Integrating Safety in Hospital Capacity Management

Predicting the Impact of Patient Exposure
to Overflow Beds on Patient Mortality

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to Overflow Beds on Patient Mortality

by

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[*the front page illustration was partially created with modified AI-generated images]*

Preface

In front of you is the master's thesis "Integrating Safety in Hospital Capacity Management", the result that marks the end of my Master's degree in Engineering & Policy at the Faculty of Technology Policy and Management at the Delft University of Technology. In addition to my graduation, this work also symbolises the end of my student life. I have always seen my time in Delft as an opportunity to engage in more than just studying and to challenge myself both academically and beyond. These opportunities have shaped me both personally and academically, but most of all has been shaped by the people I have been able to spend this time with. Countless beautiful, enlightening, humorous and sometimes difficult moments will stay with me, and I am grateful for the time I had in Delft.

The journey of the past six months has challenged me to discover how to apply my academic analytical skills in the unfamiliar field of healthcare. My time at the hospital has shown me that healthcare can be incredibly dynamic and complex. No day was the same and the opportunities to explore and experience as much as possible in the hospital inspired me and contributed immensely to the successful completion of this thesis. I am grateful to have been able to complete my thesis in this hospital.

This thesis would not have been possible without the feedback, help and inspiring discussions that have often given me much to think about. First of all, I would like to thank my first supervisor, Perla. During our weekly meetings, I felt the space to share my thoughts and ask questions. I enjoyed how our discussions really helped me to push my thesis to a higher level and to work towards something valuable for the hospital. I would like to thank my second supervisor Saba for her critical perspective on the scientific relevance and contribution of my thesis. Besides achieving practical contributions, your feedback helped me to add the right academic touch to the thesis and to place my work in a socio-technical EPA perspective.

Finally, I would like to thank my parents, brothers, roommates and friends for their support over the past few months. You have given me new insights, reminded me that sometimes just good is good enough, and helped me to better understand my findings. Sometimes by asking a tough question, sometimes by pulling me to study together in Delft or just by listening to my storm of thoughts. Thank you all!

It's done and I look forward to what the future will bring!

Mart Vloet
Delft, March 2025

Executive Summary

At a time of increasing pressure on healthcare systems, hospitals are increasingly facing the challenge of bed shortages. This requires hospitals more often to admit patients outside of the clinically appropriate ward, placing them on overflow beds. While the responsible medical team remains responsible for patient care and strategies are used to admit patients to the most appropriate available wards, concerns have been raised about the potential impact of overflow beds on patient safety. Much is still unknown about the impact of overflow beds on patient safety and, as a result, safety implications are currently not explicitly considered in the clinical decision-making during bed capacity shortages.

This research aimed to address this gap in hospital capacity management by investigating the extent to which patient exposure to bed shortages has safety implications. Specifically, it examined whether an increase in mortality risk could be predicted based on patient exposure to overflow beds. The addressed main research question was:

*"To what extent does **patient exposure to bed capacity shortages during hospital admission** increase the **risk of mortality**?"*

This study used a data analysis and statistical modelling approach using aggregated hospital capacity, patient and safety data. The research was divided into three phases: the first phase involved an initial exploration of the data to define clinically relevant patient exposure to overflow beds. The second phase quantified and predicted the potential impact of overflow beds on safety by estimating predictive models for acute admissions. The final phase focused on the clinical usefulness and practical applicability of the research findings by evaluating how predictive modelling could be used to improve clinical decision-making around overflow beds.

The first phase identified clinically relevant exposures to overflow beds by exploring potential mortality risk patterns across three dimensions: general exposure, location and duration. This exploration revealed considerable increases in observed mortality rates, adjusted for patient mix, for all three dimensions. It revealed that the *absolute* adjusted mortality rate of patients who were exposed to overflow beds (4.0%) was considerably higher than patients who were not (2.6%). In addition, an increased risk was particularly found for types of patients (classified in surgical, medical or mixed patients) placed in wards different from their intended type of ward. Increased mortality risk was also observed in the early stages, short durations, of overflow bed exposure. Certain patient characteristics - such as higher age, high urgency, severe diagnoses and comorbidities - were associated with a higher likelihood of being placed in an overflow bed.

These indications of potential increased mortality risk were quantified using predictive models. The models showed that exposure to an overflow bed was associated with a *relative* increase of 65% in odds of mortality compared with no exposure. The results of the location model showed particularly large increases in the odds of mortality for patients classified as mixed patients when outside their appropriate ward, with a more than 4 times higher risk for exposure to another mixed ward, compared to no exposure. Significant increases were also observed when medical patients were placed in surgical wards and vice versa. The odds of mortality for medical patients in surgical wards and surgical patients in medical wards were doubled and nearly tripled, respectively, compared with no exposure. Short exposures (less than 34 hours) were found to significantly increase the odds of mortality by a factor of 2.3, compared to no exposure. These findings suggest that general exposure, location and duration all significantly impact patient mortality.

The findings were subsequently translated into practical insights to improve clinical decision-making around overflow bed placement. Guidelines were developed based on common patient parameters at the time of hospital admission - age, number of comorbidities and place of origin. These guidelines, visually presented in clear heat maps, quickly show which patients can be relatively safely placed in overflow beds (patients under 60 years of age, regardless of origin or comorbidities). Conversely, patients over 80 years of age with multiple comorbidities should be avoided for overflow bed placement. For patients in between these risk ranges, the research findings provide hospital staff with a better sense of potential mortality risks, allowing them to predict individual patient risks based on the three risk dimensions.

In conclusion, this research contributes to a better understanding of the safety implications associated with overflow bed exposure. It provides new insights into exploring the risk implications across a wide range of patient types, applies new methodologies, and offers practical insights to improve the integration of safety considerations into hospital capacity management.

These findings should raise awareness among hospitals and staff of the increased mortality risks when capacity constraints require admissions outside clinically appropriate wards. It is recommended that hospitals initiate discussions across the entire organisation - medical, nursing and support staff - about the identified safety risks, and integrate the implications of the research into future policies and guidelines. This will contribute to a more risk-informed, proactive and explicit consideration of safety in hospital capacity decisions, ultimately leading to a more efficient and, above all, safer approach to managing overflow beds in times of increasing healthcare pressures.

Keywords: Overflow Bed, Hospital Capacity Management, Hospital Safety, In-Hospital Mortality, Clinical Prediction Model

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Abbreviations

AMR	Adjusted Mortality Rate
AUC	Area Under the (ROC-)Curve
DCA	Decision Curve Analysis
ED	Emergency Department
EDA	Exploratory Data Analysis
OR	Odds Ratio
LBZ	Landelijke Basisregistratie Ziekenhuiszorg
ROC	Receiver Operating Characteristic (Curve)

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1. Introduction

1.1 Problem Statement

In modern society, healthcare institutions play an important role in maintaining collective well-being by preserving and enhancing human life. Accessible, affordable, and appropriate care is an essential part of a healthy and safe society. However, in recent years, health institutions, especially hospitals, have faced escalating pressures (Henley et al., 2022; WHO, 2022). In the Netherlands challenges such as an ageing population, shifting care demands, and constraints on budgets, staff, and resources have become increasingly apparent (Centraal Bureau voor de Statistiek, 2023; NVZ, 2023; Schut et al., 2013). As a result, hospitals must meet care demands with limited capacity, potentially compromising the quality of care provided.

Efficient planning of available capacity is therefore crucial in addressing these challenges (Humphreys et al., 2022). Hospitals have the task of strategically allocating staff, equipment, and resources to meet patient needs. Once the optimal balance has been achieved, hospitals are able to deliver the appropriate clinical care and accommodate patients who require hospital admission. In such instances, patients are admitted to specialty wards where care is provided by staff with expertise in their specific conditions. This is intended and designed to improve patient outcomes. Specialty wards are staffed with professionals who have the requisite knowledge, expertise and skills necessary to respond to patient needs in a timely and effective manner, thereby ensuring the delivery of optimal and safe care.

However, when the number of patients requiring care exceeds the capacity of the hospital, a situation may arise in which there are insufficient admission spaces available to admit patients to the appropriate ward. In such circumstances, patients are frequently allocated to ‘overflow beds’ situated outside the intended specialty ward. Such exposure to capacity shortages, whereby patients are admitted to *clinically inappropriate* wards, introduces the potential for safety risks (Goulding et al., 2012). While the specialty physician remains responsible for the patient's care, the physical distance, for example, from the specialty ward to the patient may result in less frequent oversight, and, additionally, staff in the overflow ward may lack the requisite expertise in the patient's medical conditions (Cheung et al., 2020; McAlister & Shojania, 2018;Sobolewska et al., 2022). These factors, among others, may lead to a delayed and/or inaccurate response to specific care needs, which could compromise the quality of care provided. It can be argued that the continuity of the care for the patient becomes more variable, which raises concerns regarding patient safety (Allard & Lonsdale-Eccles, 2019).

Currently, safety and quality of care often tend to be overlooked aspects of hospital capacity management (Vincent et al., 2014). While hospitals strive to maintain abundant capacity to meet patient demand and avoid the need to turn away patients or provide suboptimal care, the focus tends to be on balancing safety with operational efficiency. Capacity management is generally designed to ensure that enough beds are available to accommodate expected admissions. However, when patient demand exceeds available capacity, decisions to place patients in overflow beds are often guided by ‘capacity-deficit’ protocols, which focus on assigning patients to the next available and clinically suitable ward.

Although these protocols aim to place patients in the most optimal wards, the potential safety risks of such decisions are not fully understood and prove to be difficult to quantify or measure. The extent to which placing patients in overflow wards affects safety is not explicitly considered yet in its decision-making process, leaving a critical gap in hospital capacity management. While the goal is to manage

immediate patient flow, the implications of these placements on patient safety remain largely unknown, as the impact of bed shortages on patient outcomes has not been systematically, quantitively examined.

Furthermore, hospitals collect vast amounts of data on patient admissions, medical conditions, and outcomes, but this information is predominantly used to optimize resource allocation and demand management rather than to proactively assess safety risks. Safety assessments tend to be retrospective, focusing on historical data such as complication numbers and mortality rates, rather than being proactively integrated into real-time capacity management (Rosen, 2010; Habraken, 2010). This reactive approach limits the ability to foresee and mitigate potential safety risks during times of capacity strains, where more proactive measures could help in anticipating the effects of capacity management decisions on patient safety.

1.2 Research Objective

This study aims to address the gap between hospital bed capacity shortages and potential patient safety implications by employing a data-analysis and statistical predictive modelling approach. Patient safety implications are operationalised in this study as in-hospital mortality. The objective of the research is to assess the degree to which mortality can be predicted based on patient exposure to overflow beds. In this research context, exposure to overflow beds is defined as the situation where a patient, due to a lack of capacity, is being placed in a ward outside its clinically appropriate ward, and measured by the duration of its overflow bed placement. The main research question that is sought to be answered is: "*To what extent does patient exposure to bed capacity shortages during hospital admission increase the risk of mortality?"*

To explore this question, the study will leverage routinely collected hospital data from a hospital located in the South-Western region of the Netherlands. Hospital capacity data will be linked to patient admission and safety data, which will allow for an in-depth data analysis for existing patterns related to overflow bed exposure. This explorative analysis will focus on identifying patterns related to three key aspects relevant to overflow exposure: the baseline risk of overflow exposure and associated patient characteristics, the location of the overflow bed within the hospital and the duration of time patients spend in overflow beds. By examining how these patterns relate to safety outcomes, clinically relevant exposure to overflow beds can be defined. Clinically relevant exposure to overflow beds should provide initial insights into factors contributing to safety implications and support the development of exposure variables. These exposure variables should be both clinically meaningful to hospital staff and reflect factors that may contribute to escalating safety risks associated with overflow bed exposure

With these exposure variables established, the study will develop predictive models to evaluate how well patient mortality outcomes can be predicted based on the defined clinically relevant exposure. Separate predictive models will be developed for different dimensions of risk, testing for the baseline risk, the location and the duration of overflow bed exposure and varying patient characteristics to identify which factors most significantly contribute to safety risks. The accuracy and performance of these models will be assessed to determine which model provides the best predictive accuracy.

The outcomes of these predictive models will be assessed for their clinical usefulness, evaluating their ability to improve clinical decision-making regarding overflow bed placements compared to current practices. This assessment will help determine the ranges of mortality risk in which the model adds clinical value, to subsequently translate these ranges into associated patient-characteristics. These risk ranges can provide hospital staff with a clearer understanding of where the models are useful to explore the risks associated with overflow bed exposure for individual patients and to offer practical insight into which patients may be relatively safe for overflow bed placement and which should be avoided.

This research contributes to both academic literature and hospital capacity management by exploring the relationship between bed capacity shortages and patient safety outcomes. By shifting from reactive safety assessments to proactive, data-driven capacity planning, it aims to bridge an existing gap in hospital decision-making. Quantifying potential mortality risks associated with overflow bed placements will provide actionable insights to enhance patient safety during capacity constraints. These findings will help hospital staff become more aware of potential safety risks and integrate these considerations more explicitly into capacity management strategies. This will ultimately contribute to a more proactive, efficient, and safer healthcare system.

1.3 Relevance to the EPA program

This research aims to address the increasing challenge society faces of providing safe and accessible healthcare within the context of rising capacity constraints, closely aligning with the EPA program of tackling grand societal challenges. As healthcare systems experience increasing pressure from factors like ageing populations, evolving care demand, changing patient needs, and limited resources, this study focuses on understanding how capacity limitations, especially through overflow bed usage, impact patient safety. By examining this specific aspect of healthcare, the research aims to provide insights that support effective hospital management and could contribute to solutions for broader healthcare challenges.

By employing a data analysis and statistical modelling approach, this study seeks to come up with evidence-based and data-driven insights that can support hospital decision-makers in facing these societal healthcare challenges. They are tasked with managing hospital capacity under increasing pressures, which require balancing efficiency, safety, and availability of care—goals that often come under further strain as demand increases. This could result in overflow beds frequently being used to handle capacity shortages, potentially impacting the safety of care. By offering a data-driven understanding of how capacity bed shortages may affect patient safety, the study aims to provide policymakers with new insights to make informed decisions in response to the complexities of care demands.

This research also contributes to the scientific literature on healthcare management by addressing gaps in understanding the impact of capacity shortages on patient safety, an academic area that requires a clear need for future research. This objective aligns with the EPA program's intention to expand academic knowledge and fill knowledge gaps in areas of societal importance. By advancing research on healthcare systems under pressure, this research not only addresses grand societal challenges but also builds on a data-driven academic contribution for a future of safer healthcare.

1.4 Thesis Structure

This thesis is divided into seven Chapters. Chapter two first discusses the scientific relevance of the study and presents the main research question aimed to be addressed in this research. Subsequently, Chapter three discusses the study design, defining the research context and dividing the study into three phases. For each phase, this Chapter subsequently explains the corresponding research methods and sub-questions. This is followed by three chapters that present the results of these three research phases: Chapter 4 covers the data preparation and exploration, Chapter 5 discusses the predictive modelling, and Chapter 6 assesses the validation and clinical usefulness of the developed predictive models. The research findings, limitations, scientific contributions, future research recommendations and implications are discussed in the discussion in Chapter 7. This research is concluded in Chapter 8 with a final conclusion answering the main research question.

2. Scientific Relevance & Research Question

The purpose of this chapter is to assess the current state of scientific research on the impact of patient exposure to overflow beds on patient mortality during hospital admissions. To achieve this, a targeted literature search identified relevant studies, after which a set of articles were selected. These selected articles are reviewed to highlight the study's scientific relevance. This review addresses the current understanding of the impact of overflow bed exposure on mortality and discusses the consideration of potential safety implications of overflow bed exposure in hospital (capacity) management. This chapter concludes by identifying knowledge gaps that this study aims to address and by presenting the main research question.

2.1 Literature Search Strategy

A structured search using the Scopus and PubMed databases was executed to identify relevant literature regarding the potential safety implications of overflow bed exposure. Initially, an explorative search string was employed to identify literature related to overflow beds, hospital capacity management and quality of care. This search string was defined as follows:

("hospital capacity" OR "hospital crowding" OR "bed occupancy" OR "capacity shortage" OR "bed capacity" OR "overflow bed" OR "medical outlier" OR "outlier patient" OR "bedspacing") AND ("patient safety" OR "quality of care" OR "adverse event" OR "patient outcome" OR "clinical outcome" OR "risk" OR "hospital performance")

This explorative search yielded extensive results on both Scopus (3.908) and PubMed (2.603). Whilst these results were helpful in gaining a better understanding of the common terminology used in this area of research, they predominantly yielded general and therefore primarily irrelevant literature on the broad concepts of hospital capacity management and quality of care, rather than addressing the concept of overflow beds and potential safety implications.

A more specific literature search focus was required to target towards more relevant literature. Based on an exploratory and quick scan of the keywords of the initial literature, a sharpened search string was defined, specifically operationalising hospital capacity management through (synonyms of) overflow beds. In addition, the concept of quality of care had to be refined and was detailed by including mortality in the search string. The refined search term was defined as follows:

(*"bedspacing" OR "medical outlier" OR "outlier patient" OR "outlying patient" OR "overflow bed") AND ("safety" OR "quality" OR "patient outcome" OR "adverse event" OR "risk") AND ("mortality" OR "death" OR "hospital mortality" OR "mortality rate")*

The sharpened search yielded 25 results in Scopus and 13 in PubMed. Titles, keywords and abstracts were reviewed for relevance; only studies that specifically addressed patient *exposure* to overflow beds during hospital admissions and mortality outcomes were considered. Articles were further evaluated based on their methods, with preference given to quantitative research. Based on this selection process, 10 relevant articles were identified and included in the review.

2.2 Overflow Bed Exposure and Safety Implications

In literature, the concept of an *overflow bed* is well-known but referred to by numerous terms, including *outlier patients*, *medical outliers*, *outlying patients, bedspacing*, and *overflow patients*. Despite the variation in terminology, the fundamental meaning is consistent: an overflow bed refers to a situation where a patient is admitted to a ward other than the clinically appropriate or "home" ward. As defined by Perimal-Lewis et al. (2013), the home ward is the "ward where the multidisciplinary medical team responsible for the patient's care is primarily located". This ward is determined by the specific type of care the patient requires, as the patient's medical condition or diagnosis should align with the expertise of the responsible clinical team. Therefore, patients should ideally be admitted to a ward that corresponds to their clinical needs.

Given the shared fundamental concept of overflow beds, the identified studies allow for a meaningful comparison to evaluate the current understanding of overflow bed exposure and safety implications. Table 1 provides an overview of the findings across the reviewed articles, along with a short description of the scope, methodology and definition of overflow bed exposure of each research.

