integrations can improve real-time data exchange.
- Enhancing regulatory frameworks: Policy adjustments could facilitate responsible data sharing while maintaining patient privacy.

5.3. Conclusion

This chapter explored the legal, ethical, and operational conditions necessary for enabling effective data use and sharing within PICU environments. A key requirement for system development is compliance with strict privacy legislation, including the GDPR, alongside institutional oversight from ethics committees and dedicated privacy officers. Although data sharing holds significant potential for improving clinical outcomes, predictive accuracy, and system-wide efficiency, several barriers have an effect on its implementation. These include fragmented regulations, limited interoperability, insurance-driven constraints, and the lack of a unified data-sharing infrastructure.

Interview findings suggest that secure shared systems, such as a platform for data exchange, and improved technical standards may offer viable pathways forward. These insights are essential for informing the design of a legally compliant and future-oriented PICU architecture, as developed in the following chapters.

6
Hospital Internal and External Collaboration Systems

This chapter emerged from the interview data, which is necessary input to create the new system architecture and understanding the current system architecture. During the interviews, the importance of collaboration—both within the hospital and with external organizations—emerged as a key factor in ensuring effective PICU capacity management, patient flow, and data sharing. The PICU is not an isolated entity; it relies on coordinated efforts with other hospital departments, such as emergency care, ORs, and general wards, as well as external partners, including regional hospitals, rehabilitation centers, and home care providers.

While collaboration is necessary for efficient patient care, interviewees highlighted several barriers that hinder seamless communication, data exchange, and decision-making.

6.1. Internal Collaboration: PICU Coordination with Other Hospital Departments

One of the most critical internal collaborations for the PICU involves aligning with the emergency department and the OR. Many (P)ICU admissions are the result of emergencies or planned surgeries, meaning that coordination with these departments is essential for predicting PICU occupancy (Interview, 2024).

> **Quotation**
>
> "Because the ICU is, in principle, not the owner of patients — they do not have their own patients. They have patients from other hospital departments. So if you plan those well, you can use the ICU more effectively."

This interdependency requires clear communication and real-time data exchange, but current systems are not always well-integrated, leading to inefficiencies. The emergency can be somewhat predicted, and that directly impacts PICU admissions. The same goes for surgery schedules—more surgeries mean more PICU admissions. It's always a result of another department's planning decisions. However, PICU planning differs from other departments because many admissions are unplanned and depend on acute medical needs. Unlike surgical or general hospital wards, the PICU must maintain a buffer of available beds to accommodate unexpected critical patients (Interview, 2024).

To improve coordination with internal departments, interviewees suggested that more structured forecasting models and cross-departmental planning tools are needed. Also, according to the interviews, PICU admissions are closely tied to surgery schedules. However, due to limited integration with OR and acute care planning systems, many PICUs lack direct insight into upcoming operations, leading to last-minute bed shortages and planning difficulties (Interview, 2024).

6.2. External Collaboration: Managing PICU Patient Flow Beyond the Hospital

PICUs must also coordinate with external healthcare providers, including regional hospitals, rehabilitation centers, and home care services. The transfer of PICU patients to other facilities is critical for freeing up PICU capacity, but delays in patient discharge often create bottlenecks (Interview, 2024).

> **Quotation**
>
> ”Because I currently have a student who is looking into how much delay there is — in days — between the moment that patients actually meet the criteria to be transferred and the moment they are actually transferred. Well, that delay is really enormous; there are only a few patients who are transferred within 3 days after they are actually ready.”

Similarly, in regional networks, hospitals must coordinate patient transfers to balance PICU capacity across different facilities. This became particularly relevant during the COVID-19 pandemic, where ICU capacity had to be managed across multiple hospitals. One interviewee highlighted the significant staffing shortages in regions such as The Hague. She explained that when maternity wards or clinics are forced to close due to insufficient personnel, surrounding hospitals experience a sharp increase in patient inflow. This, in turn, leads to sudden surges in demand for intensive care services. According to the interviewee, such fluctuations are difficult to anticipate and largely beyond the hospital's control (Interview, 2024). These examples highlight the need for better regional coordination, ensuring that PICU beds across different hospitals are used efficiently.

6.3. Barriers to Effective Collaboration

Despite the need for stronger internal and external collaboration, interviewees pointed out several barriers that make coordination difficult (Interview, 2024):

1. Lack of real-time data sharing – While electronic patient records (EPRs) like HiX contain essential information, they do not always facilitate real-time collaboration between departments or hospitals.
2. Rigid hospital structures – Decision-making within hospitals is often hierarchical, making cross-departmental coordination slow and bureaucratic.
3. Staffing shortages – The PICU often operates at maximum capacity, meaning that collaborating with external facilities for patient transfers is challenging if there are not enough available beds or staff elsewhere.
4. Limited forecasting tools – While some predictive models exist, they are not yet fully integrated into hospital planning systems, making it difficult to anticipate patient flow changes across departments.

6.4. Opportunities for Improvement

To overcome these challenges, interviewees suggested several improvements in collaboration systems (Interview, 2024):

- Developing shared forecasting models that link PICU occupancy predictions with the emergency department, OR, and general ward capacity.
- Creating regional PICU capacity dashboards that allow hospitals to coordinate patient transfers more effectively.
- Improving cross-departmental communication through structured daily planning meetings between PICU, emergency department, and OR teams.
- Enhancing real-time data exchange through better EPR integration and digital collaboration platforms.

The importance of interdepartmental coordination in hospital settings was highlighted through two separate interviews. Both interviewees emphasized the need for a real-time, integrated system to visualize and manage the interdependencies among PICU capacity, operating room schedules, and emergency department activities. Specifically, respondents proposed implementing a centralized dashboard displaying key data such as expected PICU discharge times, thereby enabling hospitals to achieve improved planning efficiency, resource utilization, and patient flow management (Interview, 2024).

6.5. Hospital System Influence

During the interviews, the topic of hospital-wide influence on decision-making and system limitations emerged as a key factor affecting PICU capacity, planning, and innovation. The hospital as an institution operates within a complex network of hierarchical structures, financial constraints, and workforce limitations, all of which influence the ability to implement changes effectively (Interview, 2024).

From medical decision-making and personnel shortages to financial pressures and hospital culture, several barriers and constraints shape the hospital's operational reality. These factors not only affect PICU planning but also broader strategic decisions on patient care and innovation adoption (Interview, 2024).

6.6. Organizational Constraints: Workforce and Decision-Making Power

One major challenge mentioned by interviewees is the imbalance in staffing resources and decision-making power. Healthcare institutions often have disproportionate workforce distributions, making scalable solutions essential to managing workload efficiently (Interview, 2024). This highlights the need for systems that empower staff across departments, reducing dependency on centralized decision-makers and promoting autonomy in hospital processes (Interview, 2024).

Additionally, the hierarchy within hospitals influences decision-making power, with doctors often having the final say in treatment pathways and resource allocation. This can create bottlenecks in operational processes, especially when non-medical professionals attempt to introduce efficiency improvements. Newcomers or external consultants without a healthcare background often face resistance when attempting to introduce change. However, demonstrating genuine interest and collaboration can help bridge this gap as mentioned in an interview.

This underscores the importance of institutional knowledge and interdisciplinary collaboration in hospital-wide decision-making.

6.7. Model Acceptance and Understanding

The successful implementation of predictive models in PICU management is not solely dependent on their technical accuracy; it also hinges on their acceptance by healthcare professionals and decision-makers. A model must be trusted, understood, and integrated into existing clinical workflows to be effectively utilized. Several interviewees emphasized that trust in these models is built through validation, transparency, and positioning them as supportive tools rather than absolute decision-makers (Interview, 2024).

One interviewee highlighted the iterative nature of model validation, stressing that confidence is only gained after careful assessment of model output and after validation. Another key factor influencing model acceptance is the ability of medical staff to understand how a model operates. Without clear explanations, even statistically robust models risk being disregarded by healthcare professionals who need to justify their decisions (Interview, 2024). Moreover, the positioning of predictive models as decision-support tools rather than decision-making systems appears to significantly impact their acceptance. Physicians and clinical staff are more likely to engage with models when they perceive them as augmenting rather than replacing their professional judgment (Interview, 2024).

Ensuring that predictive models are dynamic and adaptable is also critical. If a model fails to account for evolving patient conditions, its recommendations may be dismissed. PICU environments require models that continuously adjust based on new patient data and clinical updates (Interview, 2024).

6.8. Conclusion

This chapter discusses the importance of collaboration in managing capacity within PICUs. Interviews revealed that effective coordination with departments such as emergency care, operating theatres, and general wards is essential for maintaining patient flow and utilizing available resources efficiently. Beyond the hospital, collaboration with regional healthcare institutions, including other hospitals, rehabilitation centres, and home care providers, is crucial to ensure continuity of care and to relieve pressure on PICU beds.

Several barriers were identified that complicate this collaborative process. Delays in patient discharge often create bottlenecks within the PICU, particularly when transfers depend on the availability of beds or staff in other departments or external facilities. A lack of real-time data exchange and rigid hospital structures further limit the ability to respond quickly to changing situations. Moreover, staffing shortages and limited forecasting capacity make it difficult to anticipate and manage sudden increases in patient demand, especially during regional surges.

Interviewees proposed several ways to improve coordination. Suggestions included implementing shared forecasting tools that link PICU projections with emergency and surgical departments, enhancing electronic patient record systems to support real-time collaboration, and establishing regional dashboards to support coordinated patient transfers. Structured daily planning meetings between departments were also mentioned as a potential means to improve communication.

The broader hospital system also plays a role in shaping PICU capacity management. Institutional hierarchies, financial limitations, and cultural factors influence how decisions are made and how innovations are introduced. The distribution of decision-making power can slow down efforts to improve efficiency, particularly when proposals come from outside traditional clinical leadership.

Finally, the successful adoption of predictive models in the PICU context depends not only on their technical accuracy but also on the extent to which they are accepted by clinical staff. Trust in these models is strengthened through validation and clear communication about their purpose and limitations. When such tools are positioned as supportive instruments rather than replacements for clinical judgment, healthcare professionals are more likely to integrate them into daily decision-making. In the PICU environment, where conditions change rapidly, it is especially important that predictive tools are dynamic and responsive to real-time developments.

7
Current System Architecture

This chapter outlines the current structure of PICU capacity planning as observed in practice, building on the theoretical foundations established in the literature review. Within the current system architecture, much of the work performed by the PICU capacity management team remains manual. After data is extracted from databases such as HiX and other national sources and loaded into data warehouses, it is then processed and prepared for PICU prediction purposes. These databases primarily provide metrics such as Length of Stay (LoS) and patient classifications. PICU capacity predictions, including bed and staff requirements, are calculated using tools such as SPSS or Excel. Once the data is analyzed and structured, it is presented to decision-makers through visualization tools such as Power BI. These calculations and predictions are typically performed on an annual basis and communicated to the PICU management board, which then decides whether to adhere to these forecasts or adopt an alternative plan.

This chapter reflects the 'define' phase of the Double Diamond model, where the problem space is narrowed down through structured analysis. By examining the current system architecture and identifying its operational and data-related limitations, this stage builds on earlier exploration and sets the foundation for the development of an improved system design.

Despite its functionality, the current system architecture faces several challenges. As highlighted in the interviews, one of the main issues lies in the limited integration of data across different departments. PICU patients often come from a variety of hospital departments, which makes effective data-sharing beneficial. The current setup does not fully enable seamless data integration from these sources, resulting in gaps in predictions and operational inefficiencies. Interviewees pointed out that improving predictions for acute and critical care patients — particularly those coming from departments like the OR — would provide a clearer and more actionable picture of PICU patient inflow. Another limitation of the existing system is its reliance on annual predictions. While sufficient in stable circumstances, this approach is not always ideal in dynamic situations, such as during pandemics, where patient demand can shift unpredictably. Constantly updating predictions with real-time or near-real-time data would provide more accurate and timely insights, enhancing PICU capacity management and enabling quicker responses to sudden surges in demand. Creating a specialized department to address these challenges may be impractical, as noted in the interviews. However, incorporating predictive analytics into the existing system could present a viable solution. Predictive tool could streamline data integration and enhance the accuracy of predictions without requiring significant structural changes. These tools would allow for more precise forecasting and resource allocation, enabling PICU teams to adapt more effectively to changing conditions.

Throughout this thesis the legend in Figure 4 will be used for the system architectures.

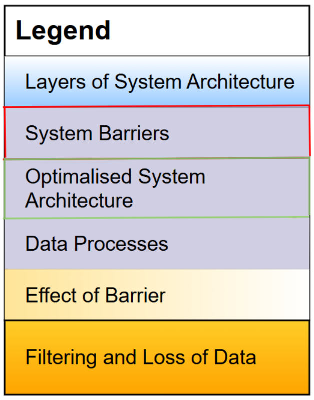

Figure 4: Legend System Architecture

7.1. The PICU system architecture

The interviews and literature gave some insights into the PICU system architecture, which will be described in this section.

7.1.1. Data extraction

Data extraction and analysis are pivotal to ICU capacity management. Data is typically retrieved from HiX and processed through tools such as Power BI, Excel, or statistical software like SPSS. These tools allow for both operational and strategic decision-making:

- Operational Analysis: Addressing short-term planning, such as determining daily bed availability and staff allocation.
- Strategic Analysis: Identifying long-term trends and forecasting future needs based on historical data.

Data extracted from electronic patient records (EPDs) is primarily stored in HiX. From there, a data warehouse is created, enabling structured data management for both operational and strategic purposes. One interviewee described this process:

> **Quotation**
>
> ”……the EPD is automatically accessed by the data warehouse/data platform, the Health Data Platform (HDP). There we combine everything in a way that makes it recognizable to the end user and then it is made available to, in this case, integrated capacity management. They do the management reports regarding capacity and capacity management. The other information is used by the Intensive Care itself and may also be available from the HiX. So it could also be that they get that information from HiX for operational use. If you use it for management and for looking at: how can we plan better? Then it is taken from the HDP…”

7.1.2. Processing and Integration of Data

Once extracted from HiX, data undergoes multiple processing steps before it can be utilized effectively. One expert explained this workflow (Interview, 2024):

Quotation

"...The first step is to extract the raw data. The second step is enriching the data with what we call business terms so that someone on the other end can recognize it. The third step is modeling in FIRE, and FIRE is an exchange standard, essentially a type of messaging service. That is one route. The second route is dimensional..."