Table 1: Overview of research findings of existing literature

Study	Scope	Mortality	Methodology	Determination of Exposure
Perimal-Lewis et al. (2013)	Single-centre study, General Medicine admissions	The risk of in-hospital mortality increased by over 40% for outlier patients	Poisson regression analysis (adjusted for patient-related confounders)	Patients admitted outside designated GM home ward
Santamaria et al. (2014)	Single-centre, all admissions	Higher mortality for outliers (2.57% vs 1.12%)	Observational cohort study	Patients spending any time outside their designated home ward
Serafini et al. (2015)	Single centre, Medical and Geriatric patients	1.8x higher mortality risk for medical patients in surgical wards	Multivariate analysis (adjusted for age & gender)	Patients admitted outside Medicine or Geriatrics
Stylianou et al. (2017)	Single-centre study, Medical admissions	No effect on in-hospital and 30-day mortality	Multivariate logistic regression (adjusted for patient-related confounders)	Patients with at least one spell of care at non-medical ward
Bai et al. (2018)	Single-centre study, General Internal Medicine admissions	3x higher mortality risk at admission, impact diminishing over time, with equal risks at third week	Cox proportional hazards model, competing risk model (adjusted for patient-related confounders)	Patients admitted outside GIM wards
Bogler et al. (2021)	Multi-centre study, General Internal Medicine admissions	Lower mortality for outliers (2.6% vs 3.3%)	Generalized Estimating Equations (adjusted for confounders)	Patients discharged from a non-GIM inpatient ward
Kohn et al. (2021)	Multi-centre study, General Medicine admission	No effect on in-hospital mortality	Logistic regression adjusted for patient-related confounders)	Patients placed outside GIM specialty wards
Asheim et al. (2022)	Multi-centre study, Acute admissions for myocardial infarction, stroke or heart failure	1.08x higher mortality risk for heart failure patients only	Stratified Cox regression (adjusted for patient- related confounders)	Patients not admitted to their designated home ward.
Patry et al. (2022)	Single-centre, Medical Patients	6-month survival probability 0.44x lower for outliers	Multivariate regression analysis	Medical patients admitted to surgical wards
Zannella et al. (2022)	Multi-centre study, General Internal Medicine admissions	No effect on in-hospital mortality	Multivariate regression adjusted for patient- related confounders)	Patients assigned to non-GIM ward directly after ED

The reviewed studies present varied findings regarding the association between overflow bed placement and patient mortality. Six studies reported an increased risk of mortality associated with overflow bed placement, three found no significant difference, and one observed lower mortality rates among overflow bed patients. Notably, only one study (Bai et al. (2018)) specifically examined how risk changed over time, finding that the increased mortality risk was highest at the point of admission and diminished over time. The variation in findings suggests that while overflow bed use may influence patient mortality, there is no consistent, generalizable evidence of an effect on mortality. These discrepancies may result from differences in patient populations, study designs, methodological approaches, and the specific healthcare contexts in which these studies were conducted.

A noticeable trend in study design was that previous studies were predominantly single-centre studies, whereas more recent studies are often multi-centre studies. Many of the earlier studies recommended external validation in different hospitals, which may have contributed to the shift towards multi-centre research in the more recent literature. Moreover, the effect of overflow exposure on mortality seems to differ between these study designs. While earlier single-centre studies found stronger associations between mortality and overflow exposure, more recent multi-centre studies more often reported no significant effect or a smaller effect. This may be because the effect of exposure to overflow beds is less apparent across multiple hospitals, or it may be explained by changes in hospital policy and attention to overflow bed management, influenced by safety concerns raised in earlier research. This aspect will be further explored in the second part of this review.

While the basic concept of overflow exposure is consistent - a patient admitted outside their clinically appropriate ward - studies define exposure differently. Some classified patients as overflow bed exposed based on the ward of admission, others used time-based definitions, and one study categorised overflow patients based on the ward of discharge. These differences could influence the results, as the associated risk may differ depending on whether the exposure is defined at admission, considers the length of stay, or is determined by the place of discharge. For instance, determining exposure at admission does not consider risks associated with exposure duration, whereas a discharge-based definition may exclude patients who were initially placed in an overflow bed but were later transferred back to their home ward. Such differences in classification may contribute to the variability of the studies' findings.

Methodological differences also play a role. While it is difficult to determine the precise impact of these differences on the findings, one notable variation is the extent of adjustment for confounders. Almost all studies accounted for patient-related variables, either selected by initial patient-demographic analyses or based on previous literature. However, the depth of these adjustments varied—some studies controlled for only a few factors, while others incorporated a broader range of potential confounders

Lastly, the study scope varied. All studies were conducted within Western healthcare systems (United States, Canada, France, Italy, Norway, and Australia), limiting generalizability to other healthcare contexts. Most studies focused on overflow patients of General Internal Medicine (GIM) or Medical wards placed outside these desired wards, meaning the findings may not fully apply to other specialties or wards. The focus on GIM wards means that the results may not fully capture the impact of overflow bed exposure across an entire hospital setting and patient sample size, as outcomes could differ for different types and quantities of patients admitted to different types of wards.

Given these variations in findings, scope, methodology, exposure definitions, and differences between previous single-centre and more recent multi-centre hospital studies, the results lack generalisability. This is also explicitly acknowledged by most studies in their limitations. They emphasise the need for follow-up studies in other hospitals to replicate findings and improve the applicability of results to different health care settings and patient populations.

2.3 Consideration of Safety Implications and Overflow Bed Exposure

Considering the current understanding of overflow beds and safety implications, this section focuses on whether this understanding is taken into consideration in hospital capacity management.

To first provide a perspective on the importance of the consideration of safety implications, a reflection can be made on the work of Goulding et al. (2012). This research took a qualitative approach to identify 5 key themes that might lead to safety risks for patients in overflow beds and developed a framework of underlying causing mechanisms.

Goulding et al. (2012) describe the need for overflow bed placement as arising from *latent conditions*—structural conditions caused by strategic, planning, design and/or policy-based decisions. In the context of overflow beds and hospital capacity management, this, for example, could entail efficiency-driven policies that might result in bed shortages, thereby necessitating overflow placements, or flow charts to assist the decision-making process of deciding to admit certain patients to overflow wards.

While these latent conditions create the circumstances for potential safety risks, Goulding et al. (2012) argues that they alone are not sufficient to cause adverse safety outcomes. Instead, it is often the combination of latent conditions with other mechanisms that may cause a risk to patient safety. Without appropriate responses to these combined factors, the probability of adverse patient outcomes may further increase. Risks increase if there is no proper response to mitigate these potential risks, so it is, therefore, important to be aware of and consider potential safety implications at the forefront

All reviewed studies clearly stated that there is little understanding and awareness of the impact of overflow beds on patient safety. This creates a challenge in incorporating potential safety risks into hospital management, as informed policy cannot be made when little is known. This seems to be reflected in the fact that none of the articles reported on existing measures or policies to mitigate the impact of safety implications that were already in place at the time of the research. Most of the studies therefore end up recommending that hospitals should be more aware of the potential safety risks of overcrowding and take them into account more explicitly in clinical decisions. Their ideas on how to implement such measures and consider the safety implications vary from study to study.

For instance, some studies suggest that more research is first needed into the underlying mechanisms that may cause safety risks, which would help to develop more targeted strategies to mitigate these mechanisms. In addition, it is stated that potential safety risks should be better informed to medical staff, indicating that these insights should lead to well-informed discussions between wards, doctors and managers, which should ultimately lead to more safe and informed policies on overflow bed placement. Hospitals should be more prepared to standardise a (safe) approach with guidelines on how and for whom overflow beds should be used. The creation of such policies, standards and/or guidelines should be based on the question of what kind of approach or practice can be used for overflow bed placement to ensure that the safety of care is maintained. This is particularly important because, as all studies indicate that overflow beds will continue to be used to respond to capacity shortages, such an approach recognises that there may be safety risks for patients, so it is important to structurally consider these.

The main message is that the literature calls for a more risk-informed approach to overflow bed management to ensure high-quality care. While existing studies have suggested ways to consider safety implications more explicitly—such as standardized policies or guidelines, and improved awareness—no research was found that has explored the actual integration or impact of such safety considerations in practice. Without a more explicit focus on safety risks, strategies regarding overflow bed placement may continue to overlook or underestimate their impact on patient outcomes. This underscores the need for a more proactive and structured approach to safety when managing bed capacity shortages.

2.4 Knowledge Gaps

Despite considerable research exploring the relationship between patient exposure to overflow bed and patient safety, there remain significant gaps in the literature. A review of the existing literature provided an overview of the current understanding of the impact of overflow bed exposure on mortality and helped to establish the scientific background for this study. Based on this review, three key knowledge gaps can be identified that demonstrate the scientific relevance of this study.

Lack of clear consensus on mortality implications

First, the existing literature revealed no clear consensus on the existence and extent of the impact of overflow bed exposure on mortality. Although the studies varied widely in terms of definitions, outcomes, scope and study design, the diversity of findings was evident. While most of the evidence suggests that there may be an association between overflow bed exposure and increased mortality risks, conflicting results were found and the magnitude of the effect varied, predominantly between previous single- and more recent multi-centre studies. Therefore, it cannot be said that there is currently a clear and agreed understanding of the relationship between exposure and mortality risks. This inconsistency highlights the need for further research to improve generalisability and provide stronger evidence of any (or no) potential adverse patient outcomes.

Limited generalisability and applicability

The current literature showed limitations in generalisability and applicable towards different hospital settings. Existing research findings were limited geographically, culturally and demographically by the examination of modern Western hospital(s). Although there may be similarities between Western healthcare systems, none of the studies included Dutch hospitals or healthcare system. There remains a gap in examining a Dutch care environment.

In addition, the majority of studies were often limited to one or a few hospitals with specific case mixes. Furthermore, most studies used narrowly defined patient groups, often restricted by a limited number of admissions of predominantly general internal medicine (GIM) patients placed outside their GIM wards. This limits the applicability of the findings to broader hospital-wide settings and a more diverse set of patient types. Exploring the impact of overflow bed exposure across an entire hospital, with a diverse mix of (surgical, medical and mixed) wards and admissions, is therefore needed to determine whether the findings are universal or location or patient group dependent. It calls for further validation of the results over other hospital settings, particularly to determine the wider applicability of these findings.

Lack of explicit integration of safety risks in hospital capacity management

A further gap in the literature is the lack of an explicit focus on the safety implications due to overflow bed exposure within hospital capacity management practices. Although safety is an important dimension of quality of care, it tends to be is often overlooked in capacity management and there is little evidence yet that it is systematically incorporated into decision-making. None of the studies reported on quality measures, guidelines or policies that where already in place to mitigate potential safety implications. Despite the existing studies suggest a potential impact on patient mortality, they do not provide concrete strategies or frameworks for integrating safety into capacity management decisions. No existing studies were identified that explored the impact of overflow bed exposure on mortality while safety implications were explicitly considered.

This gap highlights the need for a more pro-active, clinically applicable approach that integrates safety considerations into hospital capacity management. Given the retrospective nature of most studies, further research is needed to explore how potential safety risks can be more explicitly and proactively managed during periods of bed capacity shortages.

This study seeks to address these gaps by analysing empirical, routinely collected hospital data to assess the extent to which mortality can be predicted based on patient exposure to bed shortages. Although the study remains a single-centre study, the research aims to contribute to a more generalizable understanding of the potential risks associated with overflow beds by adding further empirical research and evidence with a different patient case mix and research approach.

In addition, this study aims to supplement existing research by examining a hospital setting where some awareness of potential safety implications is already integrated into capacity management. For instance, this includes capacity-deficit protocols that identify suitable ward alternatives when clinically appropriate wards are not available. While such protocols represent a step toward explicitly managing safety risks, the quantified impact of overflow bed exposure on mortality outcomes remains still unknown. This study aims to address this gap by providing predictive insights that quantify the potential safety risks associated with overflow beds.

By developing predictive models, the aim is to predict where patient exposure will significantly increase safety risks and where the impact is limited, thereby facilitating more explicit, safe and proactive overflow bed management. Ultimately, the goal is to provide hospitals with applicable, clinically relevant results that can support hospital operations and enable informed decisions to be made about safely managing the use of overflow beds during bed shortages.

2.5 Research Question

The knowledge gaps identified in the existing literature provide a clear perspective on the scientific relevance of this research. To address these gaps, a main research question is defined, which this study aims to answer. The main research question of this study is as follows:

*"To what extent does **patient exposure to bed capacity shortages during hospital admission** increase the **risk of mortality**?"*

3. Study Design

The purpose of this chapter is to introduce the study design of this research. First, the research context is outlined, providing definitions of key concepts for this study. Subsequently, the research approach is specified, which divides the research into three research phases. These phases are structured around four sub-questions, each contributing to a deeper exploration of the main research question. Subsequently, it describes how the data was collected, followed by a detailed explanation of the methodology used in each research phase.

3.1 Research Context

The context of this research can be outlined using four key concepts: overflow beds, safety, mortality and hospital capacity management. These concepts are used frequently throughout this research and require clear definitions to ensure a consistent understanding. Taken together, these definitions set the context in which this research has been conducted.

Overflow beds

The term *'overflow bed'* used in this study is derived from the Dutch term '*buitenbed*', which is commonly used in the hospital under study. It has been freely translated and adopted for this study. The term '*buitenbed*' refers to the admission of a patient to a bed outside the clinically appropriate ward when there is insufficient capacity to admit the patient to the intended specialty ward. The clinically appropriate ward was considered to be the ward where the primary clinical team responsible for a patient and the care they require is located, whereby overflow beds imply admission to a ward other than this designated ward. Overflow beds can be regarded as a solution to bed shortages, ensuring that patients can still be admitted even if they are placed in a ward not specifically designed for their care. This definition is consistent with the fundamental meaning of overflow beds identified in existing literature.

Safety

To assess the safety implications associated with exposure to overflow beds, it is essential to define safety. This study adopts the perspective on safety as one of the dimensions of quality of care as provided by the Institute of Medicine (2001).

The Institute of Medicine (2001) provides a framework to define high-quality care through six dimensions: safety, effectiveness, patient-centeredness, timeliness, efficiency, and equity. Together, these dimensions outline a comprehensive view of quality that goes beyond safety alone. Within this framework, safety is specifically defined as “avoiding injuries to patients from care intended to help them”. This definition focuses on preventing adverse patient outcomes—particularly those injuries arising from hospital care itself. A broader overview of the six dimensions is provided in Table 2.

Table 2: The six dimensions of quality of care (Institute of Medicine, 2001)

Dimension	Institute of Medicine (IOM) Description
Safety	‘Avoiding injuries to patients from care that is intended to help them’
Effective	‘Providing services based on scientific knowledge to all who could benefit and refraining from providing services to those not likely to benefit (avoiding under- and overuse)
Patient-centred	‘Providing care that is respectful of and responsive to individual preferences, needs and values and ensuring that patient values guide all clinical decisions’

Timely	'Reducing waits and sometimes harmful delays for both who receive and those who give care'
Efficient	'Avoiding waste, including waste of equipment, supplies ideas and energy'
Equitable	'Providing care that does not vary in quality because of personal characteristics such as gender, ethnicity, geographic location and socio-economic status'

This study examines safety using mortality as a key indicator. While safety is a distinct dimension in the IOM framework, it is closely related to other dimensions of quality of care, particularly in the context of the use of overflow beds. Hospitals deploy overflow beds to maintain efficiency when capacity is stretched, ensuring timely admission when beds are not available on the clinically appropriate ward. This can prevent safety risks associated with delayed admissions.

However, once admitted, the interplay between quality dimensions changes. Overflow bed admissions can disrupt the timeliness of care at the ward level - medical assessment and treatment may be delayed due to unfamiliarity with the patient's condition or physical distance from the responsible medical team. Such delays increase the risk of complications and ultimately compromise patient safety. This interaction illustrates how trade-offs can emerge between quality of care dimensions, requiring a broad perspective on the implications of overflow bed exposure.

Although multiple dimensions of quality are affected by overflow bed use, safety serves as the most direct and measurable outcome of the emerging trade-off between dimensions. Mortality reflects the consequences of complications or care delays that may arise from overflow bed use, making it a meaningful indicator for evaluating hospital safety.

Patient Mortality

In-hospital mortality is considered the key measure in this study to assess the impact of overflow beds on safety. Mortality can be seen as a crucial measure because preventing mortality and keeping patients alive can be seen as the primary goal of hospitals. To provide safe care, it should always be avoided that patients die unnecessarily.

In addition, the focus on mortality has been adopted because it is consistent with the provided research data *Landelijke Basisregistratie Ziekenhuiszorg* (LBZ), published by the DHD. In the LBZ, in-hospital mortality is included along with two other safety metrics - readmissions and unexpected length of stay - to assess hospital quality. These metrics are widely used internationally to assess the quality of hospital care (Bottle et al., 2013). The DHD suggests that inadequate or suboptimal hospital care generally leads to unfavourable outcomes, as indicated by increased mortality, longer lengths of stay and more admissions than expected (Bosman & Hekkert, 2024). This highlights the importance of hospitals having insight into these indicators to assess the quality of their care.

Hospital Capacity Management

Hospital capacity management is a broad term that can be interpreted in many different ways, both in the literature and in different hospital contexts. It seems that there is no agreed, general definition. It is therefore important to adopt a clear definition of hospital capacity management to clarify what is meant by it in this research. This study adopted the local use and context of capacity management of the hospital that provided the research data.

Hospital capacity management is defined as the management of hospital beds for the admission of patients. More specifically, this study focuses on hospital capacity management in times of capacity scarcity. This focus was chosen because capacity shortages lead to a shortage of clinically appropriate

beds, which in turn creates the need and situation for patients to be admitted to overflow beds and is therefore relevant to this research context. There are two important aspects of hospital capacity management related to overflow beds: a) the allocation of hospital beds across wards and b) the daily management of hospital beds.

Allocation of hospital beds across wards

The allocation of hospital beds aims to provide sufficient beds to meet the demand for care. This requires that there are enough beds to accommodate patients who need to be admitted to their intended clinically appropriate ward. The goal therefore is to avoid, as far as possible, the use of overflow beds, which should only be considered as a solution for admitting patients when there is a shortage of beds. This objective of optimal bed allocation is realised at a strategic and tactical level.

At the strategic level, the hospital determines the optimal number of beds and the available capacity for each ward on an annual basis. This strategic planning of bed capacity is based on data from previous years and follows a seasonal pattern to respond to expected demand for care in a data-driven and flexible way. The number of beds planned for each ward depends on certain occupancy and refusal norms. The occupancy norm is used to achieve a minimum bed occupancy to avoid empty beds, while the refusal norm reflects the maximum annual percentage of admissions for which the admission does not fit the clinically appropriate ward. The use of occupancy and refusal norms aims to balance the efficient use of resources while maintaining and striving for a high level of accessibility to care.

Based on the strategic annual bed allocation formations, bed capacity is evaluated monthly at a tactical level and adjusted as necessary. Based on input from each ward, it is assessed whether there will be a shortage or surplus of beds in the coming months and a decision can be taken to adjust the available bed capacity by opening or closing available beds.

Daily management of hospital beds.

The day-to-day management of beds is reflected on an operational level. This level is concerned with determining where a patient will ultimately be admitted. In the context of this study, this responsibility is assigned to a hospital staff member called the "patient flow coordinator" and is based on the advice and clinical judgement of the responsible physician at the point of admission. When it becomes clear that a patient will not fit into the intended clinically appropriate ward, an overflow bed is required to admit the patient and to avoid a refusal of admission.

The decision on which patients will be allocated to an overflow bed is ultimately made by the same patient flow coordinator who decides where the patient will be admitted. This decision is not based solely on available capacity, but capacity-deficit protocols are used to determine the next preferred and most appropriate ward for a particular patient. There are specific capacity-deficit protocols for each clinical ward, with flowcharts detailing where these patients should be admitted if there is no availability on the intended ward. In addition, a daily meeting is held between staff from all wards to determine a strategy for daily bed allocation and how to deal with overflow beds in times of bed shortage.

It is therefore important to emphasise that the hospital under study pays particular attention to hospital capacity management related to capacity shortages. This is ensured by aiming to avoid the use of overflow beds by striving for adequate bed allocation, but also by introducing measures to manage overflow beds through the organisation of daily bed allocation meetings, designated responsibilities for overflow beds and guidelines in the form of protocols. However, within these hospital capacity management practices, there exists a lack of explicit sense and knowledge of potential (quantitative) safety implications, to which this study aims to contribute.