Processed data is then integrated into various analytics platforms where dashboards and reports are generated. Additionally, predictive models can be developed using SAS and AI/ML solutions. These models, while not specifically designed for capacity management, serve other analytical purposes within the organization.

7.1.3. Data Storage and Business Intelligence

Some hospitals have acquired large servers to store and manage their data internally. While HiX remains the primary data source, additional resources such as business intelligence and data analytics departments contribute to building a centralized data infrastructure. As one interviewee explained (Interview, 2024):

Quotation

"...we create standard dashboards that can be easily shared and can then be used by management to make decisions. So they need that information to make certain decisions. And on the other hand, these are more analytical matters, where you try to perform a capacity calculation or conduct a specific analysis of a particular patient group and their process trajectory. This is then discussed together with the client, the person posing the question, and sometimes proposals for advice come from my side, from the capacity management department. But sometimes the line manager picks it up, or they don't, and just leave it aside.."

7.1.4. Layering the Current system architecture

Using the insights from the interviews and the literature review, each layer of the current system architecture can be described as provided in Figure 5

Layer 1: Data Sources and Collection

The foundation of the PICU system architecture lies in the collection of patient data from various sources, including EDPs such as HiX, PICU monitoring devices, and manually recorded data from other hospital departments. While these sources provide essential information for PICU capacity planning, the lack of seamless integration results in inefficiencies and delays in data availability.

Currently, much of the patient information, including LoS predictions and patient classifications, is entered manually into HiX or local EDP systems. This process increases the risk of human error and inconsistencies in data reporting. Additionally, PICU monitoring data, such as real-time vital signs, ventilator settings, and sensor inputs, is not automatically centralized but remains stored in individual departmental systems. Clinicians are required to manually retrieve and cross-check patient data across multiple platforms, leading to inefficiencies in decision making and delays in patient care.

Beyond internal hospital data, external data sharing remains underdeveloped. Information exchange with insurers, research institutions, and other ICUs is still conducted through static reports, rather than through automated data-sharing frameworks. This lack of real-time integration prevents effective benchmarking and collaborative decision-making between institutions.

Layer 2: Data Processing and Storage

Once data is collected, it must be processed and stored in a structured format that allows for effective reporting and analysis. However, in the current system, data processing remains largely manual, with minimal automation in transferring information between different hospital departments. This results in fragmented data management structures that hinder a comprehensive view of patient flow and capacity planning.

PICU, OR, and emergency department data are stored in separate, non-integrated systems, making it difficult to track a patient's journey through different hospital units in real time. Since these data silos are not interconnected, PICU managers must rely on retrospective reports rather than real-time insights when making capacity decisions. Additionally, reporting tools such as Power BI primarily provide static analyses rather than dynamic monitoring, further reducing the system's responsiveness to sudden surges in patient admissions.

The lack of a centralized, continuously updated PICU data warehouse further exacerbates these challenges. Without a unified system that consolidates all relevant data streams, decision-makers are forced to rely on outdated information, which limits the accuracy of capacity predictions and delays responses to critical situations.

Layer 3: Decision Support and Reporting

Effective PICU management requires robust decision-support tools that allow for predictive capacity planning and dynamic resource allocation. However, in the current system, decision-making remains largely experience-based, with static forecasting methods that do not leverage real-time patient data.

PICU capacity predictions, including bed and staff requirements, are primarily calculated using tools such as SPSS or Excel. These forecasts are typically generated on an annual basis and rely heavily on historical data rather than on automated predictive models. While this approach may be sufficient under stable conditions, it lacks the flexibility needed to respond to unpredictable events, such as pandemic-related surges in patient demand.

Another limitation is the lack of real-time dashboards for PICU performance monitoring. Existing reports provide only retrospective analyses, preventing clinicians from dynamically adjusting capacity based on evolving patient needs. Additionally, coordination between the PICU and other hospital departments remains manual, making it difficult to anticipate patient transfers and optimize resource allocation.

Layer 4: Operational PICU Management

Daily operations within the PICU rely on structured workflows for staff scheduling, bed allocation, and patient flow management. However, these processes remain largely manual, leading to inefficiencies in resource utilization and capacity planning.

Staffing levels and nurse-to-patient ratios are determined using static schedules, rather than dynamically adjusting based on real-time patient acuity and workload distribution. This can result in situations where PICU staff are either overburdened or underutilized, depending on fluctuations in patient admissions. Additionally, bed allocation does not integrate seamlessly with OR scheduling or emergency admissions, leading to capacity mismatches and bottlenecks in patient flow.

A positive implementation would be an PICU "cockpit", system — a centralized platform that consolidates key operational data for real-time decision making. Without such a system, clinicians must manually coordinate patient transfers, which can lead to delays in discharges and inefficient use of available PICU beds. Moreover, there remains a degree of reluctance among PICU staff to adopt predictive models for capacity planning, as many clinicians continue to rely on experience-based decision-making rather than data-driven insights. Moreover, healthcare specialist do not always have enough time to report what findings would be vauable for them to have in a prediction model.

Layer 5: External Collaboration and Data Sharing

The final layer of the PICU system architecture involves external collaboration with other hospitals, insurers, and research institutions. While these partnerships are essential for improving patient outcomes and optimizing resource utilization, the current system lacks structured and automated frameworks for seamless data sharing.

PICU performance benchmarking across hospitals is limited due to data silos, preventing institutions from comparing patient outcomes and implementing best practices. Reporting to insurers remains a manual process, which delays reimbursement procedures and reduces efficiency in financial planning. Furthermore, regulatory restrictions hinder efforts to establish real-time data-sharing networks that could facilitate coordinated regional responses during crises.

The absence of an automated inter-hospital PICU network is particularly problematic in emergency situations, where dynamic resource allocation across multiple hospitals could significantly improve patient care. Without such a system, hospitals are forced to manage PICU capacity in isolation, rather than leveraging regional data to optimize bed availability and staffing levels.

The current System Architecture Model
The current PICU system architecture consists of multiple layers, each responsible for specific functions within data collection, processing, decision support, operational management, and external collaboration. While this structure provides a clear framework for PICU capacity management, it also reveals significant inefficiencies, particularly in terms of data integration, automation, and real-time decision-making. The reliance on manual data processing, retrospective reporting, and fragmented coordination between hospital departments limits the ability to anticipate and respond to changing patient demands. A detailed examination of each layer highlights the specific challenges and areas for improvement within the existing system.

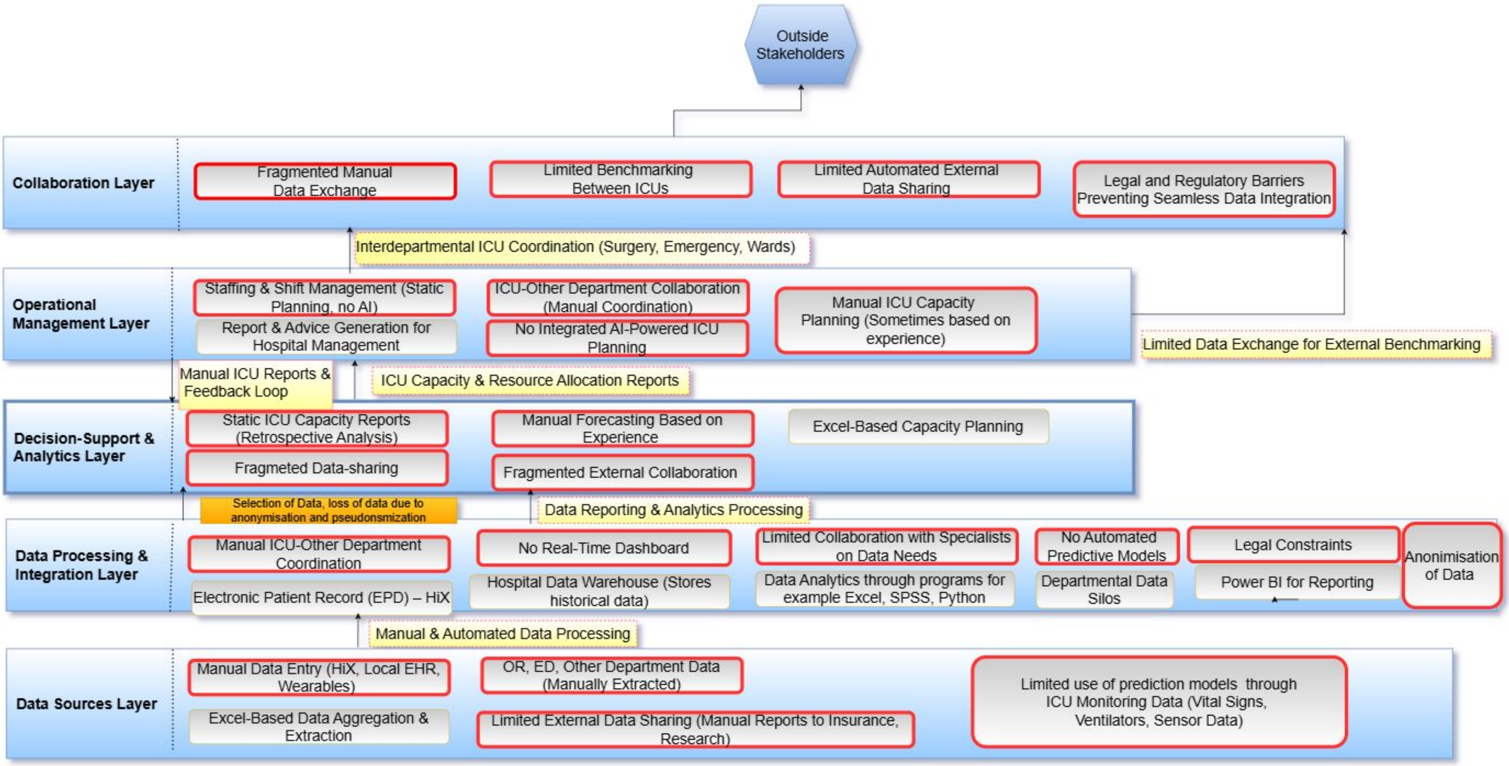

Figure 5: Current System Architecture PICU

7.1.5. Challenges in System Integration and System limitations

A significant challenge lies in the integration of collected data with the EPD. Despite the benefits of linking external sources, full integration remains complex (Interview, 2024):

Quotation

"...one of the challenges will be that the systems have different data architectures in themselves. And I don't know if they really have to be integrated, but in an ideal world you would probably want that, but I don't see that that will really happen. But yeah, the patient monitoring is very much aimed at the now — the real-time monitoring of data — and it is relevant for the present, because you want to know how the patient is doing. The planning data is more relevant for how we can make sure that we plan things better in the future. So they all have different time horizons.. And I don't see how you will integrate that really fully to be honest..."

Another challenge is the fragmented nature of ICU-related systems. One expert highlighted the difficulty of harmonizing various standalone solutions:

> **Quotation**
>
> ”...There are already four or five systems within the ICU that are disconnected or working stand alone and they’re all relevant. If you talk about architecture, the question is how are these systems related, but often they are sort of standalone...”

According to the interviews, despite its functionality, the current system architecture faces several limitations: 1. Data Interoperability: Integrating multiple data sources remains labor-intensive and prone to inconsistencies. 2. Real-Time Insights: The reliance on historical data makes it difficult to adapt to unexpected ICU demand fluctuations. Future improvements should focus on better system integration, enhanced real-time analytics, and advanced predictive modeling to optimize ICU capacity management.

7.2. Conclusion

The current PICU system architecture, while operational, exhibits significant inefficiencies that limit its ability to optimize resource allocation and improve patient outcomes. The reliance on manual data entry, retrospective reporting, and fragmented capacity planning creates bottlenecks that reduce responsiveness to changing patient demands. Data silos between hospital departments and the absence of real-time dashboards further hinder effective decision making.

Addressing these limitations requires a fundamental shift towards automation, real-time data integration, and predictive analytics. Implementing a centralized PICU data warehouse, along with automated forecasting models, would enhance the accuracy of capacity planning and improve operational efficiency. Additionally, the development of an PICU ”cockpit” system would allow for dynamic oversight of patient flow, staffing, and bed availability.

To improve external collaboration, structured and secure data-sharing frameworks must be established to enable real-time benchmarking and inter-hospital coordination. By addressing these issues, the PICU can transition towards a more integrated and predictive system architecture, capable of adapting to both routine operations and emergency scenarios. These improvements will be explored further in the discussion of the future PICU system architecture.

8

New beneficial Data, Prediction methods and architecture recommendations for PICU Capacity efficiency

Following the analysis of the current ICU system architecture presented in the previous chapter, several structural and operational limitations were identified. This chapter builds upon those insights by exploring new forms of beneficial data and forecasting methods that could support more responsive and efficient ICU management. These findings will serve as key input for the next chapter, which proposes a future-proof system architecture tailored to the evolving demands of critical care environments.

8.1. Adaption of Machine Learning

The integration of AI and ML into ICU prediction models presents significant opportunities for improving forecasting accuracy. AI-based models can analyze vast amounts of clinical data and detect patterns that may be overlooked by human decision-makers. However, AI implementation remains challenging, particularly due to concerns about interpretability and trust among medical staff. This is also mentioned in one of the interviews:

> Quotation
>
> "A predictive model will only be used if medical professionals trust it. If it deviates even slightly from expectations, people won't use it."

A successful AI-driven ICU forecasting model should:

- Be transparent in its decision making process to gain clinician trust.
- Allow for manual adjustments based on real-time patient conditions.
- Continuously refine its predictions based on updated clinical inputs.

Moreover, AI-driven forecasting could extend beyond patient admission estimates and assist in predicting disease progression, complications, and deterioration risks. This could enable ICU teams to preemptively intervene, thereby improving patient outcomes and reducing ICU burden. One interviewee mentions the use of a sepsis prediction model. Despite these advantages, AI-based forecasting must align with the practical needs of ICU staff, ensuring that predictions are not just accurate but also actionable.

8.2. Current Applications and Potential Benefits

One of the most promising developments is remote patient monitoring, where patients can remain at home while their vital parameters are continuously tracked. If abnormal readings occur, hospital staff are alerted to intervene before a critical situation arises. As one interviewee explained:

> **Quotation**
>
> “...There is also, so to speak, a kind of home monitoring being done. So that the patient is actually at home and certain body functions are then measured. The reading of that is then done here in the hospital. At the moment that it has a certain abnormal score, the hospital actually contacts the patient and says, well, we expect that you should come by after all, because then we can conduct a further examination...”