3.1 Research Approach

This research adopts a quantitative data analysis combined with a statistical modelling approach to investigate the impact of bed capacity shortages on patient safety outcomes. This approach was translated into three research phases: Data Preparation & Exploration, Predictive Modelling and Validation & Clinical Usefulness.

The first phase, Data Preparation & Exploration, focused on merging patient admission, safety and hospital capacity data to create a detailed research dataset. This dataset was used to identify initial patterns and provide an exploratory understanding of overflow bed exposure and associated potential mortality risks.

The second phase, Predictive Modelling, involved the development and iterative refinement of statistical predictive models to predict mortality outcomes based on overflow bed exposure. Different model specifications were tested to assess the influence of three risk dimensions on mortality outcomes. Model performance metrics were used to identify the most accurate and clinically relevant models.

The third phase, Validation and Clinical Usefulness, assessed the stability and applicability of the developed models. The models were validated using a separate dataset to test their generalisability over time, and model recalibration was used to adjust the models for variations in the data over time. In addition, the practical implications of the models were assessed by performing Decision Curve Analysis to determine the clinical usefulness of the models across the range of mortality risks.

The research approach is visually represented in a Research Flow Diagram in Figure 1.

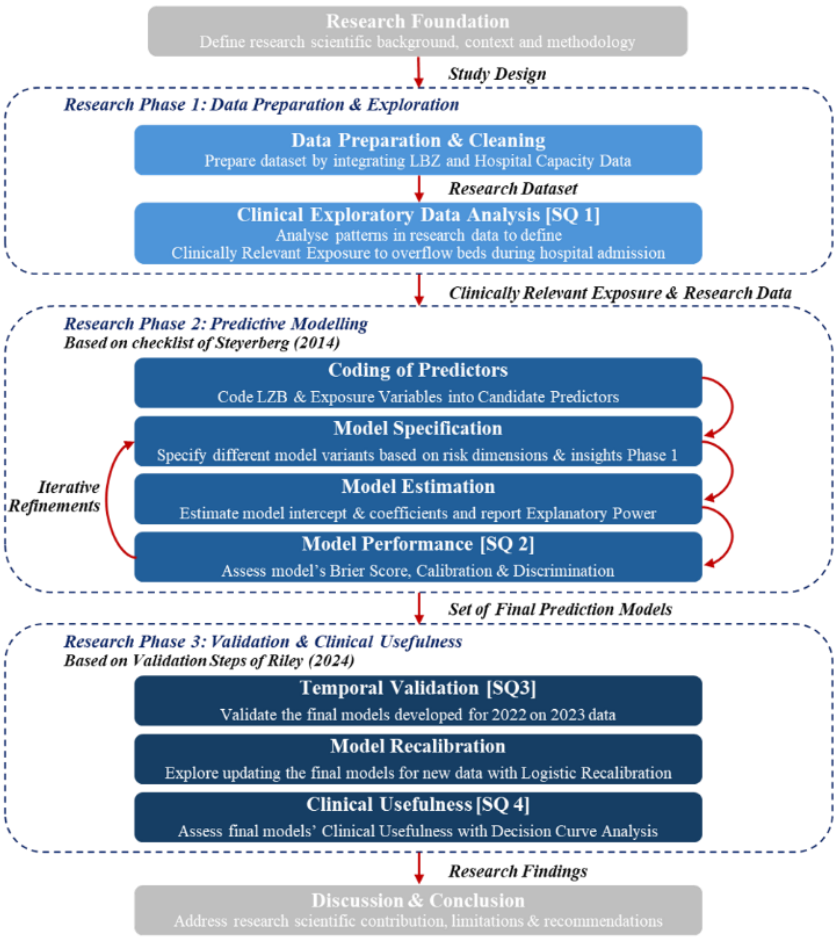

Figure 1: Research Flow Diagram visually summarising the research approach

3.2 Sub-Research Questions

To address the main research questions and provide additional structure to the research approach, four sub-questions were defined. The sub-questions indicate what question(s) needed to be answered per research phase to arrive at the desired final research outcomes.

Phase 1: Data Preparation & Exploration:

SQ 1: ***"What is clinically relevant exposure of patients to overflow beds during hospital admission"?***

This sub-question aimed to determine the clinically relevant exposure of patients to overflow beds during hospital admission by analysing how mortality may be affected by different aspects of overflow bed use. The analysis strived to identify patterns in the research data that may reveal factors that contribute to safety risks. To ensure clinical relevance, the analysis was structured around a framework of three key risk dimensions relevant to the decision-making process of hospital staff around overflow bed placement - general exposure, location and duration. The findings of this analysis provide a clinically relevant basis for the development of predictive models, ensuring that the models capture potentially effect-modifying patterns. In addition, it provides the hospital staff with initial insights into which type of patients might be exposed to high risks due to overflow bed exposure.

Phase 2: Predictive Model Development

SQ 2*: "Which models best predict patient mortality for clinically relevant exposure to overflow beds?"*

This sub-question focused on the development of logistic regression models that predict mortality outcomes. Building on the three key risk dimensions of phase 1, separate models were developed for each dimension. In addition, several model variants were specified for each dimension to test whether different model specifications (e.g. for specific patient types or characteristics) lead to different model estimates and hence different outcomes. This sub-question aimed to answer which model variant best predicts mortality given the defined clinically relevant exposure. Model performance metrics are used to assess which models provide the most accurate predictions and achieve the best and most clinically relevant outcomes. These models were included in the final set of prediction models.

Phase 3: Validation & Clinical Usefulness

SQ 3: ***"To what extent can the developed predictive models for 2022 accurately predict observed mortality for 2023?"***

SQ 4: ***"To what extent could the predictive models provide clinical usefulness to hospital staff?"***

Sub-question 3 focused on the validation of the final models by assessing the models' accuracy with new data. It was examined to what extent the model, developed with 2022 data, can accurately predict patient safety outcomes for 2023. This was done by applying the model's coefficients from the 2022 model to the 2023 data and comparing the predicted patient outcomes with the actual observed outcomes of 2023. By evaluating the differences, the accuracy of the model predictions over time was assessed.

Sub-question 4 evaluated the clinical usefulness of the developed predictive models by assessing whether the models could lead to better clinical decisions than those made without the predictive models. Clinical usefulness was determined by performing a Decision Curve Analysis. This method helped to evaluate how well the model can support clinical decision-making by comparing the potential benefits of using the model's predictions in practice with default overflow bed management strategies. The Decision Curve Analysis assessed whether the model not only provides accurate predictions but also may provide clinical benefits when used by hospital staff in clinical practice.

3.3 Data Collection

The data used in this study were obtained from a Dutch top-clinical hospital located in the South-Western region of the Netherlands. The data can broadly be categorized into three types: patient admission data, capacity data, and safety indicators. The data were routinely collected as part of the hospital's regular operations and registered at the level of individual admissions. The main datasets are briefly summarized here:

LBZ Data

The patient admission and safety indicator data originate from the *Landelijke Basisregistratie Ziekenhuiszorg* (LBZ) database, which is the national registration of medical, administrative, and financial information for patients admitted to hospitals (DHD, 2023). This data is routinely collected during clinical practice and processed to provide hospitals with insights into the quality of care. Each year, the processing institution (DHD) releases the database to hospitals, which includes information on patient admissions, such as age, gender, diagnosis, comorbidities (expressed through the Charlson Comorbidity Index), admission duration, and three key safety indicators: mortality, unexpected long length of stay, and 30-day readmissions.

The included admissions are all defined as clinical admissions, classified according to the rules of the Nederlandse Zorgautoriteit (NZa) (Bosman & Hekkert, 2024). This includes all inpatient admissions registered at the hospital, excluding the 'same-day admissions'. These are admissions for elective treatments or interventions that could be completed within 1 day and are therefore not registered in the LBZ-data (CBS, 2010).

Hospital Capacity Data

Additional data on patient admissions is provided in the form of aggregated Hospital Capacity Data, indirectly derived from the hospital's Electronic Patient Records. This dataset details the location to which each patient was admitted during their hospital stay, broken down by the time of day (day/evening/night) and the exact time spent in each location, measured in minutes. The data also indicate whether a patient was admitted to the appropriate clinical ward or whether an overflow bed was used by comparing the recorded location and specialty of the admission segment. In the case of a patient being admitted to an overflow bed, the data records which ward would have been the clinically appropriate ward. The hospital capacity data includes all registered admissions, including same-day admissions, clinical admissions and admissions registered as not requiring medical care. In the later stages of the research, the data will be cleaned and filtered to a pre-defined set of clinical admissions for selected wards. This will be further elaborated in Chapter 4. Data Preparation & Exploration.

By merging these datasets, the study gained access to all necessary data on patient admissions, overflow bed use and safety outcomes. The study used data collected over two years, from 2022 to 2023. Data collected in 2022 was used for model development, while data collected in 2023 was used for model validation. The year in which an admission is recorded is determined by the discharge date of the admission. This is how admissions in the LBZ data are recorded and hence decisive for this study.

3.4 Research Methodology

The research methodology is structured into three research phases, as outlined in the research approach. The employed research methods of each of these phases will be outlined in detail, along with the associated sub-research questions and specifications for required data input.

Phase 1: Data Preparation & Exploration

Sub-question:

SQ 1: ***"What is the clinically relevant exposure of patients to overflow beds during hospital admission?"***

Required Data: LBZ Data, Hospital Capacity Data
Research Methods: Data Preparation & Cleaning, Clinical Exploratory Data Analysis

The objective of phase 1 was to prepare the research data and to determine clinically relevant exposure of patients to overflow beds during hospital admission. This served as a fundamental base for the further phases of this research. Initially, this phase focused on cleaning and preparing the necessary data, after which a clinical Exploratory Data Analysis was conducted to explore patterns in the research data related to overflow beds and potential safety implications, structured around three key risk dimensions.

Data Preparation & Cleaning

The Data Preparation & Cleaning focused mainly on the integration of two key datasets - LBZ Data and Hospital Capacity Data (see 3.3 Data Collection) - to create a comprehensive dataset for further analysis. The LBZ data was used as a baseline to which the more detailed capacity data was added. This was done based on admission number, which means that hospital capacity data was added for all unique admissions included in the LBZ data. The research data is therefore aggregated at the level of individual admissions.

A key aspect of the integration of LBZ and hospital capacity data was the determination of the exposure to overflow beds. In the hospital capacity data, each admission is divided into admission segments corresponding to nursing shifts (day/evening/night). Each admission segment records a time and location. Based on the specialty of the main diagnosis of the patient, admission segments for which the recorded admission location does not correspond to the clinically appropriate ward(s) of its specialty were flagged as exposed to an overflow bed. By aggregating these admission segments to complete admissions, the cumulative exposure to overflow beds could be determined per admission, combined with a detailed view of where the patient was intended to be admitted versus where they were ultimately admitted. The integration of the two datasets is summarised in Figure 2.

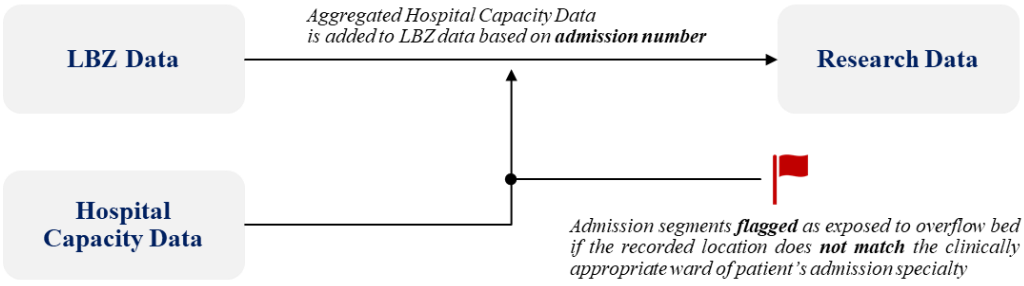

Figure 2: Visual representation of data preparation phase

In addition to integrating the datasets, it was essential to perform data cleaning to ensure accuracy and completeness and to avoid erroneous conclusions (Huebner et al., 2016). The data is checked against Huebner et al.'s list of data issues, including the removal of any inconsistencies or irrelevant entries that could affect the analysis. In addition, the data were split into a model development set (2022) and a validation set (2023) based on admission discharge date.

Finally, the research data only includes admissions to a predefined set of wards. The set of included wards was selected based on research relevance, as these are the only wards considered relevant in the context of overflow beds, according to the hospital providing the research data. In addition, each ward was classified by the hospital as a surgical, medical or mixed ward, based on the type of patients usually admitted to the ward and aligned with the medical expertise of the ward staff. An exemption has been made for the Acute Medical Unit, Day Care Unit and Oncology Care because these wards could never be considered as overflow wards. These wards, however, are still relevant for inclusion in the dataset to determine the correct starting point of admission. This will be further detailed in 4.1 Data Preparation.

[redacted]

Table 3: Overview of included wards and their classification

[redacted]

Clinical Exploratory Data Analysis

The clinical Exploratory Data Analysis (EDA) aimed to explore patterns and trends related to overflow bed exposure and potential safety risks. The purpose was to gain a deeper understanding of how patient exposure to overflow beds may lead to mortality risks and how these risks may vary across different patient types, characteristics, wards, and durations of exposure. According to Dhany & Izhari (2023), the findings of the EDA can serve as an essential guiding foundation for the subsequent predictive modelling phase. Understanding these patterns was crucial as input for the development of the predictive models as they may significantly affect the extent of safety risks, as identified factors might act as confounders or effect modifiers. The predictive models should therefore be corrected for these modifiers, to ensure accurate predictions.

In addition, the EDA could help classify patients into different risk groups, which could provide valuable initial insights for (more personalized) improvement interventions regarding overflow bed placement (Dhany & Izhari, 2023). The EDA gains explorative insights for clinicians and hospital staff on the type of patients where risks may be (too) high and could thereby inform improvement initiatives.

To ensure the clinical relevance of the EDA, the EDA was structured around a (hypothetical) decision-making process in which the hospital staff is tasked with the decision of placing patients on overflow beds. In situations where hospital capacity constraints might necessitate admitting patients outside the clinically appropriate ward, the hospital staff face challenging decisions on whether to admit the patient

to the overflow bed, where to place the patient and how long the patient should remain on the overflow bed before repatriation to the clinical appropriate ward or dismissal. These decisions might carry potential safety implications, making it trivial to assess and quantify the associated risks.

These three fundamental risk-related decisions were translated into three dimensions, which collectively provide a structured framework for the EDA. The three dimensions follow a hierarchical and chronological order in the decision-making process. In the context of a hospital, the primary objective is to ensure the prevention of patient mortality, which makes it essential to first establish the 'base' risk of mortality of placing a patient on an overflow bed compared to not doing so. The subsequent step involves determining the risks associated with the location of the overflow bed admission, to determine the optimal (safe) location for the patient. The third dimension of time is essential to evaluate the risk of the overflow bed exposure duration, which could indicate a time-dependent urge to transfer the patient back to its homeward, as safety risks might start to escalate as the time of exposure increases.

Two different analyses were employed in the EDA: a Structural Differences Analysis and a Comparative Analysis of the Adjusted Mortality Rate. These methods are described here:

Structural Differences Analysis: a structural differences analysis was employed to assess whether patient characteristics differ between the admissions exposed and those not exposed to overflow beds. Utilising statistical tests, it was evaluated whether the distribution of the patient (LBZ) variables and admission specialties of both groups statistically significantly differ. The continuous variables are assessed by using a T-test, while for the categorical variables the Chi-squared or Fisher's Exact test will be employed.

Comparative Analysis of the Adjusted Mortality Rate: to quantify mortality risks across the three risk dimensions the Adjusted Mortality Rates (AMR) was calculated using Equation 1.

$$Adjusted\ Mortality\ Rate\ (X) = Observed\ Mortality\ Rate * \frac{\sum Observed\ Mortality\ (X)}{\sum Expected\ Mortality\ (X)}$$

Equation 1: Adjusted Mortality Probability

The AMR provides a standardised measure of mortality risk by adjusting the observed mortality rate (for all included admissions) with the ratio of observed to expected mortality. This adjustment accounts for differences in patient case mix, enabling an objective comparison across patient groups. The expected mortality values are derived from LBZ data, providing predictions based on a widely validated prediction model developed by the CBS (Bosman & Hekkert, 2024). Each risk dimension requires a different AMR comparison as the relevant patient groupings differ. The analysis for each dimension is as follows:

Dimension 1 – General Exposure: the AMR is calculated separately for patients exposed and not exposed to overflow beds. This comparison will identify a potential difference in baseline mortality risk between these two groups.

Dimension 2 – Location: the AMR is calculated for patient groups categorised based on the combination of the classification of their clinically appropriate ward and overflow ward. The classification of these wards is based on the hospital's classification of wards as surgical/medical/mixed (see Table 5). Comparing the AMR between these groups will provide insight into which overflow bed locations may pose increased safety risks for certain types of patients

Dimension 3 – Duration: the AMR is calculated for equal groups by dividing the exposure time on overflow beds into deciles. By creating these 10 duration groups, the AMR can be plotted over time. Visual inspection of the AMR across the deciles will be used to identify thresholds at which safety risks begin to escalate or stabilise, allowing the creation of more meaningful duration groups that reflect similar levels of risk.

Figure 3 provides a visual representation of the framework of three key risk dimensions associated with overflow bed placement. This framework is intended to reflect the risk-related questions that hospital staff consider when deciding whether to place patients in overflow beds.