In addition, wearables are increasingly being considered for integration into EPRs, allowing real-time patient data to be included in clinical decision-making. However, data accessibility and integration with hospital systems remain obstacles. Another interviewee emphasized the importance of first ensuring data availability before advancing toward AI-driven models (Interview, 2024):

> **Quotation**
>
> “...We first need to see whether we can even make that kind of data available in the EHR or, in any case, in some sort of layer around the EHR. So that doctors can see what a smartwatch or another wearable provides in terms of information, allowing them to incorporate that into an analysis. But to immediately follow through and build all sorts of AI on top of that, I think—for healthcare—that is still a few steps too far in the short term.”

Personalized medicine regarding staffing models is also being explored as a solution to staffing shortages in healthcare. By shifting more monitoring and care to home-based settings, hospitals could reduce ICU admissions and alleviate pressure on critical care units, which could have a positive effect in dealing with the shortages. The use of telemedicine plays a key role in this transition, enabling healthcare professionals to remotely monitor patients, offer consultations, and intervene when necessary—without requiring physical presence in the hospital. This not only improves efficiency but also expands access to care for patients in remote or less accessible areas.

The integration of wearable devices, medical devices, and remote monitoring technologies as also mentioned above, has the potential to significantly enhance ICU capacity prediction by providing continuous, real-time data. These technologies support advanced data analytics and predictive modeling, which are crucial for improving ICU management, especially in the context of legal and technical constraints. A significant untapped resource for ICU predictive modeling is the vast amount of real-time data generated by patient monitoring systems, wearables, and bedside sensors. These devices continuously collect vital signs, movement patterns, and other physiological indicators, which could provide early warnings for clinical deterioration. However, this data is not yet fully integrated into predictive systems. An interviewee mentiones that the models to make use of the data coming from bedsite monitors and wearables for the PICU are not available yet.

One interviewee pointed out that this shift is not just an opportunity but a necessity:

> **Quotation**
>
> “..On the other hand, but that is then more looking towards the future, with the shortages of people who want and can go work in healthcare versus the ever-increasing care demand. I think that it also almost is a kind of task to work towards that, so that you need as few people as possible here in the care institution itself. And people simply, as much as possible, could be helped in home situation...”

Key findings have been summarized in Table 14

Table 14: Summary of Key Findings and Improvement Areas

Key Area	Findings and Recommendations
Data Integration	Current ICU systems face challenges in integrating data from different sources, including monitoring devices, EPRs (HiX), and predictive analytics. Standardization and interoperability are needed.
Predictive Analytics	The adoption of AI-based predictive models remains low due to concerns about trust, interpretability, and real-time integration. Models must be transparent, adaptable, and clinically relevant.
ICU Capacity Forecasting	Hospitals rely on historical trends rather than real-time demand forecasting. Improved predictive tools could optimize bed allocation, staff planning, and patient transfers.
Data Sharing and Privacy	GDPR compliance and data anonymization remain barriers to seamless data exchange. Hospitals need secure, federated data-sharing models that balance privacy and utility.
Collaboration and Patient Flow	ICU efficiency is heavily dependent on coordination with emergency departments, OR, and rehabilitation centers. A real-time coordination system is needed to reduce transfer delays.
Staffing and Resource Allocation	Hospitals face challenges in aligning ICU staffing with predicted demand. Integrating predictive modeling into workforce planning could help optimize staff deployment.
Future ICU System Architecture	A new system should include real-time dashboards, automated data extraction, AI-driven forecasting, and centralized capacity management. Interoperability and clinician adoption are key success factors.

The findings highlight that while some predictive models and data-sharing mechanisms exist, their adoption is hindered by concerns about usability, interpretability, and regulatory constraints. The role of legislation, particularly GDPR compliance and data anonymization, remains a critical factor in shaping ICU system design. Furthermore, internal and external collaboration within hospitals was identified as a major determinant of ICU efficiency, with bottlenecks in patient transfers and discharge processes contributing to capacity mismanagement.

From a technological perspective, the study underscores the necessity of integrating real-time data, predictive analytics, and AI-driven decision support tools to optimize ICU performance. Future improvements should focus on creating dynamic dashboards for real-time patient flow monitoring, refining predictive models for length-of-stay estimations, and developing standardized frameworks for data exchange between hospital departments.

The proposed enhancements aim to transition the ICU from a reactive management approach to a data-driven, proactive system architecture. However, achieving these improvements requires overcoming resistance to change, addressing financial and organizational constraints, and ensuring that predictive models are effectively integrated into clinical workflows.

8.3. Conclusion

This chapter has outlined critical bottlenecks and improvement areas in current ICU operations, highlighting the need for more responsive, data-driven system design. It emphasizes the importance of integrating real-time information flows, efficient capacity planning, and seamless interdepartmental coordination.

Building on these findings, the next phase of this research will propose a redefined ICU system architecture that better aligns technological capabilities with clinical and organizational realities, with the ultimate goal of improving care delivery and operational resilience.

9 Future System Architecture

Building on the insights gained from the analysis of the current PICU structure in the previous chapter, this chapter focuses on the design of a future system architecture that addresses existing shortcomings and supports more proactive and data-driven capacity management.

Developing a new system architecture for the PICU is essential for addressing the limitations of data integration, real-time decision making, capacity planning, and interdisciplinary collaboration. The current PICU infrastructure struggles with fragmented data management, lack of predictive capabilities, and a reactive approach to patient care. A future-proof PICU system must be interoperable, real-time, predictive, and fully integrated with hospital-wide decision making tools.

The Future PICU System Architecture represents a significant advancement over the current fragmented system, focusing on real-time data integration, predictive decision support, and automated capacity management. By transitioning from manual, retrospective decision making to automated, AI-driven processes, the PICU can optimize patient care, resource allocation, and interdepartmental coordination. This layered model builds upon the current system but incorporates technological innovations that improve data collection, processing, decision making, operational execution, and external collaboration. Each layer of the system incorporates advanced technological solutions that facilitate seamless data flow, predictive insights, and dynamic resource allocation.

9.1. Limitations of the Current PICU System

The existing PICU system lacks real-time insight, making proactive decision making difficult. Many decisions are still based on historical data and intuitive estimations rather than real-time predictive analytics. The fragmentation makes it difficult to coordinate between departments, leading to bottlenecks in patient flow and suboptimal use of PICU capacity.

Additionally, while predictive models exist, they are not yet fully embedded in decision making processes. PICU managers do not have immediate access to AI-generated forecasts for bed occupancy, patient deterioration, or discharge planning, making real-time adjustments challenging.

Another challenge is data extraction and system rigidity. The EPR (HiX) currently does not provide real-time insights in a structured way, and integrating AI-driven tools requires lengthy approval processes and system adaptations (Interview, 2024).

> **Quotation**
>
> ”It would, from HiX, of course, be pleasant if there were also somewhere a button that lets us see all of that at once with a capacity prediction.”

These limitations slow down decision making, create inefficiencies in resource allocation, and limit the ability to anticipate PICU needs effectively.

9.2. Key Components of the New PICU System Architecture

To overcome these limitations, the new PICU system architecture must integrate real-time data, predictive modeling, and centralized decision support tools. The proposed system is structured around four key pillars:

1. **Standardized Data Collection and Integration:** To create a unified PICU management system, it is essential to establish standardized definitions for capacity, patient flow, and discharge criteria. Currently, each department uses different parameters, leading to inconsistencies in decision-making.

   A hospital-wide data governance model is required, ensuring that all data inputs, from patient monitoring systems to EPR records, adhere to a shared standard. Additionally, PICU data must be fully integrated with OR and emergency department planning systems, allowing for accurate forecasting of PICU admissions and reducing unexpected patient surges.

2. **Real-Time Data Extraction and Automated Processing:** A major limitation of the current system is the inability to access real-time insights. The new architecture must support real-time data extraction from EPR systems, monitoring devices, and AI-driven analytics platforms.

   This will be achieved through:

   - Automated data pipelines that extract and process PICU data continuously.
   - Real-time dashboards displaying patient status, PICU occupancy, and staffing needs.
   - Instant notifications for PICU managers when critical capacity thresholds are reached.

   Instead of waiting for manual data extraction and interpretation, PICU teams will have immediate access to the most relevant information, enabling them to make informed decisions faster.

3. **AI-Driven Predictive Analytics for PICU Management:** To optimize ICU capacity, predictive analytics should be embedded directly into the decision-making framework. AI-driven models will (Interview, 2024):

   - Forecast PICU bed demand based on historical trends and real-time patient inflow.
   - Predict length of stay for each patient, enabling better discharge planning.
   - Anticipate staffing shortages based on seasonal trends and real-time workforce data.

   > **Quotation**
   >
   > ”I think we need a dashboard that is linked to HiX, to the patient system, which shows per patient a predicted discharge date and the hospital where the patient will go. And that updates in real time”

   By embedding predictive models directly into PICU dashboards, hospitals can anticipate demand more accurately, optimize resource allocation, and reduce operational inefficiencies.

4. **Centralized Capacity Management Cockpit:** A real-time capacity management cockpit will act as the central decision-making hub for PICU teams. This cockpit will provide (Interview, 2024):

   - A real-time overview of PICU capacity and resource availability.
   - Dynamic updates on pending patient transfers, discharge approvals, and OR schedules.
   - Automated prioritization of PICU admissions based on real-time severity assessments.

   > **Quotation**
   >
   > ”If you have a good overview of that in some kind of cockpit, then you can also make much better use of the ICU. There are a few—you should look it up on YouTube—videos related to a capacity cockpit. I believe there are a number of hospitals in America that have that. What you then see is that you have such an air traffic control tower where a number of nurses are sitting who monitor where a patient is at that moment.”

This integrated approach ensures that PICU managers are continuously aware of patient flow dynamics and can respond immediately to capacity challenges.

9.3. The Future of PICU System Architecture

The next-generation PICU system will rely on automation, AI-driven analytics, and real-time data processing to transition from a reactive to a proactive PICU management model as can be seen in the Future System Architecture Figure 6.

Key Focus Areas for Future Development:

1. Seamless real-time data sharing across PICU, OR, and emergency departments.
2. AI-powered predictive modeling for PICU occupancy and staffing optimization.
3. Stronger interdisciplinary collaboration through integrated data platforms.
4. Advanced patient monitoring systems that feed directly into decision-support dashboards.

By eliminating data silos, improving predictive accuracy, and enhancing real-time decision-making, the PICU will transition from a fragmented system to a fully optimized, data-driven architecture.

This renewed system architecture ensures that PICU resources are used as efficiently as possible, patient care is optimized, and hospitals are better prepared for capacity fluctuations and crisis situations.

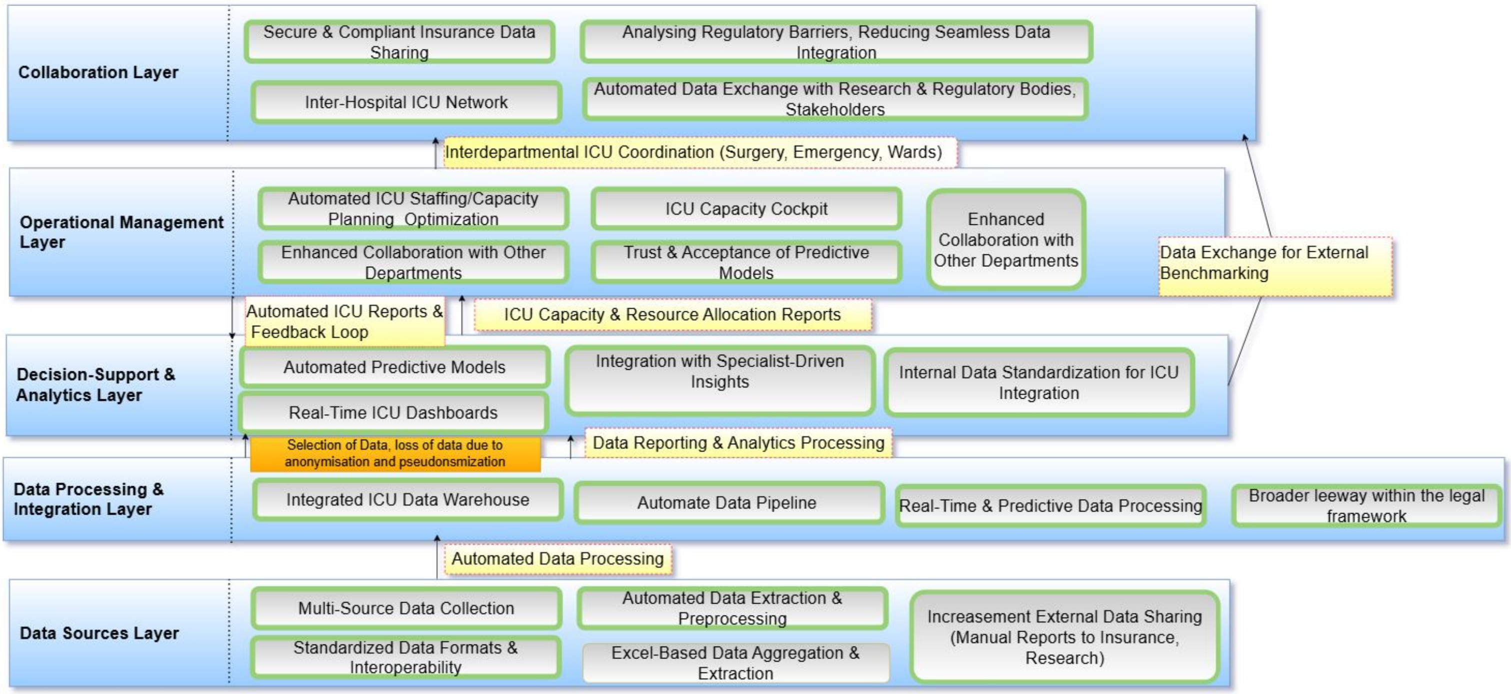

Figure 6: Future System Architecture PICU

9.3.1. Layer 1: Data Sources & Collection

The foundation of the future PICU system is a robust data ecosystem that collects structured and unstructured data from multiple sources in real-time. Instead of relying on manual data entry, the system implements automated extraction from wearables, PICU devices, and hospital-wide monitoring systems. These real-time data streams provide continuous updates on patient conditions, treatment effectiveness, and PICU occupancy.