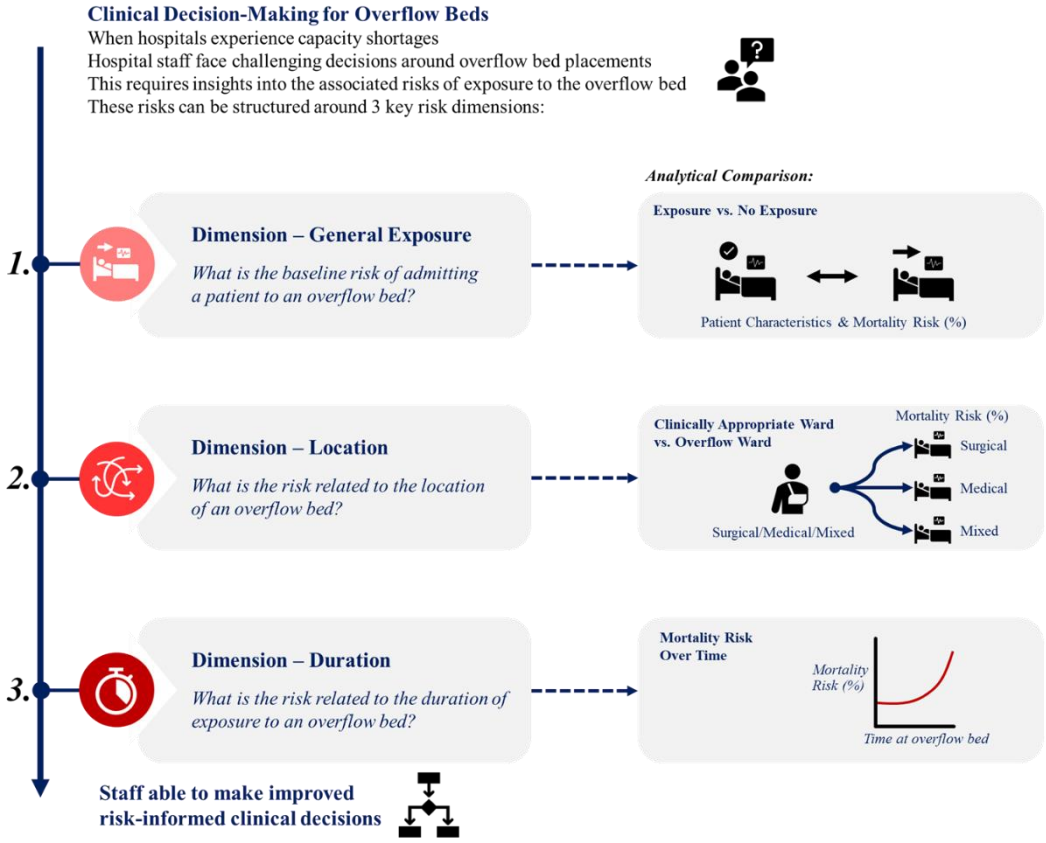

Figure 3: Framework of risk dimensions and associated scope of analysis for the EDA

Phase 2: Predictive Modelling

Sub-question:

SQ 2: ***"Which models best predict patient mortality for clinically relevant exposure to overflow beds?"***

Required Data: Research Data, Clinically Relevant Exposure insights of phase 1
Research Methods: Logistic Regression Modelling, Model Performance Analysis

The objective of phase 2 was to develop accurate models predicting mortality outcomes based on defined clinically relevant exposure and risk dimensions. The model development followed the seven-step checklist for developing clinical prediction models as outlined by Steyerberg & Vergouwe (2014). In this phase, steps 2 to 5 were specifically addressed, focusing on the stages of coding predictors, model specification, model estimation, and model performance. The initial stage of data inspection was completed in phase 1, while the stages of validation (steps 6 and 7) were addressed in the final phase of this study. The detailed description of each step is provided here:

(Step 2) Coding of predictors

The first modelling step was to code the candidate predictors. Two generic types of candidate predictors can be specified: a) exposure variables, which differ per risk dimension and therefore per model, and b) LBZ variables, which will be the same in each model. In addition, a distinction was made between continuous (numerical, e.g. patient age) and categorical predictors (e.g. severity classes). While categorical predictors may improve model comprehensibility, categorising continuous variables may result in the loss of valuable information (Steyerberg & Vergouwe, 2014). Therefore, the approach first explored both coding methods for exposure variables, with subsequent testing of categorisation where appropriate. The degree of categorisation was also analysed to test whether the use of defined categories does not hide important information that could explain patient risks. The categorical variables were dummy-coded, with one category defined as the reference.

(Step 3) Model specification

Separate logistic regression models were developed for each risk dimension to estimate the probability of binary outcomes (mortality vs. no mortality) based on the established exposure- and LBZ variables. Informed by the findings of the EDA, different model variants were specified to test the impact of variations and groupings of patient types and characteristics. Interaction effects between candidate predictors were also tested. This iterative approach helped to determine whether a single prediction model per risk dimension was sufficient or if distinct models tailored to e.g. specific patient types or characteristics were necessary for more accurate predictions. To select predictors for the models, the standard backward stepwise approach in SPSS was employed, with a p-value of 0.05 as the exclusion criterion. This approach iteratively removed candidate predictors that did not contribute significantly to the model, resulting in a final estimated model that included only significant predictors

(Step 4) Model estimation

The model coefficients and intercept were estimated with maximum likelihood estimation. To assess the explanatory power of the estimated models, the Nagelkerke R^2 was evaluated. The Nagelkerke R^2 indicates the proportion of the variance in mortality that is explained by the included significant predictors. This step also provided an indication of the effect size of the included predictors and showed how the estimated model can be applied to calculate mortality probability predictions.

(Step 5) Model performances

The model performances indicated whether the developed prediction models accurately predict mortality risks. This evaluation used three performance metrics derived from the work of Steyerberg et al. (2010) which presents a framework of measures to assess the performance of predictive models. These three metrics are labelled as ‘traditional’ performance measures and are summarised here:

Brier Score: The Brier Score measured the accuracy of probabilistic predictions by calculating the mean squared difference between predicted probabilities and actual outcomes. It served as a summary measure of both calibration and discrimination, reflecting the overall predictive performance of the model. The Brier score can range from 0 (perfect predictions) to 0.25 (uninformative predictions). A lower Brier score indicates better predictive accuracy.

Calibration: Calibration evaluated how well the predicted probabilities matched the actual observed outcomes. Calibration was assessed visually using a Calibration Graph, which plotted the predicted probabilities against the observed mortality rates. Two metrics were used to evaluate this graph: the Calibration Intercept α, which measured ‘Calibration-in-the-Large’ by comparing the mean predicted probability to the mean observed outcome, and the Calibration Slope β which represented whether predicted outcomes are consistent with observed outcomes

across risk levels. A perfectly calibrated model has $\alpha = 0$ and $\beta = 1$, aligned along the 45°-reference line.

Discrimination: Discrimination assessed the ability of the model to differentiate between patients with and without the outcome (mortality). This was evaluated using a Receiver Operating Characteristic (ROC)-curve, which plots the true positive rate (sensitivity) against 1 – the false positive rate (specificity), at different probability thresholds. The Area Under the Curve (AUC) or concordance *(c)* statistic was used as a discrimination metric. An AUC of 1 indicates perfect discrimination while an AUC of 0.5 indicates no predictive value (randomly guessing). The higher the AUC values the better the model performs in ranking higher mortality risks to patients who died compared to those who survived.

Phase 3: Validation & Clinical Usefulness

Sub questions:

SQ 3: ***"To what extent can the developed predictive model for 2022 accurately predict observed mortality for 2023?"***
SQ 4: ***"To what extent could the predictive models provide clinical usefulness to hospital staff?"***

Required Data: LBZ Data, Hospital Capacity Data, Final Set of Predictive Models
Research Methods: Temporal Validation, Logistic Recalibration, Decision Curve Analysis

The final phase of the study focused on validating and assessing the clinical usefulness of the final predictive models. This phase followed a structured approach based on five key steps for clinical prediction model validation, as presented by Riley et al. (2024): obtaining a dataset, making outcome predictions, assessing predictive performance, evaluating clinical usefulness and reporting results. These steps are embedded in conducting Temporal Validation and Decision Curve Analysis (DCA). Given the dynamic nature of healthcare, which is likely to have reduced the accuracy of the developed models to new data, an additional step of model recalibration was added. This step investigated updating the models to improve predictive accuracy over time.

Temporal Validation

Temporal validation involved evaluating the models by using data from a different time period (Collins et al., 2024). Temporal validation validates whether the performance of the model remains consistent over time, confirming the accuracy of the predictions when applied to new data. In this study, the coefficients of the model developed with 2022 data are applied to data obtained for 2023. The outcome predictions made with 2023 data will be assessed by evaluating the same performance metrics as presented in phase 2 - Brier Score, Calibration and Discrimination.

Temporal validation was considered appropriate for this research as the hospital under study was able to provide complete data for two consecutive years. Assuming that the patient population of this hospital does generally not significantly change over a year, this enabled assessing whether the models could make accurate predictions with new data and provide robust and generalisable outcomes.

In addition, temporal validation was particularly relevant as COVID-19 may still have had an impact on the patient population of 2022. Therefore, it was important to determine whether the developed models also made accurate predictions for 2023, when COVID-19 was no longer an issue.

Model Recalibration

Model recalibration was explored to update the final predictive models for 2023 and assess its potential as a practical tool to ensure model accuracy over time. In dynamic hospital settings, a 'calibration drift' can occur, leading to reduced accuracy performances when validating models over time (Van Calster et al., 2023; Jenkins et al., 2021). This drift can result from abrupt changes, such as hospital management adjustments, or gradual changes, such as shifts in patient populations (Davis et al., 2020). While major gradual changes in the patient population are not expected within a year—any population shifts are likely related to the final phase of the COVID-19 pandemic in 2022, which was no longer present in 2023—abrupt changes may have influenced the clinical context. Recalibration could provide a simple alternative to completely rebuilding the models to these changes, allowing them to remain applicable in changing healthcare contexts (Janssen et al., 2008).

This study applied logistic recalibration, which entailed adjusting the intercept β_0 and slope (coefficients β_k) of the original logistic regression model (Janssen et al., 2008). A new mortality logistic regression model was estimated using the predictions from the original model as the only input. The estimated intercept and coefficient from this recalibration process were then used to update the original model intercept and coefficients, aimed to result in improved fit and model performance on the 2023 data.

Clinical Usefulness

A Decision Curve Analysis (DCA) was used to assess the clinical applicability of the prediction models by determining the *clinically usefulness*. As defined by Steyerberg & Vergouwe (2014), clinical usefulness is "the ability to make better decisions with a model than without it". In this context, this involves assessing whether the model could help hospital staff make more informed decisions about placing patients in overflow beds.

The DCA is described as "powerful tool for assessing whether predicted outcomes are likely to benefit patients compared to standard strategies" (Piovani et al. (2023), and could contribute to improvements in (transparent) clinical decision-making. It was developed by Vickers & Elkin (2006) and has gained popularity in recent years.

The basic idea of a Decision Curve Analysis (DCA) is to plot the net benefit of different decision strategies, allowing for a quantitative and visual comparison between predictive models and alternative strategies (Vickers et al., 2019). Net benefit was calculated using Equation 2, where true positive and false positive classifications were weighted for different risk thresholds:

$$Net\ Benefit\ = \left(\frac{True\ Positive\ Predictions}{Number\ of\ Admissions}\right) - \left(\frac{False\ Positive\ Predictions}{Number\ of\ Admissions}\right) * \left(\frac{P_{threshold}}{1 - P_{threshold}}\right)$$

Equation 2: Formula for Calculating Net Benefit in the Decision Curve Analysis (Piovani et al., 2023)

In this study, net benefit was calculated to compare the predictive models against two default strategies: placing all patients in overflow beds and placing no patients in overflow beds. This comparison showed whether the use of the models improved overflow bed placement decisions compared with these default strategies. The net benefit of the models was determined by assessing the ability of the models to correctly identify high-risk patients who should not be placed in overflow beds while minimising unnecessary restricting patients who could be relatively safely placed in overflow beds.

The DCA provided valuable insights into whether the model results were not only accurate but also clinically useful for hospital staff in making risk-informed decisions about overflow bed placement. These results were ultimately used to classify patients who could be relatively safely placed in overflow beds and those who should be avoided.

3.5 Statement on the Use of AI

Artificial intelligence (AI) was used in the reporting process of this study, primarily as a tool to improve and support (academic) writing. Specifically, tools such as Grammarly, DeepL Write and ChatGPT were used to refine textual and grammatical quality, as well as to improve structure, conciseness and consistency in narrative and terminology. AI-generated suggestions were based on carefully crafted prompts such as:

"Can you check this text for grammatical and textual errors?"

"Can you help me improve the clarity and conciseness of this section?"

"Can you check this chapter for consistency? Check for flow and terminology".

These prompts were applied to original draft texts. The resulting output was critically evaluated and no AI-generated content was adopted directly; rather, the tools served as suggestive recommendations for refinement.

It is important to emphasise that AI was used solely to improve the clarity and quality of writing, without influencing the original ideas or analytical process of the study. This approach was taken to maintain the academic integrity, critical thinking and originality of the research.

4. Data Preparation & Exploration

This chapter presents the results of the first phase of the research, which covers Data Preparation and Exploration. The first part of the chapter will outline how the data provided were prepared and cleaned into research data to be used for further analysis and research stages. The second part of the chapter will present the results of the clinical Exploratory Data Analysis (EDA). This EDA is structured around the established framework of three key risk dimensions described in 3.4 Research Methodology.

4.1 Data Preparation

This section describes the process of data preparation to arrive at a comprehensive research dataset for further analysis. A systematic approach to data preparation was adopted by first creating separate, complete datasets for the LBZ and Hospital Capacity Data, before merging these two datasets based on the unique admission number in both sets.

Once a merged dataset had been created, a detailed screening and cleaning of the data was carried out, following the principles of Initial Data Analysis. This was done to ensure that the subsequent Exploratory Data Analysis and development of the predictive models could be carried out efficiently and with minimal risk of incorrect results (Huebner et al., 2016).

Data Preparation of LBZ Data

The LBZ datasets used in this study are the definitive annual datasets provided by the DHD to the hospital as part of its hospital quality reporting and benchmarking on mortality, unexpected length of stay and readmissions. The raw microdata sets were provided by the hospital and included all admissions recorded in the LBZ data. Separate datasets were provided for different safety measures and for the years 2022 and 2023. Although further analysis will focus solely on mortality outcomes, it was decided to create a dataset that includes all LBZ safety measures - mortality, unexpected length of stay and readmissions. In this way, the resulting research data can be used to conduct similar analyses and future research on the other two safety metrics.

The preparation of the LBZ data therefore primarily involved merging separate data sources into a comprehensive LBZ dataset. As mortality is considered to be the key metric of interest in this research, and as mortality data can be considered to be the most complete and definitive data, the LBZ data for mortality were used as the primary dataset, to which the data for readmissions and unexpected length of stay were added. This was done by adding the data based on unique admission numbers. For readmissions, this unique admission number refers to the index admission number, linking the readmission data to initial admission. In the comprehensive LBZ dataset it could therefore be indicated whether an admission was followed by a readmission within 30 days.

The data preparation steps for LBZ data are presented in Figure 4. The N represent the number of admissions.

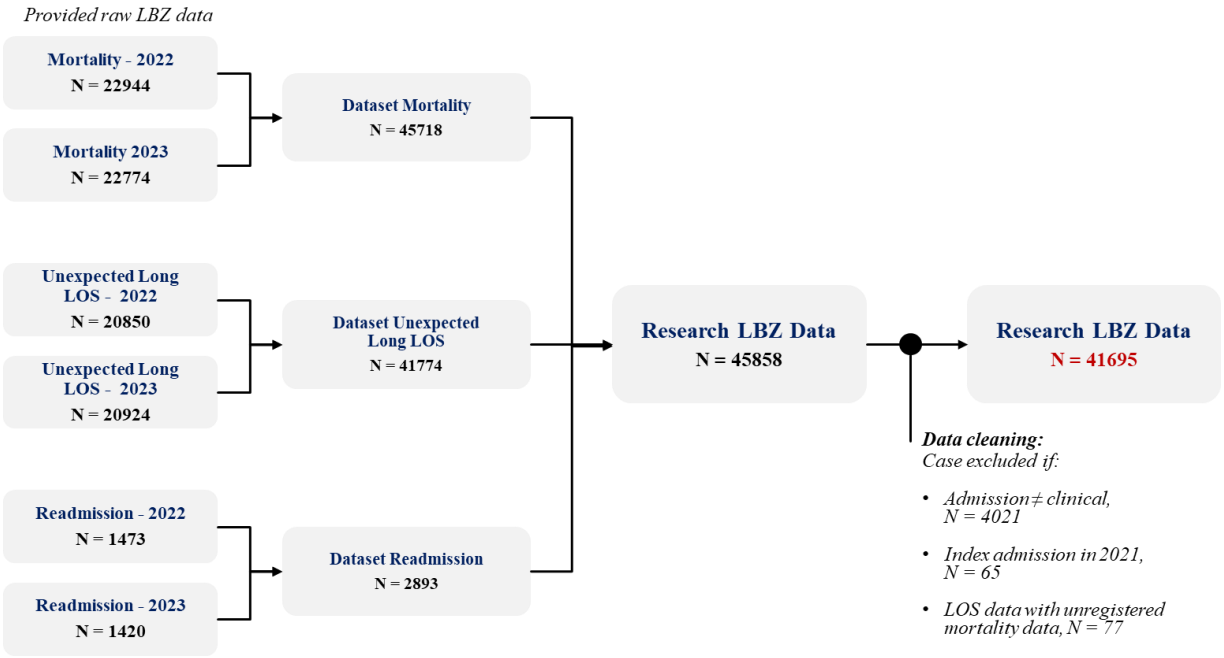

Figure 4: Data preparation of LBZ data

A number of steps were undertaken to transform the LBZ data into a final LBZ dataset. Initially, the separate datasets for 2022 and 2023 were combined for each safety metric and subsequently merged on the basis of unique admission numbers. This resulted in a dataset containing 45.858 admissions.

The next steps focused on cleaning the resulting dataset to remove inconsistencies. Admissions that were not classified as clinical admissions were excluded, removing 4.021 observational admissions. In addition, since it was decided to only include admissions with discharge dates in 2022 or 2023, 65 readmissions with an index admission in 2021 were removed. Finally, 77 entries were removed because they did not have corresponding mortality data. Mortality is considered the primary research metric, leading to the decision to exclude all admissions with incomplete mortality records. These cleaning steps resulted in a final LBZ research dataset of 41.695 valid admissions.

Data Preparation of Hospital Capacity Data

The Hospital Capacity Data has been specifically compiled by the hospital for research purposes. The data is routinely collected as part of the standard hospital operations and is indirectly derived from the hospital's Electronic Patient Records.

The format in which the data was delivered records the exact details of the care provided, including treatments, duration, and the location where care was delivered per admission. This provides a clear picture of the *occupied capacity* during an individual hospital admission, which is useful for this research purpose.

This set of variables results in a comprehensive dataset that includes all hospital admissions from 2022 and 2023, divided into one or more admission segments. These individual admission segments represent distinct units of care and are categorised into shifts for day, evening and night, which align with the shifts typically worked by the nursing staff. For each individual admission segment, the number of minutes the patient was admitted, the specialty (based on the primary responsible medical team), and a dummy variable for the admission location are recorded. This dummy variable can be translated one-to-one to the ward where the patient was admitted for that particular admission segment. This data-formatting is specific for the hospital providing the data.

Moreover, an additional variable was added to the dataset to flag whether an admission segment involved the use of an overflow bed. This classification is determined for each admission segment through a comparison of the recorded specialty with the location of the admission ward. For each specific ward, the hospital has defined a set of specialties for which this ward is considered to be the appropriate ward. This implies that any specialty other than those defined as appropriate will be considered to have been exposed to an overflow bed. However, an exemption is being made for the Acute Medical Unit, Oncology Unit and Day Care Unit, for which all specialties are defined as 'appropriate'. Consequently, admission segments admitted to these wards will never be marked as exposed to an overflow bed.

For all admission segments classified as having been exposed to an overflow bed, a variable has been included to indicate the clinically appropriate ward to which the patient should have been admitted. In order to determine these wards, the hospital has also defined which specialities should be admitted to which wards. For each ward, a definition is provided of the specialties that should be admitted to the particular ward as the primary clinically appropriate allocation.

Hospitals often define their own criteria for determining which specialities should be admitted to which wards, dependent on e.g. the hospital's spatial layout or organisational distribution of care. These definitions are often based on the expertise and knowledge of both the clinically responsible team and nursing staff related to specific wards. For the hospital under study, explicit agreements were made on these definitions, which were documented in a 'translation table'. This table was applied to the research data to classify admission segments to be exposed to an overflow bed or not. A schematic representation of the application of this table is shown in Figure 5.

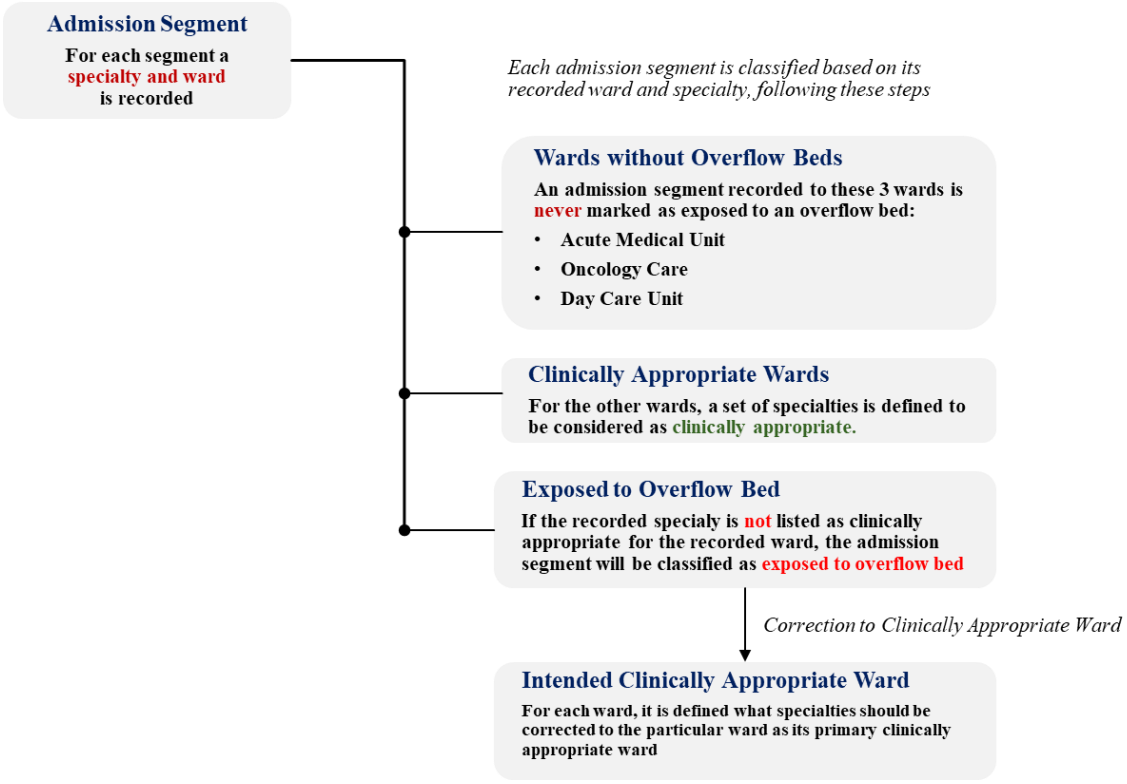

Figure 5: Schematic representation of the approach to classify exposure to overflow beds

To transform the provided Hospital Capacity Data into useful research data, a series of preparatory steps were taken, including aggregating admission segments into individual admissions. Figure 6 illustrates the structured approach used to transform the data into individual admissions, along with creating the associated variables that capture the relevant capacity information for subsequent analyses.

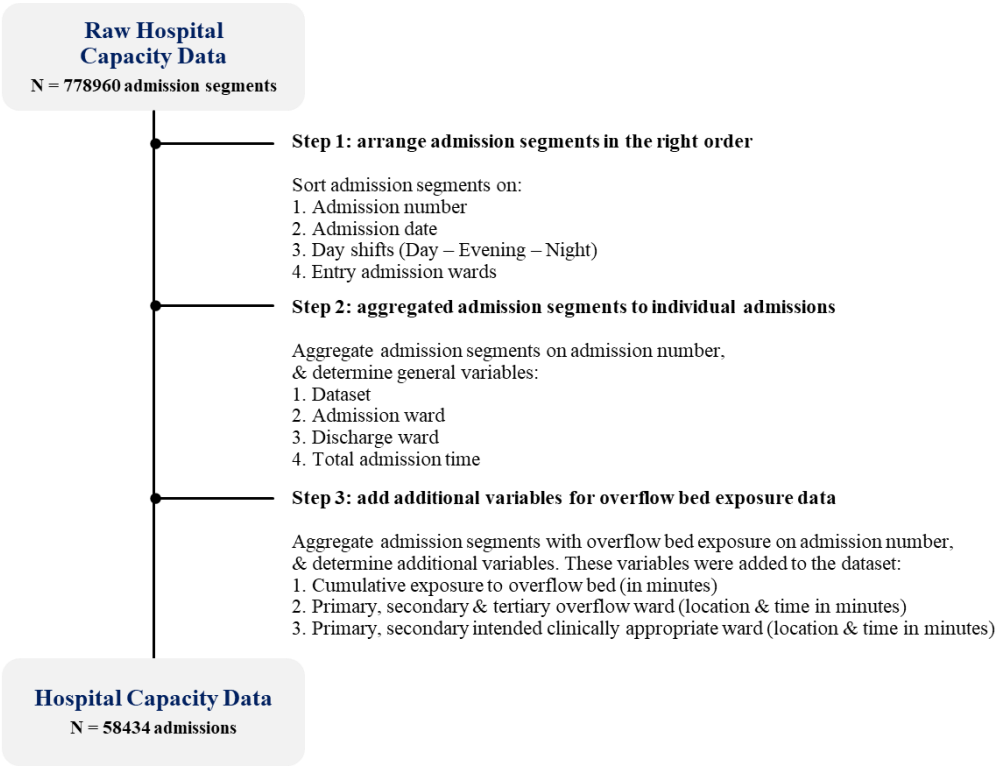

Figure 6: Data preparation of Hospital Capacity Data

Step 1 was to sort the admission segments. This step was taken to ensure that the first and final admissions segments recorded in the data accurately reflect the start and end of an individual admission. Subsequent analyses are dependent on the accurate order of the admission segments to determine whether an admission should be included in the final research set or not. The data was therefore sorted in the order of 1) the admission number, 2) the admission date, 3) day shifts, and subsequently by 4) so-called entry wards. The four entry wards, Acute Medical Unit, Emergency Unit, Cardiac Emergency Care and Day Care, are considered to be the wards where patients are most likely to be clinically admitted and were therefore sequenced before other wards to determine the first admission segment.

In Step 2, the admission segments are aggregated on admission numbers to translate admission segments into individual admissions. This aggregation was supplemented by determining the admission's associated dataset, - which ultimately determines whether the admission is included in further analyses- , the admission and discharge wards, -based on the ward of the first and last admission segment - and the admission time, which is calculated as the sum of the recorded admission time of all segments.

Step 3 once more aggregated the admission segments, but now solely for those classified as exposed to overflow beds. For these admissions, the total time spent on an overflow bed is calculated, and the primary, secondary, and tertiary overflow wards are identified. The primary overflow ward represents the ward where the patient was exposed for the longest period of time, followed by the secondary- and tertiary overflow wards. This approach was repeated to determine the primary and secondary intended clinically appropriate ward, representing the wards in which the patient should have been admitted.

These preparatory steps resulted in a final Hospital Capacity Dataset containing 58.434 admissions.

Final Research Data

Figure 7 demonstrates the data preparation steps used to combine the LBZ data with Hospital Capacity Data, resulting in the final research data. As outlined in 3.4 Research Methodology, the LBZ data serves as the primary source for the research data, with the hospital capacity data subsequently being added via the admission number. The admission number is a unique number present in both datasets, enabling the integration of capacity data to all admissions included in the LBZ data.

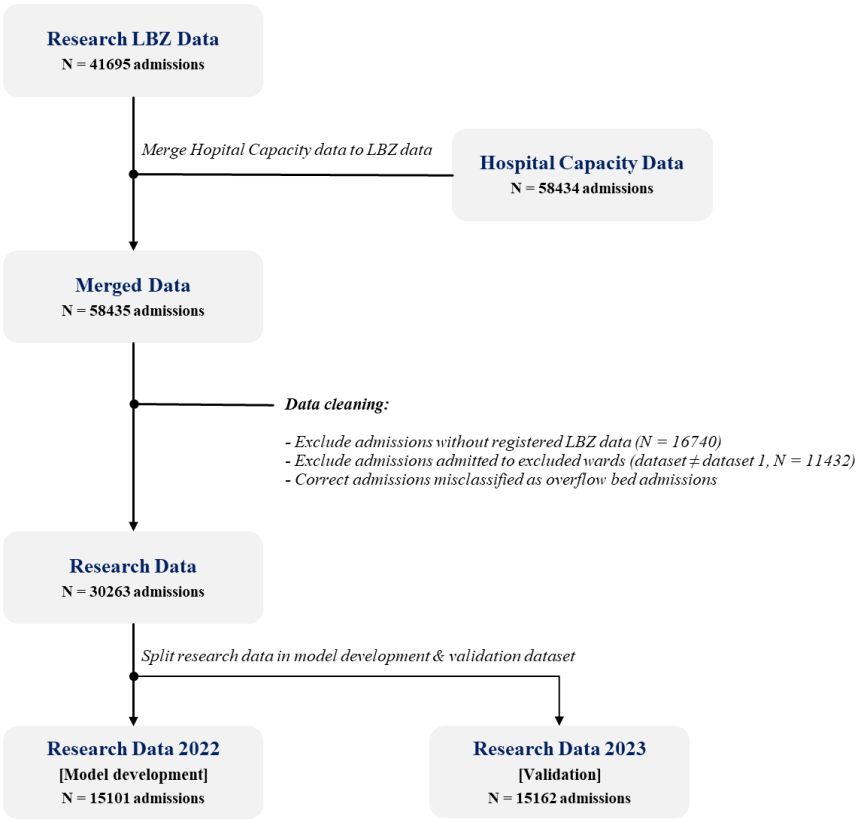

Figure 7: Data preparation of research data

A series of cleaning steps were essential to ensure the accuracy of the final research set. Firstly, admissions for which hospital capacity data was available but no LBZ data was registered have been excluded. The absence of LBZ data for these admissions may be explained by several factors; a) the admissions were of a relatively short duration, less than 24 hours, b) they were registered by discharge dates in years other than 2022 or 2023, or c) they were not considered clinical admissions by the LBZ, such as admissions for rehabilitation. As the LBZ data was seen as the primary dataset, all admissions without LBZ data registered are excluded. Furthermore, all admissions that are not admitted to wards included in this research have been excluded. The list of included wards can be found in 3.4 Research Methodology.

The final research dataset contains 30.263 admissions and is split into separate data sets for model development (2022, N = 15.101) and model validation (2023, N = 15.162)

4.2. Clinical Exploratory Data Analysis

This section presents the results of the clinical exploratory data analysis (EDA). The aim of the EDA was to identify clinically relevant exposures to guide the development of predictive models in further stages of research and to provide initial insight into factors that may lead to safety implications due to overflow bed exposure. The EDA is structured around a framework of 3 key risk dimensions and associated analyses, described in more detail in 3.4 Research Methodology. These key risk dimensions include the overall risk of exposing a patient to an overflow bed, the location of the overflow bed and the duration of exposure to the overflow bed.

Dimension 1 - General Exposure

The first risk dimension addresses general exposure to overflow beds, focusing on the extent to which there is a risk associated with exposure compared to no exposure. This dimension provides insights into the baseline risk of exposure to an overflow bed versus solely being admitted to a clinically appropriate ward. This analysis includes all admissions exposed to an overflow bed at any point during their admission. In 2022, **8,8%** of all admissions included in the research data were exposed to an overflow bed at some point during their admission.

Structural Differences Analysis

The structural difference analysis aims to provide insight into the differences between patients exposed to an overflow bed during admission and those not exposed. To assess these differences, statistical tests are performed to determine whether the distribution of various patient characteristics differs significantly between the two groups. These patient characteristics are derived from the LBZ data and are presented in Figure 8. These LBZ variables are explained in more detail in Appendix A – LBZ Variables. This appendix contains detailed descriptions of the definitions used by the DHD to compile the LBZ data. Additional clinical insights are provided by analysing the differences in the distribution of admission specialties.

Figure 8: Overview of LBZ variables

The choice of statistical test depends on the type of variable being analysed. For continuous variables (age), a t-test is used. For categorical variables (all other variables), a Chi-squared test or Fisher's exact test is used. These tests assess whether the observed distribution of a variable in the exposed and unexposed groups differs from the expected distribution, under the hypothesis that they are equal. Fisher's exact test is specifically used when the expected frequency for any category is less than 5. All tests use a significance level of 0.05 (p-value) to determine statistical significance.

The null hypothesis for these tests is that the distribution of a variable is similar for the exposed and unexposed groups. If a test shows a significant result, this null hypothesis is rejected, indicating that the distribution significantly differs between the two groups. For categorical variables, each subcategory was analysed separately.

The results of the analysis are globally presented in this section, generally discussing significant differences. A table showing the detailed observed distributions and differences of each variable, together with the corresponding p-values, can be found in Appendix B.

Age: the mean age of the patients exposed to overflow beds was significantly higher than that of the patients not exposed (Mean ± SD: 69,70 ± 17,20 years vs 64,88 ± 18,43). This indicates that older patients were more likely to be placed on overflow beds during their hospital admission.

Gender: no significant differences were found in the distributions of gender between the exposed (50,8% male, 49,2% female) and non-exposed groups (51,7% male, 48,3% female). These findings suggest that gender was similarly distributed across the two groups.

Urgency: the analysis showed a significant difference in the distribution of acute patients between the two groups. The proportion of admissions classified as acute was much higher (91,1%) for the exposed group compared to the non-exposed group (66,7%). This suggests that acute admissions were more likely to be placed in overflow beds than non-acute admissions.

Severity Class of the Main Diagnosis: all severity classes (ranging from 0-1, divided into 8 severity classes, and additional classes for COVID-19 and 'other') revealed significant differences in the observed frequency of multiple severity classes across the exposed and non-exposed group. It showed that patients classified in the lowest severity class [0-0.01] were more prevalent in the non-exposed group, while the more severe classes of [0.02-0,05], [0,05-0,1] and [0,3-0,4] were more prevalent in the exposed group. This seems to indicate that more severe patients are more likely to be exposed to overflow beds.

In addition, the analysis also showed that the distribution of the additional COVID-19 class was significantly different, with 15,1% of the admissions in the exposed group classified as COVID-19 admissions against 1,8% in the non-exposed group. This difference may be explained by the fact that COVID-19 admissions had to be isolated or clustered, making it more likely that these admissions would not be admitted to the clinically appropriate ward, resulting in overflow bed exposure.

Comorbidities: the analysis for comorbidities, assessing 17 different potential comorbidities, showed significant differences in the distributions of most comorbidities between the exposed and not exposed groups. For all comorbidities that were significantly different, the proportion of patients with the particular comorbid condition was higher in the exposed group compared to the non-exposed group. Comorbid conditions that stand out in terms of major differences include dementia, chronic pulmonary diseases, diabetes mellitus, kidney diseases and cancer. The overall findings suggest that patients exposed to overflow beds tended to have more comorbidities.

Origin location before admission: all categories for origin locations showed significant differences in their distribution between the exposed and not-exposed groups. It revealed that patients originating from home or other hospitals are less likely to be exposed, while patients coming from care institutions, nursing houses or other institutions are more likely to be exposed.

Social Economic Status: the analysis of Social Economic Status revealed that the distribution of the patients with the lowest economic status was significantly different, indicating that these patients were more likely to be exposed to overflow beds. The distribution of patients with an under-average or highest status also differed but suggested to be less likely to be exposed.

Admission Month: little significant differences were found for the admission month, except for admissions in February and December. The results showed that patients admitted in December were more likely to be exposed to overflow beds, while patients admitted in February were less likely.

Admission Specialties: the analysis of the admission specialties provides additional clinical insights by revealing that almost all admission specialties showed significant differences between the exposed and non-exposed groups. The admission specialities with lower exposed proportions, and thereby less likely to be placed to overflow beds, were: cardiology, surgery, otorhinolaryngology (ENT, *Dutch: KNO*), neurology, plastic surgery, urology, obstetrics and gynaecology. The specialities, controversially, more likely to be exposed to overflow beds were: internal medicine, pulmonology and gastroenterology.

The overall result of this Structural Difference Analysis is that the distribution of several variables is significantly different for the exposed admission compared to the non-exposed admission. This implies that potential safety complications related to overflow bed exposure may be associated with specific patient types and characteristics.

Adjusted Mortality Rate

Table 4 presents the results of the calculated AMR for the dimension of general exposure. The more detailed calculations can be found in Appendix B.

Table 4: Adjusted Mortality Rates for Dimension 1 - General Exposure

	Adjusted Mortality Rate
No Exposure to Overflow Bed	2,6% (↓)
Exposure to Overflow Bed	4,0% (↑)
Observed Mortality Rate	3,1%

The results show that, after accounting for patient characteristics, the AMR of patients exposed to overflow beds is slightly higher than those not exposed. Furthermore, the AMR for the exposed group is higher than the observed mortality rate, whereas the AMR for non-exposed admissions is lower. These findings suggest that, beyond the underlying case mix, these exposed patients face higher mortality risks.

Dimension 2 - Location

The second dimension of risk relates to the location of the overflow bed, focusing on the extent to which there is a risk associated with the location of the overflow bed. This risk is assessed by comparing the classification of an admission's clinically appropriate ward with the classification of the overflow bed ward. A clinically appropriate ward is determined for each admission based on the patient's recorded speciality. Each ward is classified into a specific ward type (surgical/medical/mixed, as shown in [redacted]). Based on these classifications, patients are grouped into combinations of clinically appropriate ward types and overflow ward types. This results in 10 groups: 1 for non-exposure and 9 possible exposure combinations of ward classifications. Table 5 shows the observed frequencies of these patient groups.

Table 5: Observed frequencies of combinations of clinically appropriate- and overflow ward classifications for patients exposed to overflow beds

	Overflow Ward →			
Clinically Appropriate Ward ↓	Surgical Ward	Medical Ward	Mixed Ward	No Exposure
Surgical Patient	25	102	53	
Medical Patient	314	351	220	
Mixed Patient	71	132	55	
No Exposure to Overflow Bed				13775

Adjusted Mortality Rate

Table 6 shows the results of the calculated AMR for the location dimension. The AMR was calculated for the defined 10 patient groups of the ward classification combination between the clinically appropriate ward and the overflow ward. The detailed calculations can be found in the Appendix B.

Table 6: Adjusted Mortality Rates for Dimension 2 - Location

	Overflow Ward →		
Clinically Appropriate Ward ↓	Surgical Ward	Medical Ward	Mixed Ward
Surgical Patient	0 % (↓)	9,4% (↑)	5,3% (↑)
Medical Patient	4,6% (↑)	2,6% (↓)	3,2% (↑)
Mixed Patient	6,5% (↑)	4,8% (↑)	7,1% (↑)
No Exposure to Overflow Bed	2,6% (↓)		
Observed Mortality Rate	3,1%		

The results show that when surgical and medical patients are placed on an overflow bed within the same type of ward, there is no increased risk, or even a lower risk, after adjusting for the patient population. This is not the case for mixed wards, where an increased risk is identified. The other combinations of patients in overflow beds outside the same type of ward all show an increased risk of mortality, which is high compared with no exposure to an overflow bed and also substantially higher than the overall mortality rate observed. Particularly when surgical patients are placed on medical wards, this leads to a significantly higher AMR.

Dimension 3 – Duration

The third dimension of risk relates to the time being exposed to an overflow bed, focusing on the extent to which there is a risk associated with the duration on an overflow bed. This risk was assessed by plotting the AMR against the time distribution of overflow exposure. To do so, the total exposure time distribution (range from 0 to a maximum of ± 42 days being exposed) was split into deciles for which the AMR can be calculated.

Adjusted Mortality Rate

Figure 9 shows the result of the calculated AMR for the duration dimension. The detailed calculations can be found in Appendix B.