A crucial improvement is the standardization of data formats using Fast Healthcare Interoperability Resources (FHIR) and HL7 protocols, ensuring seamless data exchange across departments and institutions. This standardization allows PICU data to be integrated with external sources such as national health databases and research institutions. Additionally, compliance with GDPR and AVG regulations ensures that patient privacy is maintained while allowing secure and efficient data sharing.

9.3.2. Layer 2: Data Processing and Integration

To enhance the accessibility and usability of PICU data, the manual data processing methods of the current system could be replaced with automated data pipelines. These pipelines facilitate direct integration with PICU monitoring devices, eliminating the delays and errors associated with manual data transfers. This system processes both real-time and historical data, enabling continuous updates to PICU predictions and patient flow analysis.

A centralized PICU data warehouse could be implemented to consolidate all relevant patient information, including real-time monitoring data, laboratory results, and predictive analytics. The warehouse supports both cloud-based and on-premises storage options, incorporating high-security encryption to ensure data integrity and compliance with privacy regulations. Through these improvements, PICU decision-makers have immediate access to structured and up-to-date patient information.

9.3.3. Layer 3: Decision-Support and Predictive Analytics

The future PICU system transitions from experience-based decision-making to a data-driven approach supported by AI-powered predictive models. These models analyze patient data in real-time to forecast PICU capacity needs, predict discharge timing, and assess patient risk levels. By integrating machine learning algorithms trained on historical and live patient data, the system enhances the accuracy of PICU resource planning.

A significant addition is the implementation of real-time dashboards that provide PICU managers and clinicians with comprehensive visualizations of PICU occupancy, patient acuity levels, and staffing requirements. These dashboards will integrate live monitoring data with predictive analytics, allowing for proactive adjustments to capacity planning. Collaboration with medical specialists is essential to ensure that predictive models align with clinical decision-making processes and gain acceptance among healthcare professionals.

9.3.4. Layer 4: Operational PICU Management

PICU operations are transformed from reactive, manually managed processes to proactive, to data-driven resource allocation. Staffing levels and shift planning could dynamically be adjusted based on real-time patient acuity and predicted admissions. AI-driven workforce optimization tools analyze PICU demand patterns and recommend staffing changes to ensure optimal nurse-to-patient ratios.

Another critical addition is the PICU Capacity Cockpit, a centralized control system designed to monitor and optimize PICU resource distribution. This system, inspired by aviation-style monitoring rooms, provides real-time insights into bed availability, patient transfers, and staff workload. By automating the coordination of patient movements between the PICU, general wards, and step-down units, the system minimizes inefficiencies and reduce delays in patient discharges.

Ensuring clinician trust in AI-driven models is a key priority. To facilitate adoption, predictive tools should be designed with transparent validation mechanisms, clear explainability, and user-friendly interfaces. Regular training programs and integration with clinical workflows, further support the transition to data-driven PICU management.

9.3.5. Layer 5: External Collaboration and Data Sharing

The final layer of the future PICU system architecture focuses on structured and secure data exchange between hospitals, insurers, and research institutions. Instead of relying on manually generated reports, automated data-sharing agreements ensure that PICU performance metrics are continuously updated and accessible for benchmarking, research, and financial planning.

To comply with regulatory requirements, AI-driven anonymization techniques should be implemented to protect patient privacy while allowing for large-scale data analysis. An inter-hospital PICU network should be established to facilitate regional collaboration, enabling hospitals to dynamically allocate PICU capacity in response to surges in demand. This network allows real-time monitoring of available PICU resources across institutions, improving overall healthcare system resilience.

9.4. Conclusion

The future PICU system architecture represents a fundamental shift from manual, retrospective planning to an automated, predictive, and data-driven framework. By integrating real-time data collection, predictive analytics, and dynamic operational management, the new system enables PICU teams to respond more effectively to fluctuating patient demand.

Key improvements include the implementation of automated data extraction, AI-driven decision-support models, and a centralized PICU Capacity Cockpit for real-time resource management. Additionally, secure and structured external collaboration enhances PICU benchmarking, research opportunities, and coordinated regional crisis response. These advancements ensure that PICU resources are utilized efficiently while maintaining the highest standards of patient care.

This model transforms PICU management from a reactive, manually coordinated system into a data-driven, proactive decision-making framework, ensuring that patients receive the best possible care while maximizing resource efficiency.

10 Validation

To validate the proposed system architecture, this study employed expert interviews for feedback on the models created in Chapter 7. The validation process focused on assessing the feasibility and completeness of the conceptual design in relation to real-world PICU practices and opportunities. The Double Diamond model informed the validation strategy, framing this phase as a reflection of the "delivery" stage—although full implementation and testing were beyond the scope of this thesis.

During the interviews two open questions were asked:

1. *In what ways does the current model reflect (or not reflect) the actual situation?*
2. *How attainable do you see the proposed future model, and what changes would make it more feasible in practice?*

This chapter aims to provide a new Future System architecture, based on the validation process.

10.1. Validation Current System Architecture Model

The validation interviews revealed that the model does not differ in terms of future development, but the current situation varies between pediatric and adult ICUs.

> **Quotation**
>
> '…from what I know about it and the perspective I have on it, it does indeed make sense, and I can also see the similarities with how it is going now.'

Specifically, the components in a setting of adult ICUs are more readily available, as it is more structured and integrated across various layers, and is implemented more broadly in comparison to the PICU. It was also noted that not all hospitals use SPSS and Python in the same way, particularly for practical service delivery.

Both interviews revealed that the model accurately reflects the current state of affairs, particularly with regard to the pediatric ICU. The interviewees understand the model and its practical implications, and they highlighted the challenges and potential areas for improvement, as indicated in green in Figure 8. Additionally, one interviewee mentioned that health data platforms, such as those for research or management reporting, are in use and actively generate dashboards for the ICU. Data extracted from the HiX system is processed into a data hub, which then contributes to the dashboarding (Interview, 2024).

Furthermore, both interviewees acknowledged the legal and regulatory barriers surrounding the exchange of external data. With larger data volumes, more accurate predictions can be made. One of the interviewees shared an example of a data-exchange platform between hospitals, though it remains unclear whether this system is automated, as the data is manually entered regarding bed occupancy at each hospital, which presents a disadvantage compared to real-time data (Interview, 2024).

It was also shared that management teams receive information from external departments and organizations, such as quality reports, which contribute to ICU operations and would also be relevant for the PICU (see Figure 8). The effect of available capacity in the Emergency Department or OR was also more clearly articulated. In the data processing layer, the EPR has been moved to the data source, where information is extracted to a higher layer, specifically the process and integration layers (Interview, 2024).

The current system architecture after validation is shown in Figure 7.

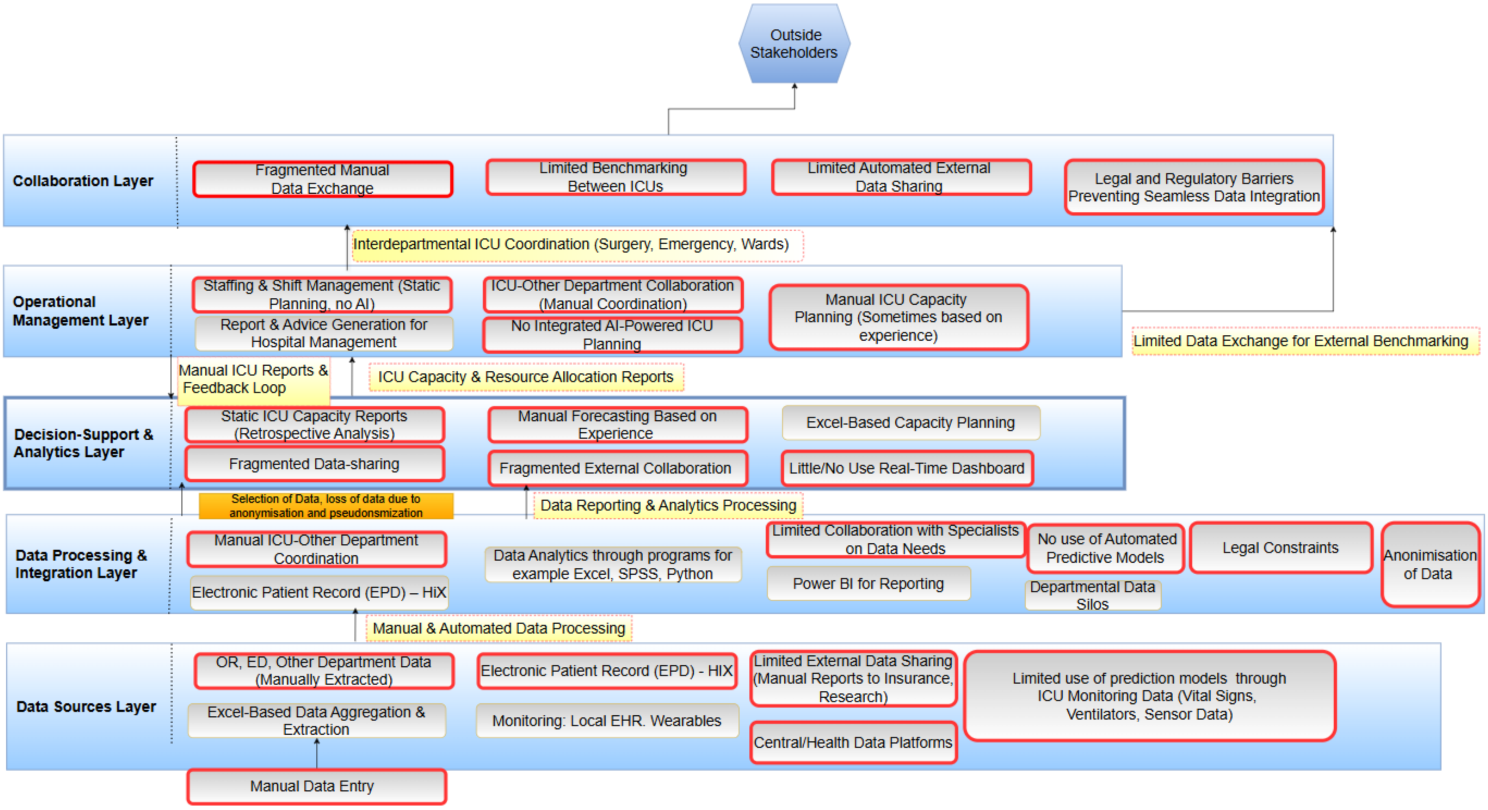

Figure 7: Current system architecture PICU after validation

10.2. Validation Future System Architecture Model

Looking to the future, the interviewees indicated that they understood the model and its practical implications, as well as the challenges and areas for improvement. Although many data-related tools are already available in the adult ICU, they are either underutilized or unknown in the pediatric ICU. Significant efforts are being made at a central level to invest in such infrastructures, but specialization for the ICU is still needed, and it must be actively utilized. The data support and decision-making layer is more developed for adult ICUs. One of the interviewees suggested that in the future, data could be automatically processed through AI, enabling faster decision-making. This is particularly relevant for situations where decisions are often made at the last minute due to time constraints, or when decisions are made with the assumption that they no longer matter. Expanding predictive models, such as the existing sepsis predictors, was also highlighted as a key area for development (Interview, 2024).

The data processing layer was further discussed in terms of potential collaboration between different stakeholders. The interviewees pointed out that broader platforms already exist and could be enhanced with larger, integrated data warehouses, which would make them more valuable for the entire hospital system. This would enable a more focused approach to the ICU, as opposed to only operating within its confines. It was mentioned that data on the influence of the OR and emergency department would thereby result for better PICU predictions. Such platforms, using real-time data and AI, would allow for proactive predictions, such as forecasting longer patient stays (Interview, 2024).

One of the interviewees also discussed the advantages of AI, noting that real-time AI-driven predictions could be used to forecast longer patient stays, moving from a reactive to a proactive approach.

Finally, regarding management, the interviewees highlighted several benefits of AI: the numerous intermediaries involved in decision-making slow down processes, whereas AI would allow for quicker decisions.

> **Quotation**
>
> "...I definitely think that, at the moment, when you use AI in real time and based on predictions, you gain insights more quickly, and that speeds up the process. Because right now, someone notices something, but that person then has to approach someone else, who in turn has to discuss it or something. So there are so many intermediate steps that it really slows things down.

It was also noted that while the value of data is not lost as initially thought, it may become less valuable due to anonymization. This can be mitigated or controlled depending on the level of anonymization applied (Interview, 2024). However, the data is lost in the sense that in the step after anonymization that particular data is not further incorporated.

Taking these advancements into account as well as the advancements mentioned in 10.1, the Future System Architecture after validation can be visualized as shown in Figure 8.

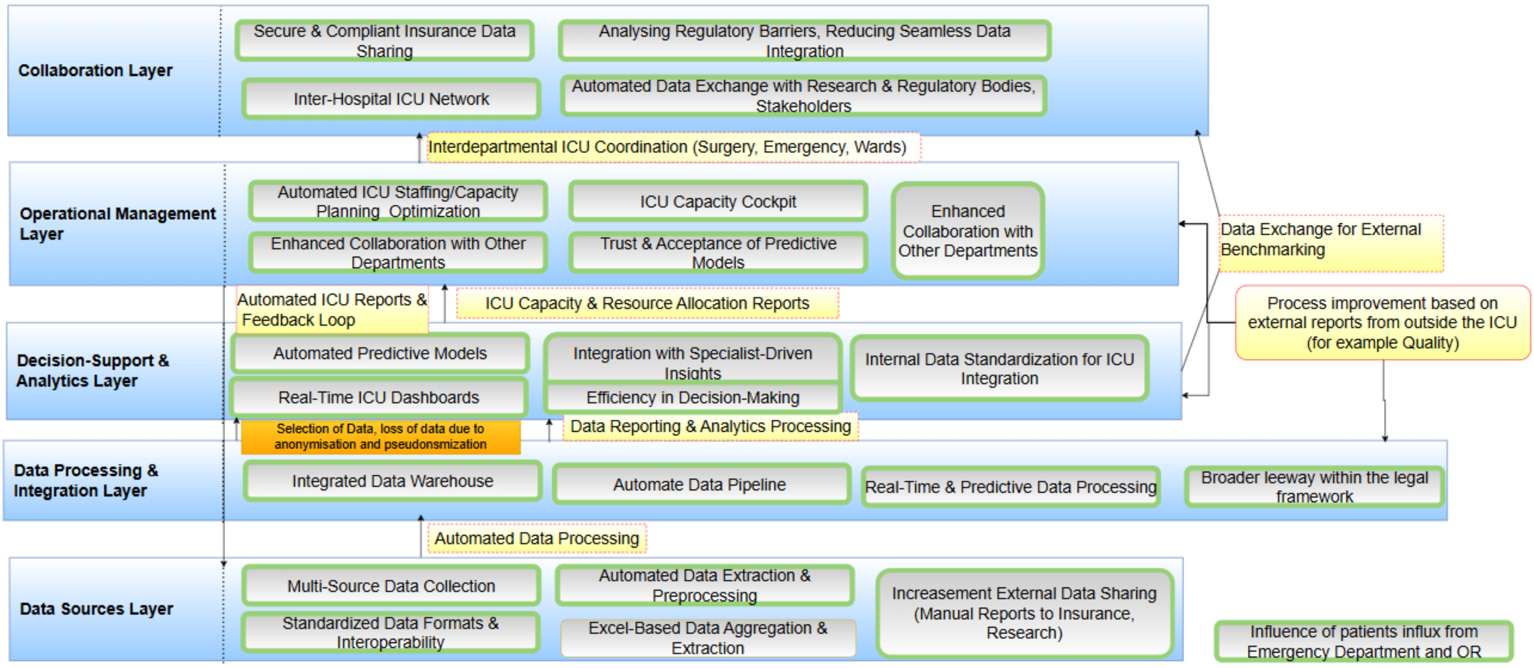

Figure 8: Future System Architecture PICU after validation

10.3. Conclusion

This chapter has presented the findings of the validation process for both the current and future system architecture models within the PICU context. Feedback from expert interviews indicates that the current model aligns well with existing practices, particularly in pediatric intensive care.

The future model was perceived as a meaningful and structured representation of a desirable direction for development. Realisation will require careful alignment with institutional priorities, technical capabilities, and interdepartmental collaboration.

In sum, the validation phase affirmed the conceptual soundness of the models while also identifying practical considerations for future refinement. The revised architecture offers a credible foundation for further exploration and development in the evolving landscape of pediatric intensive care.

11 Discussion

This study explored the limitations of existing PICU capacity planning systems and proposed a new system architecture to address these inefficiencies. By integrating predictive analytics, the research offers a pathway to enhance PICU management within the regulatory constraints of Dutch hospitals. This chapter critically reflects on the findings, their alignment with existing literature, and the limitations that provide avenues for future research.

11.1. Reflection on Research Findings

The research findings reveal significant inefficiencies in the current system architecture for PICU capacity planning. Existing systems predominantly rely on static, retrospective data, with annual forecasts guiding resource allocation. While this approach may suffice under stable conditions, it struggles to adapt to dynamic scenarios such as pandemics or sudden patient surges. These limitations were emphasized during validation interviews, where participants acknowledged that while the model aligns with pediatric ICU realities, the current level of integration and technological infrastructure varies significantly from adult ICUs, which are generally more advanced and structured.

The proposed system architecture aims to overcome these limitations by integrating predictive analytics and real-time data streams. Predictive models powered by machine learning support dynamic forecasting of PICU demand, utilizing data from wearable devices, remote monitoring systems, and regional databases. Interviewees confirmed the feasibility of this direction, noting the potential of AI-driven decision-making and the benefits of moving from reactive to proactive planning. This aligns with findings by Pinsky et al. (2024), who emphasize the role of real-time analytics in optimizing patient flow and resource allocation.

Table 15 summarizes the differences between the current and proposed systems, highlighting the transformative potential of predictive analytics.

Table 15: Comparison of Current and Proposed PICU Systems

Aspect	Current System	Proposed System
Data Utilization	Retrospective, annual forecasts	Real-time, dynamic predictions
Integration	Limited to departmental silos	Interoperable frameworks across departments and hospitals
Privacy Compliance	Basic anonymization; restricted sharing	Advanced encryption and GDPR-compliant anonymization
Decision-Making	Manual; dependent on staff interpretation	Automated decision-support tools leveraging predictive models

Despite its potential, integrating predictive analytics presents notable challenges. Resistance among staff—particularly around maintaining autonomy in decision-making—was a recurring theme in the validation interviews. Participants expressed concerns about the trustworthiness of predictive tools and the fear of replacing clinical judgment. However, they also recognized the value of AI, especially for faster decisions in time-constrained scenarios. Addressing these concerns will require targeted training and clear communication about the supportive, rather than substitutive, nature of such technologies.

The research also highlights the need for privacy-preserving data-sharing mechanisms. While GDPR compliance remains a barrier, validation feedback confirmed the existence of platforms for health data exchange, albeit with limitations such as manual data entry and reduced data value due to anonymization. Interviewees noted that the degree of anonymization can be controlled to balance privacy and utility. Moreover, the data-processing layer is already being developed, with data extracted from systems like HiX and used to create dashboards, suggesting a readiness to evolve toward a more integrated architecture.

Finally, regional collaboration remains a crucial area for development. Validation findings confirmed the value of shared platforms and dashboards, which are currently in use for management reporting and quality control. However, integration across institutions is still limited. The proposed system's emphasis on regional, GDPR-compliant platforms aligns with existing efforts and offers a pathway toward more robust, real-time PICU coordination—provided that organizational and technical challenges are addressed.

11.2. Limitations

While this study provides valuable insights, it is essential to acknowledge its limitations, which suggest directions for future research.

First, the proposed system architecture is conceptual and has not been validated in practice. While its design draws on extensive literature and qualitative data, its feasibility and effectiveness in real-world PICU settings remain speculative. This also means that the delivery phase of the Double Diamond model was only partially addressed, as implementation and real-world testing fall outside the scope of this thesis. Future research should prioritize pilot testing to evaluate its impact on patient outcomes and operational efficiency.

Second, the research focuses exclusively on Dutch hospitals and their PICU department, which operate within specific regulatory and organizational frameworks. Although the findings have broader applicability, adapting the proposed solutions to other healthcare systems will require further investigation. Comparative studies across countries with differing legal and technological contexts could enrich the understanding of how such systems can be effectively implemented. Furthermore, even-though the research focuses on the PICU, information from the literature review was often about the ICU as a whole.

Third, the reliance on qualitative interviews, while providing depth, limits the generalizability of the findings. Expanding the sample size and incorporating quantitative analyses, such as simulations of predictive models, could provide a more robust basis for the proposed framework. Quantitative validation is particularly critical for assessing the scalability of predictive analytics and privacy-preserving methods.

Finally, the study addresses technical and legal aspects in detail but does not sufficiently explore organizational and cultural barriers. Interviews revealed that resistance to change and hierarchical decision-making structures often impede the adoption of new technologies. Strategies for overcoming these barriers, such as fostering interdisciplinary collaboration and cultivating a culture of innovation, require further exploration.

11.3. Comparison with Published Research

The findings of this study resonate with, yet also diverge from, several themes in the existing literature on ICU capacity management and the use of predictive data. This section compares the empirical insights from the PICU setting with broader academic discourse, focusing on collaboration, data integration, and system-specific challenges.

11.3.1. Collaboration and Interdepartmental Coordination

A particularly noteworthy finding from this research is the central role of collaboration, both within the hospital and across regional partners, in shaping PICU capacity management. Interviewees consistently identified bottlenecks in patient flow as the result of misaligned processes between departments such as the emergency room, operating theatre, and general wards. This observation aligns with studies on adult ICUs, which emphasize the importance of multidisciplinary coordination in achieving efficient care delivery, especially in surge planning and systemic responsiveness. However, the findings presented here add nuance by showing that collaboration in pediatric settings often depends on ad-hoc communication and informal networks, rather than standardized protocols or integrated digital systems. Although the literature on this topic in pediatric contexts is limited, this difference may be explained by the relatively smaller scale and highly specialized nature of PICUs, which afford greater flexibility but typically lack formalized coordination infrastructure.

11.3.2. Use and Availability of Data Sources

Consistent with previous research, this study confirms that access to timely and high-quality data remains a structural challenge in critical care. Literature on adult ICUs often assumes the existence of advanced data infrastructures, including centralized monitoring systems and automated data pipelines. In contrast, the PICU environment examined here reveals a fragmented system in which essential data—from bedside monitors, wearables, or home-monitoring devices—is technically available but not routinely integrated into operational decision-making. This discrepancy suggests that existing models for real-time analytics, while theoretically transferable, require careful adaptation to the infrastructural and workflow realities specific to pediatric critical care.

11.3.3. Applicability of Predictive Models

The proposed system architecture in this thesis is informed by a growing body of research advocating the use of predictive analytics in ICU planning. Studies have demonstrated that dynamic forecasting can support more effective resource allocation, optimize patient flow, and improve operational resilience. However, much of this research is situated in adult ICU contexts, where higher patient volumes, standardized data practices, and stronger institutional investment in data science facilitate adoption. The findings from this study indicate that while predictive models are viewed positively in PICUs, actual implementation is hindered by technical immaturity, regulatory complexity, and cultural hesitation. This suggests that PICUs, while conceptually aligned with broader trends in digital innovation, face unique practical constraints that warrant further attention.

11.3.4. Legal and Ethical Constraints

Although privacy and data protection are widely discussed in the literature, this study foregrounds these issues as central obstacles in pediatric intensive care. Interviewed participants underscored the heightened sensitivity of pediatric data, particularly regarding long-term storage and parental consent. While the GDPR provides a uniform regulatory framework, its application in pediatric contexts often involves additional ethical layers and institutional scrutiny. These findings contribute to the literature by offering a more detailed and practice-oriented account of how legal and ethical requirements influence technological decision-making in PICUs.

11.3.5. Organizational Culture and Change Readiness

Resistance to technological innovation, a recurring theme in ICU literature, also emerged in this study. However, rather than being solely attributable to system-level limitations, resistance in PICUs appears rooted in deeper cultural dynamics. Interviewees highlighted the lack of shared strategic goals, limited familiarity with data-driven tools, and concerns about diminished clinical autonomy as key factors impeding adoption. These insights suggest that successful implementation of predictive systems in pediatric care requires more than technical readiness; it demands alignment with professional identities, collaborative governance, and context sensitive capacity building.

11.4. Conclusion

In conclusion, this discussion has critically analyzed the research findings, situating them within the broader context of healthcare innovation. While the proposed system architecture offers a promising solution to the inefficiencies of current PICU capacity planning, its success will depend on addressing the identified limitations. Future research should focus on empirical validation, cross-contextual comparisons, and strategies to overcome organizational challenges, contributing to the development of resilient and adaptive PICU management systems.

12 Conclusion

This Chapter will address the research questions, provided in Chapter 1, as a conclusion of this thesis.

12.1. Research questions

This study delved into the current system architecture of the IC department, aiming to improve this system architecture by efficiently using data and prediction methods. Employing thematic analysis and a layered architecture model, the research sought to uncover aspects that could improve the current system architecture of the PICU, while adhering to legislation. To guide this process, the Double Diamond model was applied, supporting the structured progression from problem exploration to solution development.

This involved identifying key values involving the current system architecture by the use of interviews and a literature review. Secondly, the research involved the layered architecture model approach to visualize the current system architecture, points of improvement and subsequently the new system architecture. The validation phase confirmed the accuracy of the current model for the PICU setting, and helped refine the future system architecture based on practical feedback.

Given the research's objective, the main research question was formulated as follows:

How can new approaches to patient data analytics improve planning for PICU utilization?

In order to answer this main question, three sub-questions have been formulated which will be answered separately each.

Research sub-question 1

How do current PICU capacity planners use data to manage and predict patient flow?

PICU capacity planning in the Netherlands relies on various data sources, including EHR, HIS, and national coordination efforts, to manage and predict patient flow. Current methods primarily use descriptive analytics, historical data analysis, and manual calculations to estimate PICU occupancy and demand.

Length of Stay (LoS) is a key parameter in PICU capacity planning. Hospitals calculate LOS based on historical data to anticipate bed turnover rates and predict PICU availability. However, the reliance on static LoS models, often calculated using simple mathematical formulas, limits adaptability to real-time changes in patient conditions and result in calculation for yearly predictions. Furthermore, LoS predictions do not always account for external factors such as seasonal surges or emergency cases, leading to inefficiencies in bed allocation.

National coordination bodies such as LNAZ, play a role in managing ICU capacity, particularly during crises. These organizations use emergency department data to coordinate patient transfers and balance ICU load. Furthermore, NICE data registry provides data of ICUs. However, real-time LoS forecasting is not fully integrated into these processes, limiting proactive planning.

Hospital systems such as HiX and Epic provide structured data storage and real-time access to patient information, but they are not yet fully equipped for predictive analytics. Manual input of patient data and limited interoperability between hospitals contribute to data silos, making it difficult to share real-time LoS insights across institutions.

Centralized data environments, such as hospital data warehouses and national registries offer a valuable but currently underused resource for capacity planning. Although these platforms contain large volumes of relevant ICU data, they are mainly applied for retrospective analysis rather than operational forecasting. Several barriers hinder their effective use in real-time planning, including fragmented data governance, limited standardization, and technical restrictions in existing hospital IT systems. Furthermore, data sharing across institutions is hindered to be used system-wide, resulting in less insight into current and expected PICU-load. To improve adaptability and responsiveness, it is essential to embed existing data platforms more directly into daily planning routines and foster collaboration across institutional and departmental boundaries.

Research sub-question 2

What are current system and legal constraints to manage and predict patient flow?

Although dashboards and data hubs are becoming more common, their integration into daily PICU operations appears to be limited in practice. During the validation phase, it was observed that data from systems such as HiX is often extracted and processed into centralized data hubs, which could form the basis for predictive planning. However, these tools do not yet seem to be fully embedded in clinical workflows, which may limit their impact on operational decision-making. In many cases, staff still rely on manual processes and fixed planning structures that are not directly connected to real-time data.