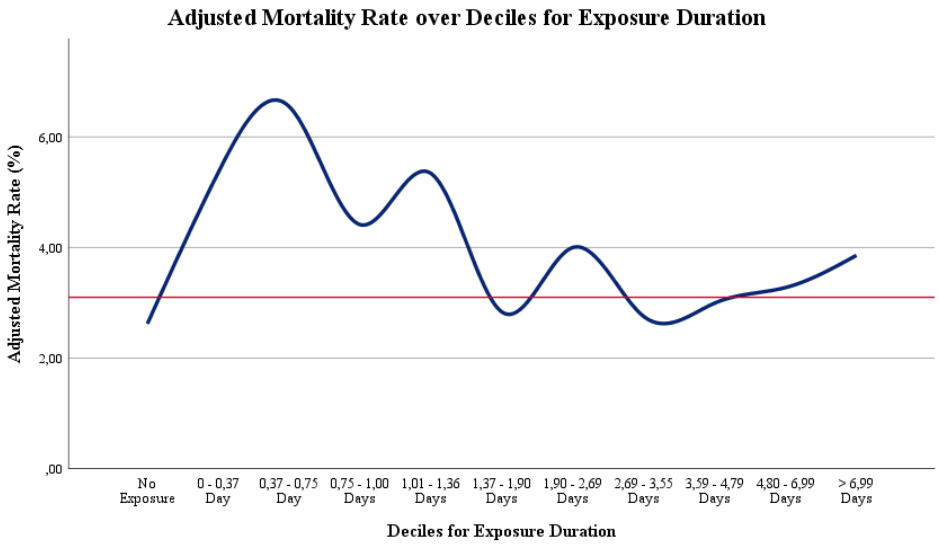

Figure 9: The AMR plotted against Deciles for Exposure Duration

The graph shows how the AMR rises with short exposure, indicating an increased risk of mortality at the initial point of overflow bed exposure. After 0.75 days, the AMR begins to decrease. After about 1.37 days to about 7 days, the AMR seems to stabilise around the observed mortality rate. After 7 days, the graph shows an increasing trend again, suggesting that the risk of mortality increases with prolonged exposure durations. These findings can be used to aggregate groups capturing similar degrees of risk into combined, more meaningful exposure groups.

This leads to a derived trend of AMR over time, as shown in Figure 10, which shows how mortality risks increase for short exposure durations, then stabilise and begin to increase again after 7 days.

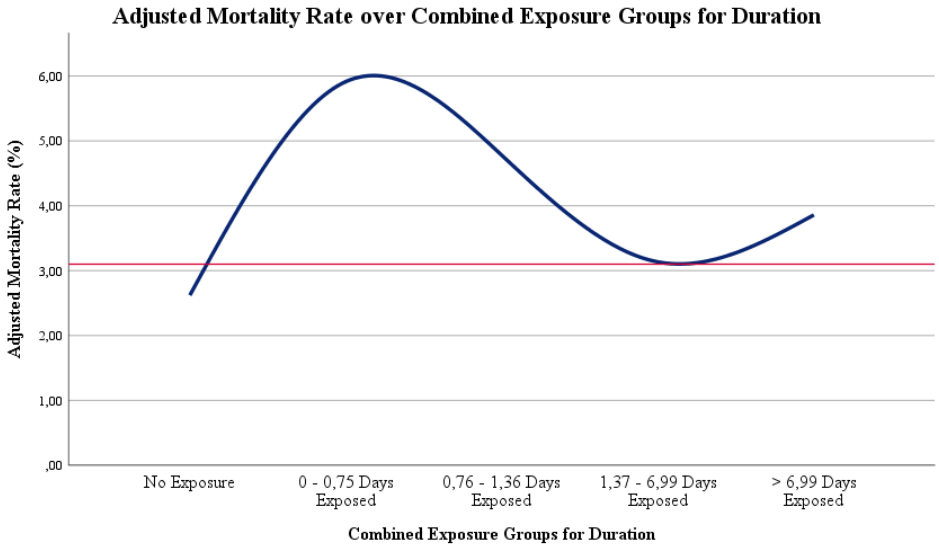

Figure 10: AMR plotted against Combined Exposure Groups for Duration

4.3 Summary of Research Phase 1

The first research phase aimed to answer:

SQ 1: ***"What is clinically relevant exposure of patients to overflow beds during hospital admission"?***

Clinically relevant exposure to overflow beds can be defined using 3 key risk dimensions. The first risk dimension shows that exposure to an overflow bed leads to a higher risk of mortality compared to no exposure. This dimension also shows that different patient characteristics are associated with overflow exposure, such as age, urgency, the severity of the main diagnosis, origin location before the admission, the social economic status or admission month. In addition, particular admission specialties – internal medicine, gastroenterology and pulmonary – were more likely to be exposed to overflow beds. These patient characteristics may act as potential effect modifiers, requiring separate model specifications, or as confounders, for which the prediction models should be adjusted.

The location dimension shows that a difference between a patient's intended clinically appropriate ward type and overflow ward type may also lead to increased risks, especially when patients are placed in wards classified as different types. Finally, the duration dimension shows that mortality risk varies over time in a wave-like pattern., showing an increased mortality risk for short exposure, that stabilizes over time but starts to increase again after one week of overflow bed exposure. The findings from these dimensions and their exposure groups can be translated into exposure variables to guide the development of predictive models in the next phase.

5. Predictive Modelling

This chapter presents the results of the second phase of the research, which focused on developing predictive models based on clinically relevant exposure to overflow beds during hospital admission. The chapter is based on Steyerberg & Vergouwe's (2014) checklist for developing clinical prediction models and begins with the coding of candidate predictors. The model specification subsequently shows which model variants were tested and how this specification process led to the specification of the final models. The next section discusses the estimated models, followed by an assessment of the predictive performance of the final models The chapter concludes with a summary that addresses the second research question that this phase of the research aimed to answer.

5.1 Coding of Predictors

The coding of predictors involved translating exposure and patient-related variables into candidate predictors that could be included in the development of prediction models. The approach to coding was different for each type of variable.

The exposure variables represent the clinically relevant exposures defined in phase 1. Separate models were developed for each risk dimension, meaning that the exposure variables are coded differently for each model. The exposure groups belonging to each risk dimension were dummy coded, i.e. admissions belonging to a particular exposure group were coded as 1 and others as 0. The reference category 'No Exposure' was used for all exposure variables.

For patient-related variables, the LBZ variables were coded. The coding of the LBZ variables differed according to the type of variable: continuous variables were included as a numerical value, while categorical variables were coded into multiple dummies, coded at two levels (1=belongs to group, 0=does not belong to group) with specified reference categories. The reference categories chosen were either the most chronologically logical category (month of admission) or the category with the most observations (the others). Only in the case of comorbidities, no cross-variable reference was defined, as patients could have 0 or more comorbidities. Comorbidities are therefore binary dummy coded, with each comorbidity included as a separate variable (1 = presence, 0 = absence)

An attempt was made to include more continuous variables to lose less information in the delimited categories by turning severity classes into a continuous variable. This proved impossible as no severity class was known for COVID-19 and therefore could not be translated into a numerical value. Nevertheless, the two most severe severity classes were merged because these groups had few observations and model development showed that these groups contained approximately the same risk.

Table 7 presents a summary of the coded candidate predictors. A detailed overview of all the candidate predictors and their associated subcategories and references can be found in Appendix C – Coding of Predictors.

Table 7: Overview of Candidate Predictors

Candidate Predictor	Type of Predictor	# Categories	Reference Category
Exposure Variables			
Model – General Exposure	Categorical	2	No Exposure
Model – Location	Categorical	5	No Exposure
Model – Duration	Categorical	10	No Exposure
LBZ Variables			
Age	Continuous	-, Numerical	-

Gender	Categorical	2	Male
Urgency	Categorical	2	Non-Acute
Severity Class of Main Diagnosis	Categorical	10	[0-0,01)
Comorbidities	Binary Categorical	17	Absence of Comorbidity *x*
Origin Location before Admission	Categorical	3	Home
Social Economic Status	Categorical	6	Lowest SES
Admission Month	Categorical	12	January

5.2 Model Specification

The Model Specification followed an iterative process in which different variants were tested based on 4.2. Clinical Exploratory Data Analysis. The aim was to produce a final set of models that accurately reflected clinically relevant exposure while taking into account potential effect modifiers.

A separate logistic regression model was specified for each risk dimension, incorporating the corresponding exposure groups identified in phase 1. Each separate model included all LBZ candidate predictors except for the reference category, allowing for a predictor-selection process to identify which predictors contribute significantly to the final estimated models. In addition, interaction effects were tested to identify whether candidate predictors acted as effect modifiers, influencing the relationship with mortality. If effect modifiers were found, separate model specifications were needed to accurately capture these differing effects. Mortality was taken as a dependent binary outcome (yes/no), meaning that the logistic regression models estimate the probability of mortality based on the specified candidate predictors. Figure 11 provides a visual overview of how the initial models were specified.

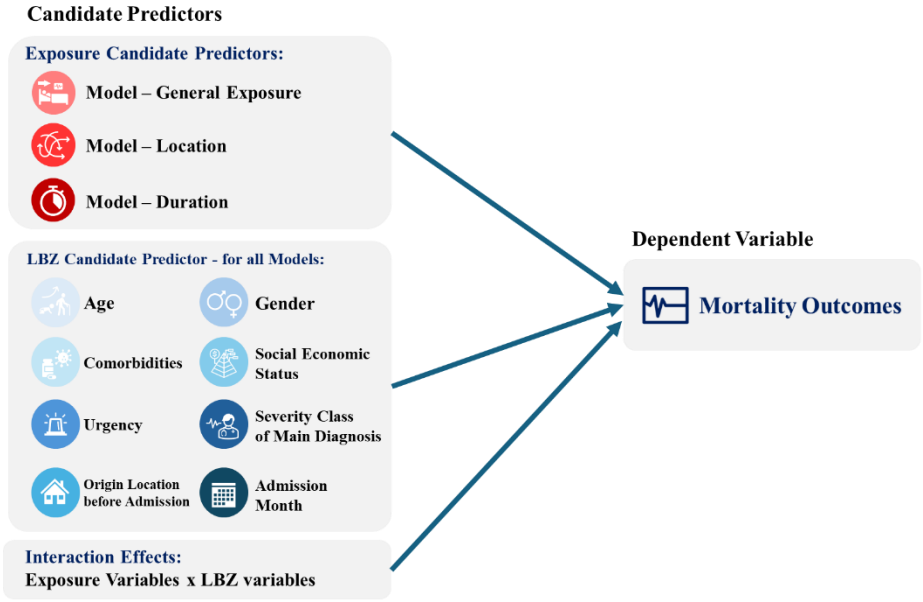

Figure 11: Visual overview of Model Specification

Multiple interaction terms were tested in multiple model variants to assess whether the significant differences observed in the Structural Differences Analysis of phase 1 influenced the association between overflow bed exposure and mortality. Specifically, the interaction effects were examined for patient characteristics that were more prevalent for overflow bed admissions - urgency and COVID-19 sub-diagnoses - to determine whether these variables modified the effect of overflow exposure on mortality. Given that COVID-19 patients were likely to be almost always admitted as acute admissions due to the nature of the disease, the interaction effect between urgency and COVID-19 was also tested, to assess whether their combined effect influenced mortality outcomes.

The estimated models showed that only the interaction between urgency and overflow bed exposure was significant (p-value < 0.05), indicating that the effect of overflow exposure on mortality differs between acute and non-acute admissions. In contrast, the interaction between COVID-19 and overflow exposure was not significant, meaning that COVID-19 did not modify the effect of overflow exposure on mortality. As a result, COVID-19 was included in the model as a standard candidate predictor, similar to the other patient characteristics. To account for the effect modification observed for urgency, it was decided to specify two separate models: one for acute admissions and one for non-acute admissions.

For both groups, the initial model specification included all candidate predictors according to the specification structure in Figure 11, except for the now irrelevant urgency and interaction terms. Stepwise backward selection in SPSS was used to iteratively remove non-significant predictors using a p-value criterion of 0.05. This ensured that only significant predictors were included in the final models.

The non-acute models, however, produced extremely high estimated coefficients. This raised concerns about the ratio of Events (actual mortality cases) to the number of final predictors (Variables) included in the model, as low Events-per-Variable ratios can lead to model instability and overestimated coefficients (Steyerberg & Vergouwe, 2014; Ogundimu et al., 2016). For the non-acute models, this ratio was approximately 2, whereas a minimum range of 5-20 with 10 as a widely accepted rule-of-thumb is generally recommended (Ogundimu et al., 2016).

Rather than excluding the non-acute models based on statistical selection and criteria alone, clinical input was consulted, as recommended by Steyerberg & Vergouwe (2014). Input from hospital staff indicated that the exposure to overflow beds is primarily relevant in acute care, where patients need to be admitted even if there is no bed available on the appropriate ward. In contrast, non-acute admissions tend to be more elective or planned, meaning that hospital staff may delay an intervention or admission if a clinically appropriate bed is not available, thereby avoiding overflow bed exposure. Given both the statistical instability and reduced clinical relevance of the non-acute models, the research focus was restricted to acute admissions.

The acute models were specified using the same stepwise backward selection approach. The event-to-variable ratio ranged from approximately 17-20 across the separate risk dimension models, confirming adequate model stability. The final predictors and estimated models for acute admissions are discussed in 5.3 Model Estimation. A visual summary of the model specification process is provided in Figure 12.

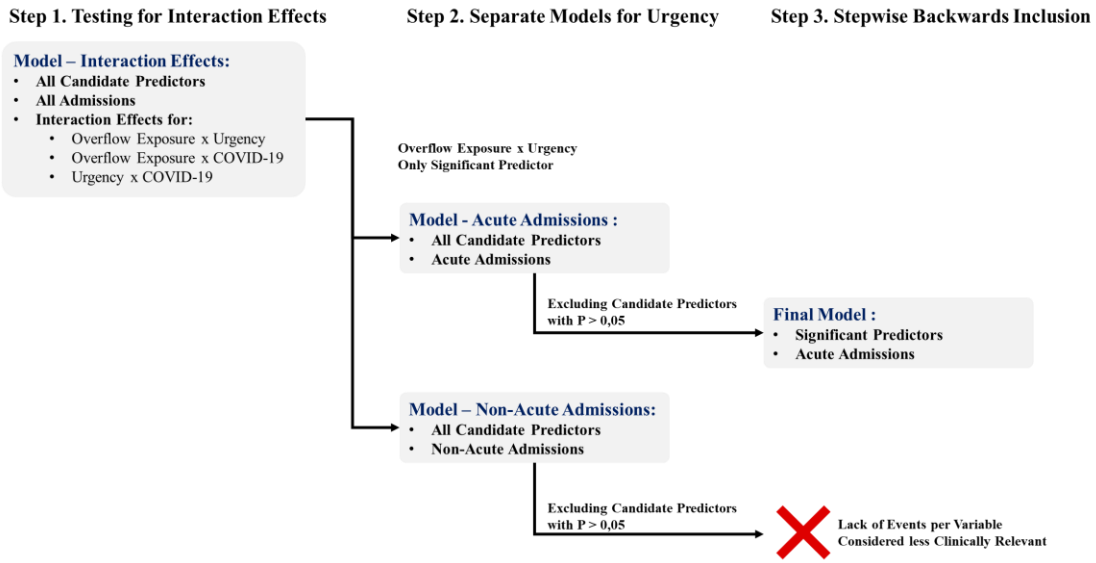

Figure 12: Process of Model Specification

5.3 Model Estimation

The Model Estimation presents the estimated results of the final specified models for acute admissions. These models are estimated separately for each risk dimension using maximum likelihood estimation in SPSS, which calculates the model intercept (β_0) and coefficients (β) for all significant predictors included in these final models. The significant predictors indicate which exposure and patient-related variables have a statistically significant effect on mortality.

Explanatory Power of Estimated Models

First, the Nagelkerke R^2 is used to assess the explanatory power of the estimated models. This indicator represents the proportion of the variance in mortality - i.e. the differences in mortality outcomes across all admissions - that can be explained by the included predictors. This indicates how much of the variability in mortality is accounted for by the model, while the remaining proportion is due to unknown or missing factors. Table 8 shows the Nagelkerke R^2 values for the final models.

Table 8: Nagelkerke's R^2 of the final models

	Nagelkerke's R^2
Model - General Exposure	0,224
Model - Location	0,227
Model- Duration	0,227

The results in Table 8 show that the models explain approximately 22-23% of the variance in mortality. The interpretation of the Nagelkerke R^2 requires careful consideration for clinical models, as the relationship between the predictors and the predicted mortality outcomes is highly dependent on the clinical context. Clinical outcomes such as mortality can be influenced by numerous external factors, such as human genetics, behavioural aspects, and organisational or environmental factors, which are difficult to incorporate into predictive models (Gupta et al., 2024). Gupta et al. (2024) suggest that high R^2 results are therefore generally unexpected and unrealistic for clinical models and, after reviewing numerous clinical studies, conclude that an R^2 above 15% can typically be considered clinically meaningful. The models surpass this threshold and it could therefore be argued that the models provide meaningful predictive value by explaining an acceptable proportion of the variance in mortality.

Effect-size of Exposure & Patient-related Predictors

To evaluate the estimated impact of exposure and patient-related variables on mortality, the effect size of the significant predictors can be interpreted by using odds ratios (OR). The OR quantifies how the odds of mortality change with a one-unit increase of a predictor, assuming all other predictors remain constant, and thereby provides an insight in the *relative* effect of an predictor on the outcome. An OR above 1 indicates an increased odds of mortality associated with a particular predictor, while OR below 1 suggests a decrease in mortality odds.

It is important to note that ORs differ from the predicted mortality probabilities; while the OR indicates the independent effect of a specific predictor on mortality risk, the predicted probability is calculated by the combined impact of all significant predictors and therefore differs per admission.

Table 9 presents the estimated ORs for the significant exposure predictors, providing insight in the effect size of exposure to overflow beds on mortality across the 3 risk dimensions. In addition to the OR, the 95% confidence interval (C.I.) and p-values are reported. The full estimated models can be found in Appendix D - Model Estimations, providing the estimated model intercept, model coefficients and ORs for all significant predictors.

Table 9: Estimated Effect-size of Exposure to Overflow Bed Predictors on Mortality

	Effect-size on Mortality (OR)	95% C.I. OR	P-value
Model – General Exposure			
Exposed to Overflow Bed	1,651	1,274 – 2,139	< 0.001
Model – Location			
Mixed Patient to Mixed Ward	4,586	1,769 – 11,889	0,002
Surgical Patient to Medical Ward	2,700	1,034 – 7,049	0,043
Medical Patient to Surgical Ward	2,082	1,392 – 3,115	< 0,001
Mixed Patient to Surgical Ward	3,620	1,240 – 10,568	0,019
Mixed Patient to Medical Ward	1,230	1,230 – 5,507	0,012
Model - Duration			
0 – 0.75 Day Exposed	2,394	1,497 – 3,828	< 0,001
0.76 – 1.36 Days Exposed	2,351	1,341 – 4,122	0,003

General Exposure

The OR for Exposed to Overflow Bed is 1,651. This suggests that admissions who are exposed to an overflow bed have 65,1 % higher odds of mortality compared to those who are not exposed, keeping all other predictors constant. These findings highlight a higher risk of mortality associated with overflow bed exposure.

Location

The significant predictors in the location model show several significant combinations between the type of patient and overflow ward with increased mortality risks. The combination of mixed patients to mixed wards shows a considerable OR, indicating that the odds of mortality are approximately 4.x higher for this combination compared to no overflow bed exposure. When a surgical patient is admitted to a medical ward, the odds of mortality are 2.7x higher, while when a medical patient is admitted to a surgical ward, the odds of mortality are slightly lower but still considerable, doubling the odds of mortality, both compared to no exposure. In addition, mixed patients have increased odds of mortality when admitted to a surgical (3.62x) or medical (1.23x) ward compared to no exposure. Conversely, there is no significant effect when these types of patients are placed on a mixed ward.