A frequently mentioned barrier concerns the fragmented nature of IT infrastructure. While data is available in several systems, the lack of seamless interoperability seems to hinder its real-time use in forecasting or planning. Predictive tools are not always directly linked to electronic patient records, which may make it more difficult to apply model insights during routine care. Some interviewees pointed out that the absence of integrated dashboards reduces the visibility of factors such as expected discharge timing, making it harder to anticipate short-term capacity shifts.

Although forecasting is already applied to some extent often based on historical trends, these approaches do not always reflect daily fluctuations in patient flow. This can be particularly challenging in the PICU, where both planned and unplanned admissions need to be accommodated. While there are efforts to align surgical scheduling with PICU capacity, the lack of integrated planning systems between departments such as the OR, ED, and general wards complicates this coordination. Interviewees suggested that this fragmentation often results in reactive rather than proactive management. On the level of external collaboration, similar challenges were described.

Another constraint lies in the process of model validation and implementation. While technical infrastructure is increasingly available, standardization across data sources remains limited, and trust in predictive tools varies. Interviewees noted that validation is often carried out in separate data analysing programs, which makes it harder to integrate model output directly into the EHR. This separation may reduce usability in practice and slow down feedback cycles between prediction and action.

Altogether, although the foundation for predictive PICU planning seems to be in development, its full potential is not yet being realized. Gaps in system integration, coordination, and model implementation may currently limit the extent to which predictive tools can support patient flow management.

A final barrier to the effective use of predictive models lies in the limited interdisciplinary alignment between clinical experts, data scientists, and technical staff. Without shared understanding of which data sources are most clinically relevant, predictive tools risk being misaligned with practical needs. Furthermore, familiarity with these models among healthcare professionals may hinder their integration into routine workflows, reducing their potential impact on patient flow management.

Legal frameworks such as GDPR, WGBO, and Wabvpz regulate the use of patient data in PICU management. While these regulations ensure privacy and data security, they also impose constraints on data sharing, requiring explicit parental/guardian consent for certain applications. The AI Act further categorizes PICU predictive models as high-risk, imposing strict validation and oversight requirements before implementation. Interviewees indicated that anonymization of data can reduce its predictive value, although the extent of this limitation depends on how the anonymization is applied. In addition , national regulations mandate that hospitals maintain accurate and up-to-date medical records and restrict the reuse of data without specific consent, especially in cases where data are intended for secondary purposes beyond direct care. Institutional review boards and hospital privacy officers play a central role in ensuring legal compliance before implementing new systems. Interviews highlighted that access to patient data is role-dependent and strictly regulated within hospital systems, which limits broader use for predictive purposes. It is important for hospitals to carefully navigate between legal obligations. Finally, the absence of a centralized legal infrastructure for real-time interhospital data exchange was mentioned as a structural barrier to effective predictive planning.

Research sub-question 3

What data could be beneficial to tackle these system and legal constraints?

To address current system constraints in managing and predicting PICU patient flow, more integrated and operationally relevant data is needed. Real-time physiological data from bedside monitors and wearable technologies could enable earlier detection of clinical deterioration and support more accurate short-term capacity forecasting. Additionally, standardized indicators of patient acuity and care dependency—applied consistently across departments—would help improve prioritization in admissions and interdepartmental transfers. Data on expected discharge timelines, when regularly updated and made visible across units, could support dynamic bed allocation. Incorporating external factors, seasonal disease patterns, may further improve forecasting accuracy. However, for these data sources to have real operational value, technical interoperability and shared data definitions are essential. A key barrier identified in practice is the misalignment between available data and clinical planning needs, which highlights the importance of joint input from clinicians, data analysts, and system managers to define which data points are most actionable in daily practice.

To overcome legal constraints related to data sharing and predictive modeling, the use of securely de-identified datasets is essential, but must be carefully balanced with the need to retain sufficient clinical detail. Data that have been stripped of patient identifiers, while preserving key variables such as diagnosis, duration of treatment, or physiological scores, can support model development without compromising privacy. Consent-related barriers could be mitigated by implementing broader consent mechanisms for secondary data use, provided patients are adequately informed. In addition, federated data systems, where data remains locally stored but accessible for analysis through secure protocols, could allow for multi-center collaboration while maintaining compliance with data protection legislation such as the GDPR. To ensure these legal strategies are effective, trust and transparency are crucial. Clinical professionals must understand how data will be used and have confidence that privacy safeguards are in place, especially when predictive tools become part of clinical workflows.

Research sub-question 4

What new system architecture could be used for improving intensive care facility management, considering current system and legal constraints?

To improve intensive care facility management, a new system architecture should address both system-level and legal constraints currently limiting the effectiveness of PICU operations. The existing architecture in the Netherlands remains heavily reliant on manual data processing and retrospective decision-making. Although platforms like HiX and Epic support electronic data storage, they lack real-time decision support and predictive functionalities. Validation interviews confirmed that while tools for data visualization and extraction already exist, their full integration into day-to-day PICU workflows remains limited.

To address systemic limitations, the proposed architecture emphasizes real-time interoperability across hospital departments, automated data pipelines, and the adoption of standardized data formats to eliminate silos between PICU, emergency departments, and surgical units. Integrating AI-based forecasting models into a centralized decision-support dashboard—referred to as the PICU Capacity Cockpit can assist in predictions identifying discharge opportunities, and optimizing staffing allocation. Interviewees highlighted that decisions in current practice are often delayed or made under time pressure; predictive systems could help shift this paradigm toward proactive planning. To ensure alignment with clinical practice, these models should be interpretable and refined in collaboration with healthcare professionals.

From a legal perspective, implementing such a system requires strict adherence to data privacy legislation. GDPR-compliant data sharing and anonymization procedures must be embedded within the architecture to ensure ethical use of patient information. Moreover, the classification of predictive models under the AI Act as high-risk tools necessitates thorough validation, documentation, and human oversight, understanding and acceptation before deployment. Validation interviews pointed out that while anonymization can reduce data utility, the extent depends on how it is applied. Structuring consent procedures more uniformly could further facilitate responsible reuse of data for predictive modelling.

Importantly, the success of this future architecture hinges on interdisciplinary cooperation. Clinical experts, data scientists, and technical stakeholders must jointly determine which data sources are most relevant to clinical decision-making. Furthermore, trust in predictive tools is essential for adoption; models must be transparent and support instead of replace clinical judgment, and integrate seamlessly into existing workflows.

Taken together, the proposed architecture offers a structured and scalable foundation for enhancing PICU capacity management. Its realization will require phased implementation, robust governance, and continued alignment between technological potential and clinical reality.

12.2. Future Research

Scientific Contributions

This research advances the academic discourse by introducing a layered system architecture that integrates data analytics and legal considerations within the context of PICU capacity management in the Netherlands. By employing thematic analysis in conjunction with the layered architecture model, this study proposes a novel conceptual design that addresses the complex interplay between data sources, regulatory frameworks, and operational management. This interdisciplinary approach bridges a notable gap in the literature, offering a structured framework that can inform the work of system architects and healthcare administrators aiming to optimize PICU resource allocation.

Furthermore, the research contributes to the academic field by systematically identifying and analyzing key legislative constraints, data-sharing challenges, and potential benefits of improved capacity management — areas that have not yet been comprehensively examined in this specific healthcare context. Furthermore a scientific contribution is bringing together data analytics and automation while taking into account legal constraints for capacity management in the PICU is one contribution of this research, but it is also a genuine contribution to how we bring together predictive modeling from different data sources within the system architecture, also considering legal constraints for capacity management. While the study followed the principles of the Double Diamond model — guiding the research through discovery, definition, and development — the delivery phase remains partially unaddressed, as the proposed model was validated through expert feedback but not empirically tested in a real-world PICU setting. This represents both a limitation and an opportunity for future research.

Practical Recommendations & Future Research Directions

Building on the findings of this study, several promising avenues for future research are proposed. While this thesis maps out the relevant legislation governing data sharing in PICU environments, it stops short of developing a practical tool for its application. Future research could focus on creating a clear, actionable checklist or framework that healthcare organizations can use to determine the permissible scope of data sharing for various data types — supporting compliance while enabling innovation in capacity management.

Moreover, although the proposed architecture alludes to inter-hospital data exchange, further investigation is warranted into the design and feasibility of a centralized “data marketplace.” This concept, still underexplored, could foster secure and flexible data sharing across institutions, ultimately enhancing the predictive capabilities of capacity forecasting models.

Another important direction involves exploring strategies for fostering acceptance and enthusiasm for automation within PICU teams. This study highlighted some resistance to technological change; thus, further research could examine effective change management practices, training programs, and incentive structures that promote adoption of intelligent systems in sensitive healthcare environments.

Finally, as the proposed system architecture remains conceptual, future studies should investigate how this architecture could be operationalized in real-world PICU settings. Developing implementation guidelines and evaluating their impact on capacity efficiency would not only validate the model but also provide a roadmap for healthcare institutions seeking to modernize their infrastructure.

Beyond these follow-up steps, the study opens new opportunities for interdisciplinary research that expands the conceptual and practical horizons of PICU system design. Several additional directions are proposed:

- **Development of Legal and Ethical Decision Tools**
  Research could focus on translating complex data legislation into operational tools for clinical and administrative use. A decision-support tool or checklist could help institutions assess the lawful sharing of specific data types under different use cases.
- **Design of Federated or Regional Health Data Infrastructures**
  Building upon the idea of cross-institutional collaboration, further investigation is needed into federated data architectures or regional “data trusts” that enable secure, standardized, and transparent data exchange between PICUs and partner institutions.
- **Exploring Change Management in Pediatric Care Teams**
  Future work could focus on identifying and testing strategies that support behavioral change, digital literacy, and shared usership of predictive tools among clinical teams in pediatric settings.
- **Engaging Patients and Families in System Design**
  Given the ethical sensitivity of pediatric data, future research may examine how families perceive data use in critical care. Participatory design methods could help develop more transparent, trustworthy communication practices.
- **Technical Integration of Longitudinal Monitoring Data**
  Finally, further technical research is needed on how to incorporate continuous data from wearables and home monitoring into predictive models. Such integration could enhance early warning systems and link pre-admission monitoring with inpatient care planning.

These research directions reflect both the gaps identified in this study and the potential for broader innovation in the field of pediatric intensive care. Together, they offer a foundation for a long-term research agenda that supports ethical, data-driven, and context-sensitive system transformation.

12.3. Reflection

Reflecting on the journey of writing my MSc thesis, I found that using thematic analysis in combination with the layered system architecture model provided a clear framework to explore the limitations of the current PICU system architecture. Additionally, I applied the Double Diamond model to structure the research process, guiding me through stages of discovery, definition, development, and delivery. My aim was to conceptualize and develop a novel system design that could enable more efficient capacity prediction through the integration of patient data analytics.

This process came with its fair share of challenges. Recruiting participants for the interviews was more difficult than anticipated, and gathering sufficient and reliable information from the literature required significant effort. One of the most intense periods was analyzing the validation interviews, which coincided with the week leading up to my green-light document deadline—definitely a high-pressure moment. These kinds of situations tested my ability to adapt and persevere under stress, which I’ve come to understand is a common thread in academic research. I also used tools like ChatGPT throughout the thesis to streamline my writing process and improve clarity, especially when working through complex sections on legislation and emerging data analytics.

An important insight emerged from the interviews: a significant lack of trust in automation within the PICU environment. The current system heavily relies on manual processes, with limited predictive capabilities. Although legal and ethical concerns were expected barriers, I was surprised to learn that data-sharing for the sake of improving patient care might be more feasible than initially thought.

This contrasted with my expectations, as many other government sectors seem more progressive in adopting automated systems. These findings underscored the importance of building trust alongside technological solutions. Furthermore, I gained a deeper appreciation for the academic community's ongoing struggle to align legal boundaries with the need for data-driven innovation in healthcare.

On a personal note, the quote "A smooth sea never made a skilled sailor" resonates with my thesis journey. The final stages were undoubtedly the most demanding, but also brought the most growth—both academically and personally. From conducting literature reviews to designing interview questions and navigating academic supervision, the journey was a significant learning experience that strengthened my resilience and critical thinking.

Looking ahead, I see myself pursuing a role as an advisor in a field where I can contribute to solving complex problems — perhaps as a systems or business architect in healthcare or civil infrastructure. This project allowed me to address a pressing issue — optimizing PICU system architecture through data analytics — using both research and strategic thinking. It has equipped me with a valuable set of skills and a broader perspective that I hope to apply in impactful ways in my future career.

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Appendices

A

Gap Search and Literature Search

A.1. Gap Search

The following tables summarize the Gap search:

Table 16: Summary of Scopus Search Result

Number	Search Terms	Hits (number)
1	("intensive care units, pediatric"[MeSH Terms] OR "PICU"[Title/Abstract] OR "Pediatric Intensive Care"[Title/Abstract])	19,372
2	("capacity"[Title/Abstract] OR "management"[Title/Abstract])	2,375,498
3	("data"[Title/Abstract] OR "gap"[Title/Abstract] OR "predictive"[Title/Abstract] OR "barrier"[Title/Abstract])	6,095,178
4	#1 AND #2 AND #3	1477

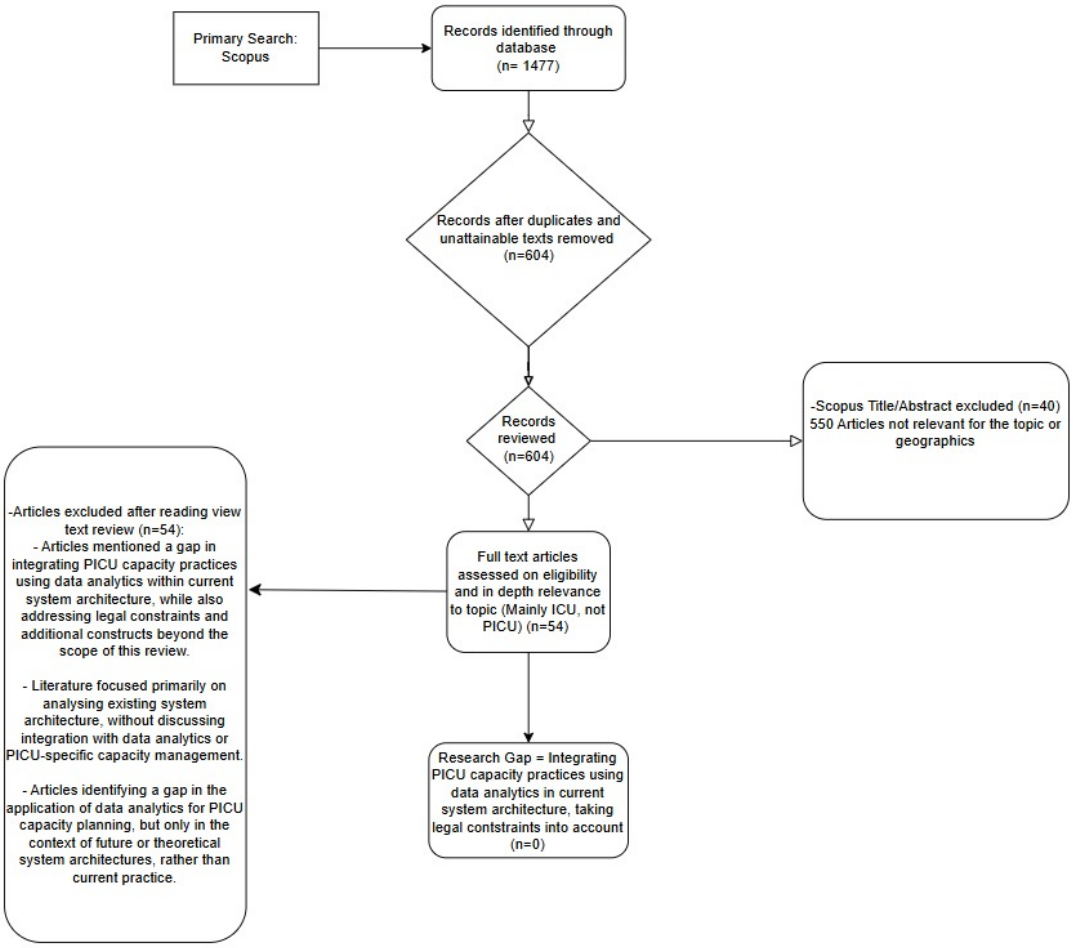

Figure 9: Flowchart of study selection process.

A.2. Literature Review

The following table summarizes the search terms and results:

Table 17: Summary of Scopus Search Results

Number	Search Terms	Hits (number)
1	TITLE-ABS-KEY (”ICU” OR ”intensive care” OR ”intensive care Units” OR ”acute care”)	478,176
2	TITLE-ABS-KEY (”data management” OR ”predictive analytics” OR ”capacity manag*” OR ”capacity plan*” OR (predict* AND demand))	211,391
3	TITLE-ABS-KEY (legal OR ethical OR gdpr OR law OR regulat* OR ”data protection OR ”compliance data” OR ”legal constraint*” OR ”benefit*” OR ”advantage*” OR ”opportunity*”)	12,068,085
4	#1 AND #2	1,693
5	#3 AND #4	288
6	#4 OR #5	1,981

The following articles were subtracted from the literature search. The exclusion criteria following from the search were:

1. Older than 2004 2. Duplicates 3. Research in countries not relatable to Europe 4. Only focusing on one decease and . 5. Only focused on using ICU for making trials better and not efficiency. 6. Only focused on mathematics 7. Focused on different departments than ICU and acute care 8. Focused on OR in the broad tense 9. Focused on reopening or new hospitals 10. No/very small use of patient data

In the following diagram, a flowchart is presented. The flowchart represents the steps within selecting the articles for the literature review which are listed in table 14.

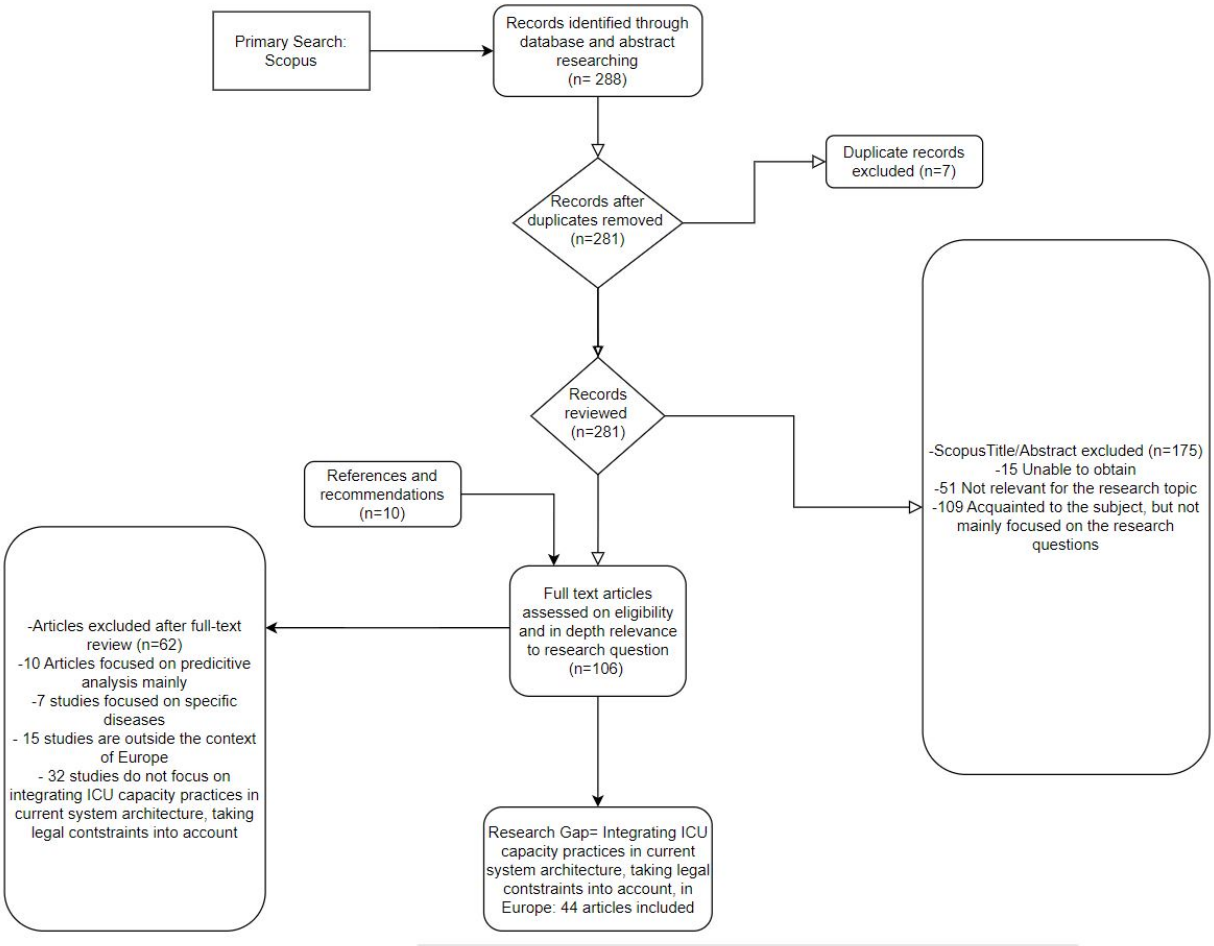

Figure 10: Flowdiagram Literature Review

Table 18: Summary of Relevant Articles for ICU Capacity Planning Research

Author(s)	Year	Title and Key Points
Sent, Danielle et al.	2024	**A quality improvement study on how a simulation model can help decision making on organization of ICU wards** - Use of a simulation model to study ICU capacity effects. - Key findings: Non-dedicated ICUs are more efficient in resource use. - Implications: Simulation models can aid in ICU design decisions.
Prithula, Johayra et al.	2024	**Improved pediatric ICU mortality prediction for respiratory diseases: machine learning and data subdivision insights** - Machine learning techniques to predict pediatric ICU mortality. - Key findings: Subdivision technique improved prediction accuracy. - Implications: Enhances readiness and response in pediatric ICUs.
Friedrichson, Benjamin et al.	2024	**Web-based Dashboard on ECMO Utilization in Germany: An Interactive Visualization, Analyses, and Prediction Based on Real-life Data** - Development of an ECMO Dashboard for resource management. - Key findings: High prevalence of ECMO support in Germany. - Implications: Supports informed decision-making and resource allocation.
Zhang, Weiwei et al.	2024	**A data-driven combined prediction method for the demand for intensive care unit healthcare resources in public health emergencies** - Combined prediction model for ICU resource demand. - Key findings: BILSTM-GASVR model improves prediction accuracy. - Implications: Enhances ICU resource planning during public health emergencies.
Pinsky, Michael R. et al.	2024	**Use of artificial intelligence in critical care: opportunities and obstacles** - Overview of AI applications in critical care. - Key findings: AI systems face technical and ethical challenges. - Implications: Calls for careful integration and governance of AI tools.
Stahel, Philip F. et al.	2024	**The Rothman Index predicts unplanned readmissions to intensive care associated with increased mortality and hospital length of stay** - Evaluation of the Rothman Index as a predictor of ICU readmissions. - Key findings: Lower Rothman Index scores correlate with higher readmission rates. - Implications: Rothman Index can inform safe discharge decisions from ICU.
Keim-Malpass, Jessica et al.	2024	**Prospective validation of clinical deterioration predictive models prior to intensive care unit transfer among patients admitted to acute care cardiology wards** - Validation of predictive models for ICU transfer needs. - Key findings: Models remained accurate despite data drift. - Implications: Supports timely identification of patients needing ICU care.
Hardenberg, Jan-Hendrik B.	2024	**Data-driven intensive care: a lack of comprehensive datasets** - Discussion on the need for larger, diverse ICU datasets. - Key findings: Current datasets limit machine learning model generalizability. - Implications: Calls for development of multicentric, multinational datasets.

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Table 18: (continued)

Author(s)	Year	Title and Key Points
Wu, Jacky Chung-Hao et al.	2024	**Deep-Learning-Based Automated Anomaly Detection of EEGs in Intensive Care Units** - Development of a model for EEG anomaly detection. - Key findings: High accuracy in detecting brain anomalies. - Implications: Reduces workload and improves patient monitoring in ICUs.
Chatzimichail, Christina et al.	2024	**Cost Evaluation for Capacity Planning Based on Patients' Pathways via Semi-Markov Reward Modelling** - Semi-Markov model for cost evaluation in capacity planning. - Key findings: Effective for strategic planning and cost evaluation. - Implications: Enhances resource allocation and cost management in hospitals.
Kuntz, Ludwig et al.	2007	**Incorporating efficiency in hospital-capacity planning in Germany** - Alternative metric for hospital capacity planning. - Key findings: Identified efficient and inefficient hospitals in Rheinland-Pfalz. - Implications: Influenced medium-term planning cycle in the region.
Mohammadi Bidhandi, Hadi et al.	2019	**Capacity planning for a network of community health services** - Queuing network approach for capacity planning. - Key findings: Optimized capacity allocation for community health services. - Implications: Supports efficient management of community care resources.
Nguyen, Jean-Michel et al.	2007	**An objective method for bed capacity planning in a hospital department: A comparison with target ratio methods** - Objective approach for bed capacity planning. - Key findings: Superior performance in accessibility and clinical effectiveness. - Implications: Suitable for quantitative healthcare planning in ICUs.
Patrick J. et al.	2015	**A simulation model for capacity planning in community care** - Simulation model for determining necessary downstream capacity in LTC. - Key findings: Efficient management of patient flow and wait times. - Implications: Informs policy recommendations for LTC capacity planning.
Sarac Guleryuz S. et al.	2023	**Simulation of intensive care bed capacity based on mixture distribution** - Mixture distribution model for ICU bed capacity planning. - Key findings: Improved estimates for bed requirements. - Implications: Enhances capacity planning and resource management in ICUs.
Campbell, Christiana	2010	**The benefits of designing a stratification system for New York City pediatric intensive care units for use in regional surge capacity planning and management** - Stratification system for NYC PICUs. - Key findings: Aids in surge capacity planning and management. - Implications: Improves emergency preparedness and resource allocation.

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Table 18: (continued)

Author(s)	Year	Title and Key Points
Asaduzzaman, Md	2014	**Capacity planning of a perinatal network with generalised loss network model with overflow** - Generalised loss network model for perinatal network capacity planning. - Key findings: Model applicable to renewal arrival and discharge processes. - Implications: Estimates required cots based on rejection probability.
Azcárate, Cristina et al.	2012	**Sensitivity analysis in bed capacity studies including the medical staff's decision making** - Sensitivity analysis framework for ICU capacity planning. - Key findings: Highlights impact of discharge policies on service quality. - Implications: Informs efficient discharge policies and bed capacity management.
Goic, Marcel et al.	2021	**COVID-19: Short-term forecast of ICU beds in times of crisis** - Forecasting model for ICU bed demand during COVID-19. - Key findings: Accurate short-term predictions for ICU utilization. - Implications: Supports capacity planning during health crises.
Qian, Zhaozhi et al.	2021	**CPAS: the UK's national machine learning-based hospital capacity planning system for COVID-19** - Machine learning system for hospital capacity planning. - Key findings: Effective deployment across UK hospitals. - Implications: Provides insights for national-scale resource management.
Bleibtreu, Elena et al.	2022	**Service-, needs-, and quality-based hospital capacity planning – The evolution of a revolution in Switzerland** - Comprehensive update of hospital capacity planning model for Zurich. - Key findings: Transparent and participative planning process. - Implications: Enhances needs-based, high-quality, efficient inpatient healthcare.
Antmen, Z.F., Oğulata, S.N.	2013	**The capacity planning of intensive care units via simulation: A case study in university hospital** - Prediction of available beds in ICUs and PICUs using simulation model. - Key findings: Simulation model more accurate than queuing models for bed prediction. - Implications: Supports better bed availability planning to prevent issues such as patient deaths due to bed shortages.
Sloane, E.B., Gehlot, V.	2007	**Use of Coloured Petri Net models in planning, design, and simulation of intelligent wireless medical device networks for safe and flexible hospital capacity management** - Use of Coloured Petri Net (CPN) formal simulation modelling tools. - Key findings: Effective Verification and Validation (V

Continued on next page

Table 18: (continued)

Author(s)	Year	Title and Key Points
V) process for wireless medical devices in Virtual Intensive Care Units (VICUs). - Implications: Ensures patient safety while meeting clinical capacity demands.		
Murray, L.L., Wilson, J.G., Rodrigues, F.F., Zaric, G.S.	2023	**Forecasting ICU Census by Combining Time Series and Survival Models** - Development and evaluation of ICU census forecasting algorithm. - Key findings: Combines time series and survival models for accurate ICU census predictions. - Implications: Provides a tool for better ICU capacity planning and management.
Ghorbani, R., Ghousi, R., Makui, A., Atashi, A.	2020	**A New Hybrid Predictive Model to Predict the Early Mortality Risk in Intensive Care Units on a Highly Imbalanced Dataset** - Hybrid predictive model using Genetic Algorithm and ensemble classifier. - Key findings: Model outperforms other classifiers and traditional scoring systems. - Implications: Improves early mortality risk prediction in ICU patients.
Mathews, K.S., Long, E.F.	2015	**A conceptual framework for improving critical care patient flow and bed use** - Framework for data-driven modeling of ICU patient flow. - Key findings: Simulation model reduces ICU admission delays. - Implications: Enhances ICU bed assignment and patient flow management.
Fernandes, M.P.B., Silva, C.F., Vieira, S.M., Sousa, J.M.C.	2014	**Multimodeling for the prediction of patient readmissions in Intensive Care Units** - Fuzzy C-Means (FCM) clustering algorithm for readmission prediction. - Key findings: Multimodel approach improves prediction accuracy. - Implications: Supports better clinical management and medical diagnosis.
Inan, T.T., Samia, M.B.R., Tamanna, I., Islam, M.N.	2018	**A decision support model to predict ICU readmission through data mining approach** - Predictive model using Naïve Bayes, decision tree, and neural network. - Key findings: Artificial neural network achieved highest prediction accuracy. - Implications: Assists doctors in making informed decisions to prevent ICU readmissions.
Zhang, W., Li, X.	2024	**A data-driven combined prediction method for the demand for intensive care unit healthcare resources in public health emergencies** - BILSTM-GASVR combined prediction model for ICU resource demand. - Key findings: Model accurately predicts demand for ICU healthcare resources. - Implications: Supports efficient ICU resource planning during public health emergencies.