These location findings suggest that admitting patients to a ward type other than the clinically appropriate ward may result in significantly higher odds of mortality compared to not being exposed to an overflow bed. For mixed patients, the risk of mortality is increased even if they remain within their ward type, whereas this effect was not significant for exposed patients remaining within surgical or medical ward types.

Duration

The significant predictors for duration show that short exposure to overflow beds increases the odds of mortality, for the groups exposed between 0 and 0.75 days (increase of 2.395) and 0.76-1.36 days (increase of 2.351), compared to no exposure. This suggests that there is an increased risk of mortality only in the first hours to days of exposure to an overflow bed, with the risk decreasing slightly after the first 18 hours. The predictors for longer exposure times are not significant, so prolonged exposure has no significant effect on mortality.

In addition to exposure variables, the effect size of patient-related variables can also be interpreted. For the sake of readability, it was decided not to present these ORs here, as a large number of patient-related predictors have a significant effect on mortality. The estimated ORs for patient variables are presented in Appendix D - Model Estimations, while the result will be discussed more generally here.

The estimated models show that age consistently increases the odds of mortality in all three models, with an estimated increase of ~3.5% per year. The severity class of the main diagnosis shows a strong association, with more critical severity classes corresponding to a greater increase in mortality risk, compared to the lowest severity class. The additional severity class for the COVID-19 sub-diagnosis also significantly increases the odds of mortality (OR: ~2.5). Various comorbidities affect the risk of mortality differently between models, with peptic ulcer disease showing the largest increase in all models (OR: ~9-10), while cerebrovascular disease unexpectedly reduces the risk of mortality by 70% (OR: ~ 0,3). Other significant comorbidities leading to increased odds of mortality in all models include heart failure, kidney and liver diseases, and metastases.

Admissions from other healthcare facilities (both other hospitals and nursing homes or other institutions) increase the odds of mortality compared to admissions from home. Finally, seasonal variation is observed: in the general exposure and duration models, the risk of mortality is increased in December and February (OR: ~1,6) compared to January. Conversely, in the location model, certain months - April, August, September and October - are associated with a reduction in the odds of mortality (OR: ~0,6) compared with January.

Mortality Predictions

While the ORs provide insights into the *relative* effect of one predictor on mortality, the ORs do not represent the *absolute* mortality risk for an individual patient. To predict the actual probability of mortality for a given patient, the full estimated model formula must be considered. The estimated model intercept and coefficients for each predictor can be used to calculate the Logit for any given patient, adjusting for all other predictors in the model. The Logit is calculated with Equation 3, where β_0 is the model intercept, β_1, β_2,…β_k the model coefficients and X_1, X_2, X_k the input values for the given patient.

$$Logit\ (Y) = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \cdots + \beta_k * X_k$$

Equation 3: Formula to calculate the Logit

The Logit can be used to obtain the probability of mortality, by applying Equation 4

$$P(Y = 1) = \frac{1}{1 + e^{Logit\ (Y)}}$$

Equation 4: Formula to translate Logit into Prediction

To illustrate the application of these equations and the predictive models, a hypothetical patient scenario can illustrate the potential impact of overflow bed exposure for an individual admission based on the predicted mortality risk. This patient scenario was developed based on clinical input, obtained by consulting hospital staff to identify a representative case for which in clinical practice the decision to place the particular patient on an overflow bed frequently arises. This representative illustrative case can be described as follows:

"During the flu season in February, the hospital is managing a large inflow of patients. An elderly woman of average socioeconomic status, living at home, needs to be admitted because of respiratory symptoms. The woman is a 72-year-old pulmonary patient with known COPD and delirium. Her symptoms are suggestive of influenza, which is recorded as the main diagnosis (severity class [0,02-0,05)). No beds are available at the Acute Medical Unit and the clinically appropriate ward, the pulmonary ward, so the patient has to be admitted to an overflow bed. The hospital's capacity-deficit flow-charts are applied, indicating that the next admission preference ward is to admit the patient to the gastroenterology ward, which is classified as a mixed ward. The expectation is that the patient can be repatriated to the pulmonary ward after one night, limiting the overflow bed stay to less than 18 hours."

The patient-specific characteristics and overflow bed exposure details from the illustrative scenario are applied to the predictive models across the three risk dimensions. By entering this data into the model equations, the corresponding mortality probability is obtained. The mortality probability is compared between the patient being admitted to the overflow bed and being admitted to the clinically appropriate ward (no exposure). This comparison illustrates the potential impact of overflow bed exposure on the risk of mortality for the scenario patient. The predicted results are presented in Figure 13.

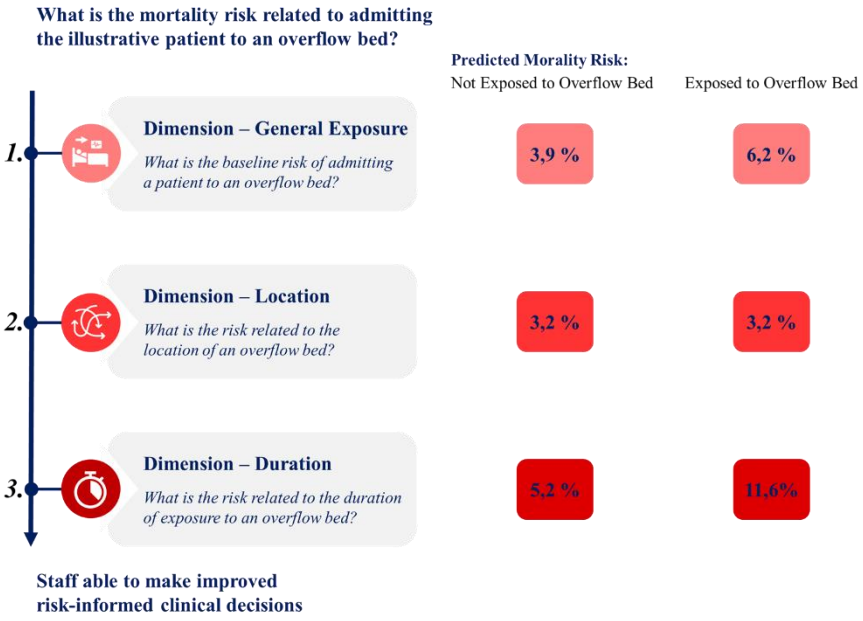

Figure 13: Predicted Mortality Outcomes for the Illustrative Patient Scenario

Figure 13 shows the differences in predicted mortality outcomes across the three dimensions. The differences in outcomes for no exposure can be explained by small differences in the estimated coefficients and larger differences in the model intercepts between the three models. It is also shown that general exposure leads to an increase in mortality risk, almost doubling the mortality probability for this patient. The location does not lead to an increased mortality risk, as expected since the combination of a medical patient to a mixed ward was not found to be a significant predictor. The short time spent on an overflow bed leads to a considerable increase in risk, suggesting that even a short time spent on an overflow bed leads to a substantial mortality risk.

5.4 Model Performances

The Model Performances present how well the final predictive models perform based on three performance metrics: Brier score, Calibration and Discrimination. Although the model performances were also assessed for the other specified model variants, it was decided to present only the results of the final model performances here, as these models produced the most statistically and clinically relevant results, explained in 5.2 Model Specification. The model performances are summarised in Table 10.

Table 10: Summary of the Model Performances of the Final Predictive Models

	Model – General Exposure	**Model - Location**	**Model - Duration**
Brier Score	0,0364	0,0362	0,0362
Calibration			
Intercept α	0,000	0,000	0,000
Calibration slope β	0,990	0,998	0,993
Discrimination			
Area Under the Curve (AUC)	0,838	0,839	0,840
AUC Confidence Interval (95%)	0,822-0854	0,823-0,855	0,824-0,856

Brier Score

The Brier score provides an overall assessment of the predictive performances by calculating the mean squared error between the predicted probabilities and actual outcomes, ranging between 0 for perfectly predicting models to 0.25 for uninformative models. The calculated Brier scores for all models were around 0.036, indicating strong overall predictive performances. This suggests that the models generate probabilities close to the actual outcomes, with small prediction errors.

Calibration

Calibration assesses how well the predicted probabilities align with the actual observed outcomes. This can be evaluated by plotting a Calibration Graph, where perfectly calibrated models will align along the 45°- reference line with an Intercept α of 0 and Slope β of 1.

The Intercept α's (0,000) of the Calibration Graphs show that the models are very well-calibrated in the large, indicating that the mean predicted mortality risk perfectly aligns with the observed mean mortality rate. The Slope β's just below the 1 suggests that the models are well-calibrated, but show a slight underestimation of the mortality risk. This is especially evident in the visual inspection of the Calibration Graph for the Model - General Exposure (Figure 14), where for the higher mortality risks the Graph shows a slight deviation from the reference line, indicating a minor underestimation of the observed risk with a Slope β below 1. The Calibration graphs of the other models can be found in Appendix E - Model Performances.

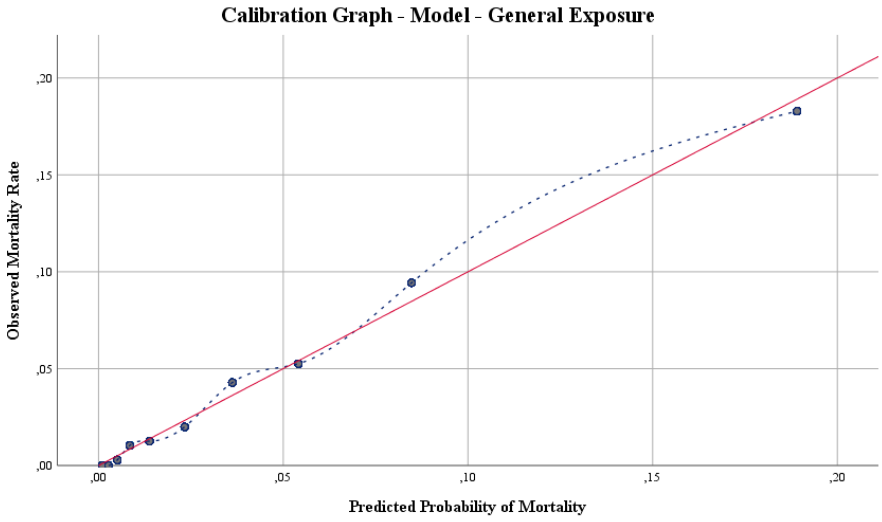

Figure 14: Calibration Graph for Model - General Exposure

Discrimination

Discrimination evaluates the ability of the model to differentiate between patients who experience the outcome mortality and those who do not. This Discrimination performance can be assessed by plotting the ROC-curve and calculating the associated Area Under this Curve (AUC). An AUC of 1 represents perfect discrimination while an AUC closer to 0.5 suggests poor discrimination.

For all models the AUC was approximately 0.84, indicating that 84% of the time the models correctly assigned higher mortality risks to those patients who died, compared to those who survived. This suggests that the models are highly effective at differentiating between these two outcomes. The ROC curve for the Model – General Exposure is presented in Figure 15, illustrating how this curve is drawn. The ROC curves of the other models show a similar pattern and can be found in Appendix E - Model Performances.

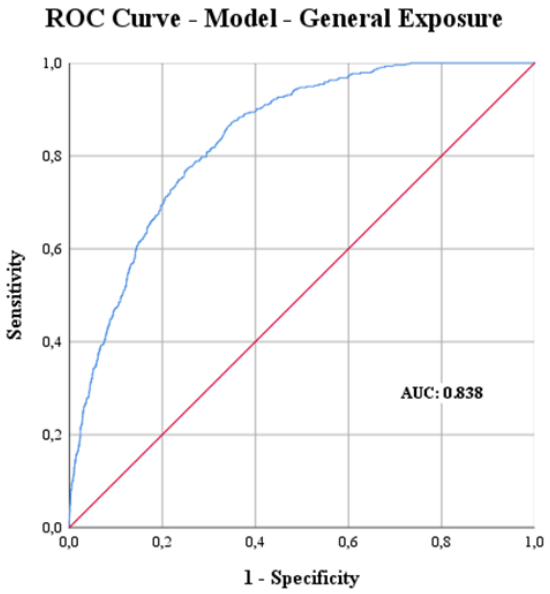

Figure 15: ROC Curve for Model - General Exposure

5.5 Summary of Research Phase 2

The second research phase aimed to answer:

SQ 2*: "Which models best predict patient mortality for clinically relevant exposure to overflow beds?"*

The model development phase showed that the models for acute admissions provided the best statistically and clinically relevant predictions of mortality risk. By specifying different models based on the defined clinically relevant exposure variables and patient-related variables, it became clear that there appeared to be an interaction effect between overflow exposure and urgency. This led to the specification of separate models for acute and non-acute admissions. It turned out that unstable model estimations were made for the non-acute model and the non-acute models were considered less clinically relevant, to which the decision was made to focus solely on acute admissions.

The resulting final models reveal that exposure to an overflow bed is associated with a higher risk of mortality on all dimensions; for general exposure, for different combinations of patient types and wards, and for a short duration on an overflow bed. The model performances demonstrate that the final models are capable of predicting reliable mortality outcomes. Both good calibration and strong discrimination were observed, suggesting that the models not only generate predictions that are well aligned with observed mortality rates, but also demonstrate a strong ability to discriminate between mortality and survival outcomes. The next step is to validate these models and assess their clinical utility by determining their generalisability and practical applicability.

6. Validation & Clinical Usefulness

This chapter presents the results of the third phase of research, which focused on validating and assessing the clinical usefulness of the final prediction models. Five key steps of clinical predictive model validation identified by Riley et al. (2024) were applied in this final phase of research, including (1) obtaining an appropriate validation dataset, (2) generating outcome predictions, (3) assessing predictive validation performance, (4) assessing clinical usefulness with decision curve analysis, and (5) clearly reporting results. After the first three steps related to validation, an intermediate step of model recalibration was added as a response to the poorer calibration outcomes found in the validation steps. Model recalibration explored model updating to ensure predictive accuracy to new data. The chapter is structured by first presenting the results of Temporal Validation, followed by Model Recalibration, and concludes with the assessment of Clinical Usefulness

6.1 Temporal Validation

Temporal Validation was conducted to validate the final prediction models, by assessing their predictive performances over time. This validation was considered important to assess whether the models can make accurate predictions when applied to new data, and therefore generalise to future admissions. Temporal validation was identified as a suitable approach for model validation because the hospital was able to provide complete data for two consecutive years. Cautiously assuming that the hospital's patient population did not change drastically within a year, this made it possible to assess how well the models generalize to new data.

The validation data was therefore readily available and was obtained (step 1 of Riley et al.) by simultaneously preparing and cleaning the provided data of both years, as described in 4.1 Data Preparation. This enabled ultimately splitting the data into a development set including all admissions discharged in 2022 and a validation set including all admissions discharged in 2023. The temporal validation thus compares the model performances of the developed 2022 models applied to 2023 data.

Since this obtained validation dataset was in a similar data format as the development data, it was possible to apply the models directly to the new data. Outcome predictions for the 2023 data were generated by applying the estimated model equations to calculate Logits for all admissions and converting these into mortality predictions, covering step 2 of Riley et al. (2024).

The predictive performances of these predictions are evaluated by using the same three performance metrics as applied in 5.4 Model Performances, including the Brier score, Calibration and Discrimination. The results are summarised and compared with the performances of the developed 2022 models in Table 11.

Table 11: Summary of the predictive performances of Temporal Model Validation

	Model – General Exposure		**Model - Location**		**Model - Duration**	
Model Year	2022	2023	2022	2023	2022	2023
Brier Score	0,0364	0,0325	0,0362	0,0330	0,0362	0,0327
Calibration						
Intercept α	0,000	0,002	0,000	0,003	0,000	0,003
Calibration slope β	0,990	0,868	0,998	0,781	0,993	0,818
Discrimination						
Area under the Curve	0,838	0,830	0,839	0,827	0,840	0,829
C.I. AUC (95%	0,822-0,854	0,812-0,848	0,823-0,855	0,809-0,846	0,824-0,856	0,811-0,847

Brier Score

The results show that the calculated Brier scores of the 2023 models were approximately 0.003 lower than the 2022 models. This suggests that the overall predictive accuracy of the models is slightly improved, but this interpretation requires careful consideration. It was observed that the mortality incidence rate for acute admissions was 0.5% lower in 2023 than in 2022, which may have contributed to the differences in the Brier score (Steyerberg et al., 2010). When the incidence rate of the event (mortality) is lower, prediction errors have less impact on the overall Brier score. This can be better understood by examining how the Brier score is determined, presented in Equation 5.

$$Brier\ Score = \frac{1}{Number\ of\ Admissions} * \sum_{All\ Admissions} (Observed\ Outcome\ (1/0) - Predicted\ Risk)^2$$

Equation 5: Formula to determine the Brier score

As the event mortality becomes rarer, there are fewer observations with large errors (i.e. the mortality cases where the model's predicted risk considerably differs from the actual outcome (1)). For non-events, prediction errors are typically smaller because the model predicts a low risk of mortality (close to 0). Therefore, with fewer observations of the event, the overall impact of errors is reduced, which could explain the lower Brier score in relation to the lower incidence rate.

Calibration

The model calibration can be used to assess how well the predicted outcomes of the validation models match the observed outcomes of 2023. Calibration is evaluated by interpreting the Intercept-α and Slope-β. The Intercept-α of the validation models is slightly higher than the developed models. This indicates that the average predicted risk is slightly higher than the average observed mortality in 2023.

In addition, there is a noticeable difference in the Slope-β's for the validation models, which are considerably lower compared to the developed models. For all models, it can be seen that the Slope-β is below 1, which suggests that the models produce too extreme predictions relative to the observed mortality rate.

This is well reflected by visually inspecting the Calibration Plots for validation. The Calibration Plot of the Model – Location (Figure 14), for which the largest deviation in Slope-β was observed, clearly shows that the model's predicted probabilities considerably deviate from the 45°-reference line.

The model appears to be well calibrated for the lower risks (<5%), with predictions close to the reference line. However, as the risk increases, the calibration line drops below the reference line, indicating that the model overestimates the risk of mortality with predictions that are too extreme compared to the observed mortality rate. This suggests that for patients with a higher predicted risk of mortality, the models generate probabilities that are systematically higher than the actual observed risk in the 2023 data.

A similar trend was observed in the Calibration Plots for the other models, which are provided in Appendix F - Model Validation.

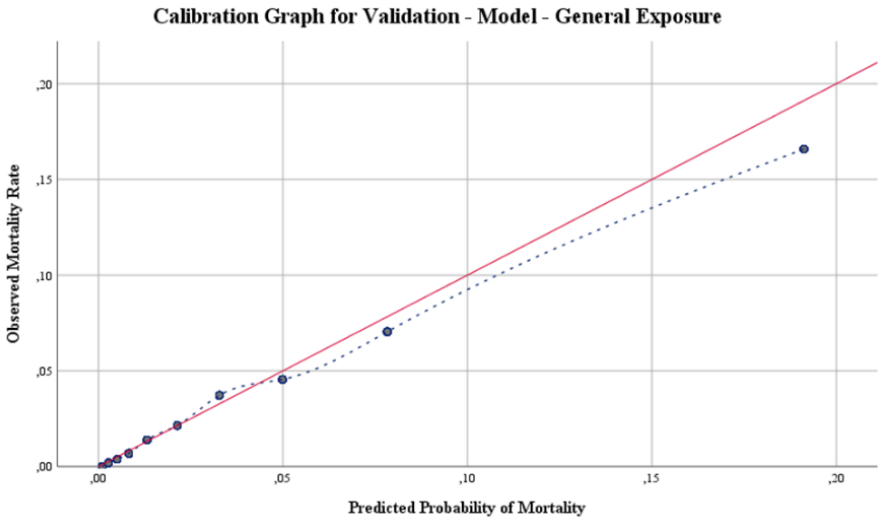

Figure 16: Calibration Graph for Validation - Model - Location

Discrimination

Discrimination indicates the ability of the models to differentiate between those who experience the outcome (mortality) and those who do not. The discrimination results for the models for validation are calculated with the Area Under the Curve (AUC) of the ROC curve. The ROC curves of the validation models are included in Appendix F - Model Validation.