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Table 18: (continued)

Author(s)	Year	Title and Key Points
McManus, M.L., Long, M.C., Cooper, A., Litvak, E.	2004	**Queuing Theory Accurately Models the Need for Critical Care Resources** - Application of queuing theory to model ICU patient flow. - Key findings: Queuing model accurately predicts ICU admission turn-away rates. - Implications: Helps determine appropriate supply of ICU beds.
Cismondi, F., Fialho, A.S., Vieira, S.M., Sousa, J.M.C., Finkelstein, S.N.	2013	**Missing data in medical databases: Impute, delete or classify?** - Approach to manage missing data in ICU databases. - Key findings: New method improves modeling performance. - Implications: Enhances predictive risk modeling in ICU.
Keim-Malpass, J., Clark, M.T., Lake, D.E., Moorman, J.R.	2020	**Towards development of alert thresholds for clinical deterioration using continuous predictive analytics monitoring** - Use of continuous predictive analytics monitoring for clinical deterioration. - Key findings: Risk spikes provide early warnings for ICU transfer. - Implications: Improves timely identification of clinical deterioration.
Zaleski, J.	2019	**Big Data for Predictive Analytics in High Acuity Health Settings** - Use of big data in high-acuity healthcare settings. - Key findings: Data capture and predictive analytics improve patient monitoring. - Implications: Supports better patient care in ICUs, ORs, and EDs.
Assaf, R., Jayousi, R.	2020	**30-day Hospital Readmission Prediction using MIMIC Data** - Predictive model for 30-day readmission using MIMIC III dataset. - Key findings: Random Forest model achieved best prediction accuracy. - Implications: Helps hospitals reduce readmission rates.
Ahmad, F., Ayub, H., Liaqat, R., Nawaz, A., Younis, B.	2021	**Mortality Prediction in ICU Patients Using Machine Learning Models** - Machine learning models for mortality prediction in ICU patients. - Key findings: SVM and LDA models improve early mortality prediction. - Implications: Supports better ICU resource allocation and patient care.
Michard, F., Teboul, J.L.	2019	**Predictive analytics: beyond the buzz** - Overview of predictive analytics in healthcare. - Key findings: Predictive analytics improve mortality prediction and risk stratification. - Implications: Supports proactive medicine in acute care.
Ozyurt, Y., Kraus, M., Hatt, T., Feuerriegel, S.	2021	**AttDMM: An Attentive Deep Markov Model for Risk Scoring in Intensive Care Units** - Attentive deep Markov model for ICU risk scoring. - Key findings: AttDMM outperforms state-of-the-art methods in risk prediction. - Implications: Provides early warnings for ICU patient deterioration.
Alkhachroum, A., Kromm, J., De Georgia, M.A.	2022	**Big data and predictive analytics in neurocritical care** - Use of predictive analytics in neurocritical care. - Key findings: Multimodal monitoring improves patient outcomes. - Implications: Supports personalized medicine in neurocritical care.

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Table 18: (continued)

Author(s)	Year	Title and Key Points
Weiss, B., Paul, N., Balzer, F., Noritomi, D.T., Spies, C.D.	2021	**Telemedicine in the intensive care unit: A vehicle to improve quality of care?** - Use of telemedicine in ICU. - Key findings: Telemedicine increases adherence to best practice guidelines. - Implications: Improves quality of care and patient outcomes in ICUs.
Krishnan, G.S., Sowmya Kamath, S.	2019	**A Supervised Approach for Patient-Specific ICU Mortality Prediction Using Feature Modeling** - Supervised learning approach for ICU mortality prediction. - Key findings: Model outperforms traditional scoring systems in accuracy. - Implications: Assists hospitals in making informed decisions.
Guerra, D., Gawlick, U., Bizarro, P., Gawlick, D.	2011	**An integrated data management approach to manage health care data** - Integrated engine for real-time data processing in ICUs. - Key findings: System improves data assimilation and prediction accuracy. - Implications: Enhances ICU data management and patient monitoring.
Rooney, S.R., Clermont, G.	2023	**Forecasting algorithms in the ICU** - Evaluation of forecasting algorithms for ICU use. - Key findings: Barriers to implementation persist despite advances. - Implications: Clinicians play a crucial role in successful deployment.
Angelo, S.A., Arruda, E.F., Goldwasser, R., Salles, A., e Silva, J.R.L.	2017	**Demand forecast and optimal planning of intensive care unit (ICU) capacity** - Time series and queuing model for ICU capacity planning. - Key findings: Model provides optimal ICU bed number to reduce waiting time. - Implications: Supports better ICU resource management.
Fernandes, M.P.B., Silva, C.F., Vieira, S.M., Sousa, J.M.C.	2014	**Multimodeling for the prediction of patient readmissions in Intensive Care Units** - Fuzzy C-Means (FCM) clustering algorithm for readmission prediction. - Key findings: Multimodel approach improves prediction accuracy. - Implications: Supports better clinical management and medical diagnosis.

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B

Code Manager

Table 19: Code Manager

Code	Hits	Code Groups
Accuracy Current Models	6	Current Prediction Method
Limitations Current Models	2	Current Prediction Method
Use of AI in current models	1	Current Prediction Method
No Capacity Current Prediction Methods	1	Current Prediction Method
Used Prediction Methods	10	Current Prediction Method
Predicting Materials/Patient	2	Current Prediction Method
Opinion on Prediction Methods	2	Current Prediction Method
No Use Prediction Methods	3	Current Prediction Method
Unpredictability IC	1	Current Prediction Method
Seasonal Predictions	4	Current Prediction Method
Mortality Rates Predictions	1	Current Prediction Method
Challenges Current Prediction Methods	3	Current Prediction Method
LOS Predictions	2	Current Prediction Method
Predicting Personell Numner	2	Current Prediction Method
Prediction Methods TUTwente	2	Current Prediction Method
Predicting IC from Bedoccupancy	5	Current Prediction Method
Predicting / Month	1	Current Prediction Method
Prediction Breathing Patterns	1	Current Prediction Method
Predicting Detoriation Health	1	Current Prediction Method
Questions for Data-Analysis	1	Current Prediction Method
Predicting Sepsis	4	Current Prediction Method
Limitations Predicting IC	1	Current Prediction Method, ICU Management
ED & OK as Predictors	3	Current Prediction Method, ICU Management
Current Sytem Architecture	8	Current System Architecture
Management IC System Architecture	3	Current System Architecture

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Code	Hits	Code Groups
Challenges Current System Architecture	1	Current System Architecture
Challenges Technical System Integration	1	Current System Architecture
Management IC System Architecture	1	Current System Architecture
Hospital Data Server	1	Current System Architecture
BI Data Department	1	Current System Architecture, Data Analysis Process
5 way Data Analysis	1	Data Analysis Process
Complete Data Collection	1	Data Analysis Process
Importance Output Validation	2	Data Analysis Process
...	...	...

C
Interview Questions

C.1. Interview session 1

C.1.1. Introductory and Warm-Up Questions

- Describe your role.
- How long have you been working here?
- What main skills are required in your role?

C.1.2. Interview Questions

1. Can you describe the type of data that is used for planning and capacity management in the ICU?
2. How do you obtain this data – what are the sources?
    - **Follow-up:** Most papers focus on historical data such as length of stays and mortality. Do you do the same here or do you do it differently?
3. What predictive models do you use to forecast ICU capacity needs?
    - **Follow-up:** How accurate are these models in practice?
    - How do you handle missing data in your predictive analytics processes?
    - **Follow-up:** What strategies do you use to manage and impute missing data?
    - **Follow-up:** How does missing data affect your predictive model outcomes?
    - **Follow-up:** What improvements would you suggest for these models?
4. Which (new) data of patients could be useful to make predictions and why?
5. I already researched some new types of data from the literature and would like to follow up with some of these ideas with you, for example: (see CHapter 5)
    - **Follow-up:** How feasible is it to integrate wearable devices, remote monitoring systems, and personalized medicine in your current data management practices?
    - **Follow-up:** What social determinant data do you find crucial or could be beneficial for predicting ICU patient flow and outcomes?
    - **Follow-up:** What are other AI/ML predictive models that could be used?
    - Any other ideas?
6. For each of the ideas above, could you comment on the legal challenges associated with these new data sources?
    - **Follow-up:** How do you ensure compliance with GDPR?
    - **Follow-up:** What specific privacy-preserving techniques do you employ when sharing patient data?

7. Can you describe the current system architecture used for ICU data management?
   For each of the ideas above, could you comment on the technical and system integration challenges associated with these new data sources?
   - **Follow-up:** What improvements would you suggest for optimizing the current system architecture to better support ICU management?
8. Are there any documents, research papers, or guidelines that you would recommend I read to gain a deeper understanding of ICU capacity planning and data management in the Netherlands?
9. Can you recommend any colleagues or other professionals who might provide valuable insights into ICU capacity planning and data management?

C.2. Validation Interview (Interview session 2)

1. In what ways does the current model reflect (or not reflect) the actual situation?
2. How attainable do you see the proposed future model, and what changes would make it more feasible in practice?

D

COREQ Checklist

Table 20: Coreq Checklist

No.	Item	Question / Description	Response
Domain 1: Research Team and Reflexivity: *Personal Characteristics*			
1	Interviewer/facilitator	Who conducted the interviews or focus groups?	The interviews were conducted by the sole author of this thesis. See front page.
2	Credentials	What were the researcher's credentials?	Master's student. See Acknowledgements.
3	Occupation	Occupation at time of study?	Full-time Master's student. See Acknowledgements.
4	Gender	Male or female?	not relevant for research (not mentioned*)
5	Experience/training	What training/experience did the researcher have?	Bachelor's thesis and Master's-level work. (not mentioned*)
Relationship with Participants			
6	Relationship established	Was a relationship established before study?	No. (not mentioned*)
7	Participant knowledge	What did participants know about the researcher?	Participants were informed about the study's context and goals. See Chapter 2.
8	Interviewer characteristics	What characteristics were reported?	Not discussed. (not mentioned*)
Domain 2: Study Design: *Theoretical Framework*			
9	Methodological orientation	What was the methodological approach?	Thematic analysis using the Double Diamond model. See Chapter 2.
Participant Selection			
10	Sampling	How were participants selected?	Purposeful sampling. See Chapter 2.
11	Method of approach	How were participants contacted?	Email. (not mentioned*)
12	Sample size	Number of participants?	Seven. See Chapter 2.

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No.	Item	Question / Description	Response
13	Non-participation	Any dropouts or refusals?	None. (not mentioned*)
Setting			
14	Setting of data collection	Where was data collected?	Microsoft Teams or workplace. (not mentioned*)
15	Presence of others	Was anyone else present?	No. (not mentioned*)
16	Description of sample	Important characteristics of the sample?	ICU management professionals. See Chapter 2.
Data Collection			
17	Interview guide	Were guides used? Pilot tested?	Yes, checked by supervisor. Not pilot tested. (not mentioned*)
18	Repeat interviews	Were interviews repeated?	No. (not mentioned*)
19	Recordings	Were recordings used?	Audio only. (not mentioned*)
20	Field notes	Were notes made?	No. (not mentioned*)
21	Duration	How long were interviews?	30 minutes to 1 hour. (not mentioned*)
22	Data saturation	Was saturation discussed?	No. (not mentioned*) and it could be that it was not reached due to new arising topics and different answers.
23	Transcript return	Were transcripts returned to participants?	No. (not mentioned*)
Domain 3: Analysis and Findings: *Data Analysis*			
24	Number of coders	How many coders?	One. See front page.
25	Coding tree	Was a coding tree described?	Yes. See Chapter 2.
26	Derivation of themes	Were themes derived from the data?	Yes. See Chapters 2.
27	Software	What software was used?	ATLAS.ti. See Chapter 2.
28	Participant feedback	Did participants review findings?	Two participants provided feedback. See Chapters 2 and 10.
Reporting			
29	Quotations presented	Were quotes used to illustrate findings?	Yes, anonymised. See Chapters 4–10.
30	Consistency	Were data and findings consistent?	It seems so, but data saturation might not have been achieved, which can affect consistency. See Chapter 10.
31	Major themes	Were major themes clear?	Yes. See Chapters 4–10.
32	Minor themes	Were minor themes described?	Yes. See Chapters 4–10.

* “Not mentioned” means not explicitly stated in the main thesis text.