The AUC results show a slightly reduced ability to discriminate outcomes, compared to the 2022 models. The results suggest that the models for 2023 are about 1% less effective at assigning higher risks to patients who die compared to those who survived, relative to the 2022 models. Nevertheless, the models still maintain strong discriminative abilities, with an AUC of approximately 0.83. This score indicates that the models remain clinically relevant in distinguishing between outcomes, as the AUC is close to 1.

The Temporal Validation results indicate that the model predictions remain largely robust when applied to new 2023 data, especially maintaining strong Discrimination by effectively differentiating between mortality and survival outcomes. The evaluation of Calibration, however, showed that the model predictions for particularly higher-risk patients were overestimated and too extreme, aligning poorer with the observed mortality risks. This thus suggests a decline in Calibration over time.

Multiple factors may explain this reduced performance. First, it may be the case that the Events-to-Variables (EPV) ratio, which led to unstable and too extreme model estimates for the Non-Acute models, was also on the low end for the final models. While the model EPVs ranged between 17 and 20 and thus surpassed the widely accepted EPV threshold of 10, research by Ogundimu et al. (2016) suggests for logistic clinical prediction models higher EPVs (>20-40) are recommended to avoid poorer performances over time. Too many predictors for a relatively small dataset might have influenced temporal performance differences on new data (Efthimiou et al., 2024).

In addition, the dynamic nature of the clinical context may have led to 'calibration drift', due to changes in the hospital context (Davis et al., 2020). This may be explained by a small shift in the patient population due to the last part of the COVID-19 pandemic in 2022, which was no longer an issue in 2023. Moreover, it is possible that in 2023 the hospital integrated new guidelines or bed allocation plans to reduce the need to use overflow beds, resulting in a decrease in the observed mortality risks. To further investigate these potential effects, an additional step was added to the research, to assess whether model recalibration can improve and maintain calibration performance over time.

6.2 Model Recalibration

Model Recalibration presents the results of applying recalibration methods to update the models to new data. The previous Temporal Validation showed that model calibration had declined over time, with predicted outcomes for 2023 aligning less well with the observed outcomes. Recalibration is explored to asses whether updating the models can improve their accuracy for future admissions.

Logistic recalibration was applied to update the models and was chosen due to its simplicity and effectiveness. Simplicity and effectiveness of the recalibration method were prioritized as in clinical practice potential model updates should be easily comprehensible, yet result in reliable and improved outcomes. Logistic recalibration avoids major model changes by only updating the estimated model intercept (β_0) and coefficients (β_k). In addition, this method does not alter the model discrimination, which proved to remain strong during validation, and solely focuses on required calibration improvements.

Logistic recalibration involved specifying a new logistic regression model using the validation outcome predictions as the sole independent predictor to predict mortality outcomes. The estimated model update-intercept and coefficient of this logistic recalibration model indicate the necessary model adjustments: the recalibrated model intercept can be obtained by adding the new estimated update-intercept to the original intercept, while the recalibrated coefficients can be derived by multiplying the original coefficients by the newly estimated update-coefficient. This process will allow to recalibrate the initial final models to improve their fit and predictive performance to the 2023 data. The recalibration process is visually summarised in Figure 17. The estimated model adjustments for the three final models are presented in Table 12.

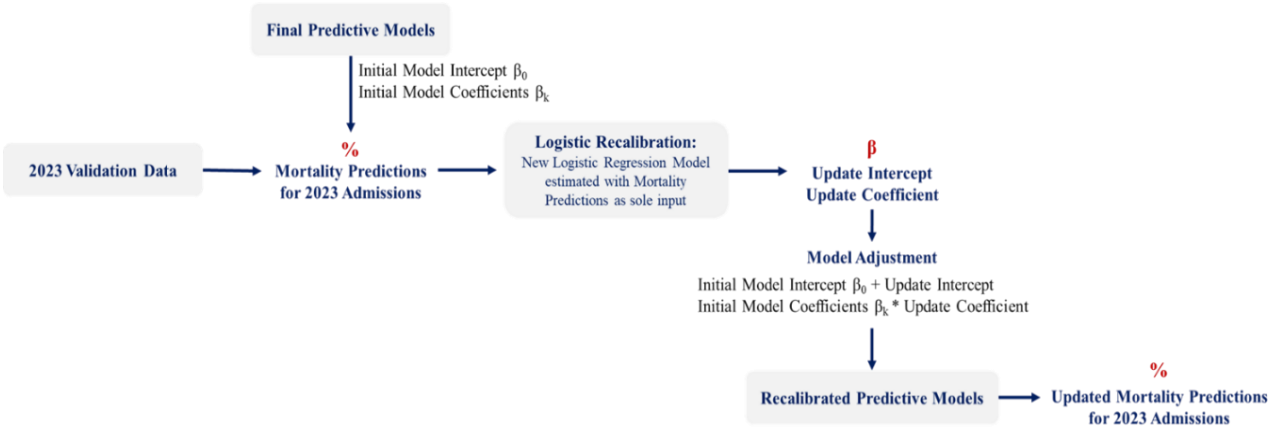

Figure 17: Visual Representation of the Model Recalibration Process

Table 12: Model Adjustments for Model Recalibration

	Model – General Exposure	Model - Location	Model - Duration
Model Adjustments			
Update Intercept	-0,294	-0,448	-0,372
Update Coefficient	0,926	0,892	0,906

Table 12 shows that the initial model intercepts were lowered by adjustments ranging between 0.29 to 0.45. The coefficient adjustments ranged between 0.89 and 0.93. The largest correction was needed for the Location Model, as expected given its largest deviation in calibration.

To assess the impact of recalibration, the recalibrated model performances are summarized in Table 13. The discrimination metric is not included, as logistic recalibration did not affect model discrimination.

Table 13: Summarised Model Performances after Model Recalibration

	Model – General Exposure		**Model - Location**		**Model - Duration**	
	Validation	Recalibration	Validation	Recalibration	Validation	Recalibration
Brier Score	0,0325	0,0323	0,0330	0,0326	0,0327	0,0324
Calibration						
Intercept α	0,002	0,000	0,003	0,000	0,003	0,000
Calibration slope β	0,868	1,009	0,781	0,993	0,818	0,993

A minor decrease in the calculated Brier score was observed for all models, moving closer to 0. This suggests a slight improvement in the overall predictive performances of the recalibrated models.

A more considerable change was seen in calibration performances. The Intercept-α of all models was adjusted to 0,000, indicating strong overall calibration with the average predicted mortality now aligned with the average observed mortality.

The Slope-β's of all models improved towards the desired value of 1. The Model – General Exposure now appears somewhat conservative (β > 1), producing slightly lower mortality predictions than observed. The other model remains still overpredicting mortality risks with too extreme predictions compared to the observed. However, these deviations from the desired Slope-β of 1 are very minor, suggesting that these updated models are now well-calibrated.

This recalibration impact can also be observed in the Calibration Plots. The updated Calibration Plot of the Model – Location is shown in Figure 18. Compared to the initial Calibration Plot, the recalibrated model shows substantial improvements with predicted outcomes now closely aligned along the reference line.

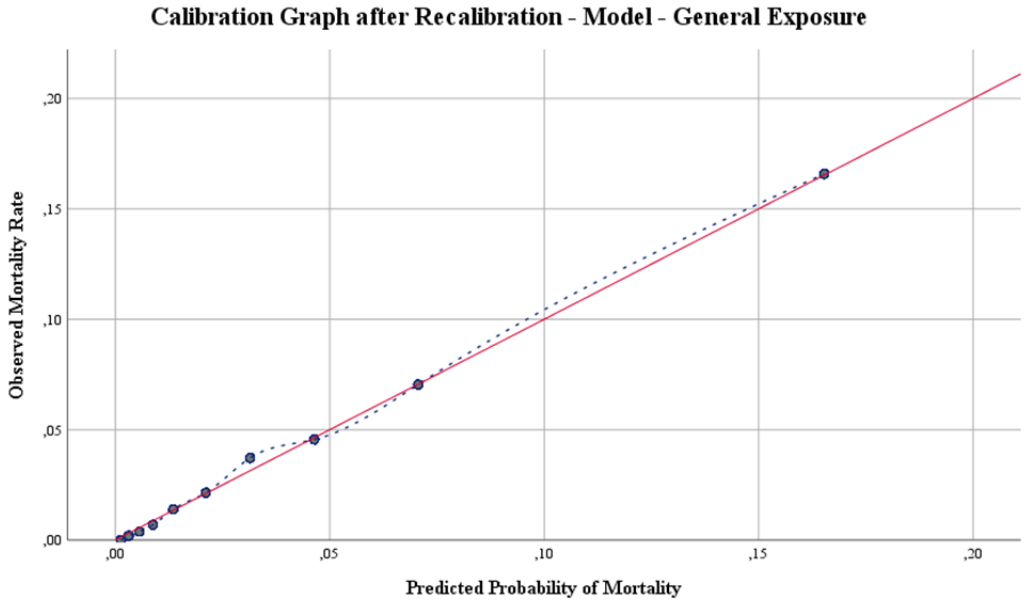

Figure 18: Calibration Plot after Model Recalibration for Model - Location

The results of Model Recalibration prove that a straightforward method can be used to adjust the final models to accommodate new data. This suggests that recalibration can be an effective tool for adapting models to changes in the hospital context, such as organizational or management changes, or gradual shifts in e.g. the patient population. Recalibration requires less effort than constantly developing entirely new models to manage changes in dynamic clinical settings, while ensuring that predictions remain aligned with observed outcomes, thereby maintaining accuracy over time.

6.4 Clinical Usefulness

The Clinical Usefulness of the final models was assessed by conducting a Decision Curve Analysis (DCA). The aim of the Clinical Usefulness assessment was to determine whether the developed prediction models could improve clinical decision-making regarding overflow bed placement, compared to alternative decision strategies. The DCA was performed on the developed models for 2022.

This analysis was conducted from the perspective of hospital staff, focusing on whether the models can support their clinical decisions on overflow bed placement. The primary objective of hospital staff is to provide the highest quality of care and ensure patient safety, with mortality prevention as their considered top priority. Given that overflow bed exposure has been associated with increased mortality risk, staff aim to prevent high-risk patients from being placed in overflow beds. The predictive models seek to assist in this decision-making process by identifying high-risk patients, enabling staff to better determine who could and who should not be placed in overflow beds

To assess whether the models can provide clinical usefulness, the DCA compared the *Net Benefit* of using the models against alternative strategies. The Net Benefit is calculated by weighing the benefit gained through True Positives against the benefit lost through False Positives when employing the model to classify high risk patients. The Net Benefit is calculated across varying Risk Thresholds ($P_{threshold}$), where each patient with a predicted risk above $P_{threshold}$ is classified as high-risk, and should therefore not be placed on an overflow bed.

The formula to calculate Net Benefit is presented in Equation 2: Formula for Calculating Net Benefit in the Decision Curve Analysis (Piovani et al., 2023)Equation 2.

$$Net\ Benefit\ = \left(\frac{True\ Positive\ Predictions}{Number\ of\ Admissions}\right) - \left(\frac{False\ Positive\ Predictions}{Number\ of\ Admissions}\right) * \left(\frac{P_{threshold}}{1 - P_{threshold}}\right)$$

Equation 2: Formula for Calculating Net Benefit in the Decision Curve Analysis (Piovani et al., 2023)

The True Positive and False Positive definitions used in the application of the prediction models are described here, illustrating how they contribute to the calculation of Net Benefit:

True Positive Predictions

True Positives represent the benefit gained from using the model, reflected in the first fraction of the formula. True positives are patients whom the model correctly identifies as high risk and should thus be prevented from overflow bed exposure. These patients have a predicted risk above the Risk Threshold and are therefore classified as high-risk. The key factor is that these patients died, confirming that the decision to avoid overflow bed placement was correct. The model generates benefits by correctly preventing patients with high mortality risks from being exposed to overflow beds.

False Positive Predictions

False Positives represent the benefit lost from using the model, reflected in the second fraction of the formula. These are the patients whom the model also identifies as high risk and prevents from being placed on an overflow bed. However, these patients survive, implying that the model incorrectly identified them as high-risk patients. This means they could have safely been placed in an overflow bed without resulting in mortality. The model loses benefit by wrongly classifying these low-risk patients as high-risk, restricting the use of overflow beds for patients who were not at high risk and incorrectly advising against overflow bed placement.

By weighing the True Positive and False Positive predictions, the overall Net Benefit is calculated by subtracting the benefit lost from the benefit gained, for varying Risk Thresholds. The goal is to maximize this Net Benefit by avoiding as many high-risk patients from overflow beds as possible while minimizing the number of incorrectly predicted high-risk patients. This can enhance clinical decision-making, primarily to improve patient safety, but also efficiency. It will provide a clearer understanding to the staff of which patients should not be placed in overflow beds and, conversely, which patients are relatively safe to be placed on overflow beds.

To determine the range in which the prediction models provide clinical usefulness, the results of the DCA can be visually presented in a graph. This graph plots three lines comparing the Net Benefit of the models to two alternative strategies. The alternative strategies are detailed here:

Place all patients to Overflow Beds

This strategy assumes that all patients, regardless of their predicted risks, are placed in overflow beds. The net benefit of this strategy is achieved by identifying those patients who could be safely placed in overflow beds. This strategy helps define the lower threshold at which overflow bed usage is considered relatively safe. The formula to calculate the Net Benefit of placing all patients to overflow beds is slightly different and depends on the actual mortality rate. This formula was derived from Riley et al. (2024) 'Treat all- Strategy' and is detailed in Equation 6.

$$Net\ Benefit\ 'Treat\ All' = Observed\ Mortality\ Rate\ - (1 - Observed\ Mortality\ Rate * \left(\frac{P_{threshold}}{1 - P_{threshold}}\right))$$

Equation 6: Formula to calculate the Net Benefit for the "place all patients to Overflow Beds" strategy

Avoid all patients from Overflow Beds

This strategy assumes that no patients are placed in overflow beds, regardless of their predicted risks. This strategy yields zero benefit because it assumes that overflow beds are too risky for all patients. While hospitals always strive to avoid overflow bed use in favour of admitting patients to clinically appropriate wards, this strategy serves as a reference point in the DCA. It helps identify the threshold at which placing any patient in an overflow bed is no longer beneficial, indicating the point where overflow bed placement always should be avoided.

Both of these strategies represent extreme scenarios that may not fully align with real hospital practices. However, they serve as valuable reference strategies within the context of the DCA. In practice, it is not always feasible to avoid using any overflow beds when hospitals face capacity constraints. Similarly, it would not be desirable to place all patients in overflow beds, given the associated risks. Thus, these theoretical strategies help define the risk ranges where overflow bed use may be relatively safe and where the model can help guide staff in decisions about which patients to avoid placing in overflow beds. Moreover, they assist in identifying the risk threshold at which placing any patient in an overflow bed should be completely avoided.

Table 14 presents the identified risk ranges for all models. To illustrate how these risk ranges are determined, the DCA plot for the Model – General Exposure is presented in Figure 19**.** While identified risk ranges may vary for each model, they all show a similar pattern as observed for the General Exposure Model. The plots for the other models are provided in Appendix H - Decision Curve Analysis.

Table 14: DCA Results of the identified Risk Ranges for Mortality

	Relatively Safe	Apply Model Range	Avoid Overflow Beds
Model – General Exposure	< 4%	4 – 42%	> 42%
Model - Location	< 4%	4 – 54%	> 54%
Model - Duration	<4%	4 – 50%	> 50%

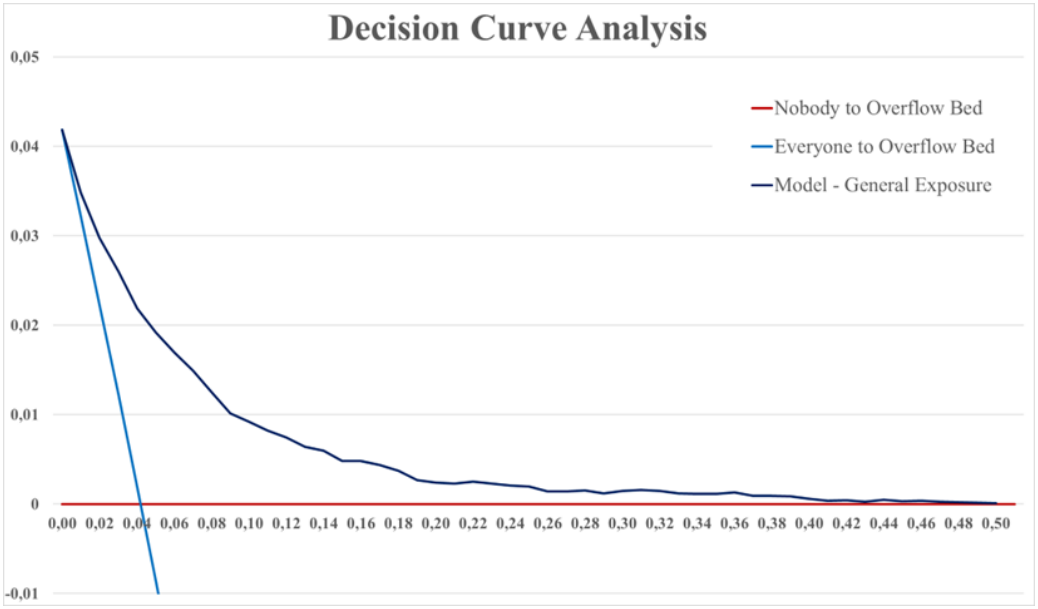

Figure 19: DCA Plot for Model - General Exposure

The Risk Ranges presented in Table 14 were determined by interpreting the DCA graphs by comparing the lines of each different strategy.

Relatively Safe Range (Predicted Mortality < 4%)

The Relatively Safe range is identified where the 'Everyone to Overflow Bed' line is above the zero line on the DCA graph. In this range, placing all patients in overflow beds (predicted mortality below 4%) provides a net benefit compared to not using overflow beds at all. This does not mean that overflow beds are the preferred choice - hospitals strive to admit patients to clinically appropriate wards—but rather that, within this range, the potential negative impact on mortality appears limited. The net benefit suggests that for these patients, the risks of overflow bed placement are not substantially higher than the baseline mortality risk of acute admissions. While applying the predictive model would gain even more net benefit, this range indicates that placing these low-risk patients in overflow beds may be an acceptable and relatively safe alternative when capacity constraints make it necessary.

Apply Model Range (Predicted Mortality 4 - 42 %)

The Apply Model range is identified as the range where the model provides the highest net benefit compared to alternative strategies, between a predicted mortality of 4% and 42%. In this range, the model is clinically useful for hospital staff by providing a net benefit: it helps correctly identify high-risk patients who should avoid overflow beds while minimizing lower-risk patients who are unnecessarily withheld from overflow placement. Rather than setting a strict threshold for avoiding overflow beds, the model provides valuable information to the hospital staff on the relative risks of overflow bed exposure for individual patients, enabling more informed clinical decisions. Within this 4–42% predicted mortality range, using the model adds clinical value by providing a sense of the risks associated with overflow bed exposure, as opposed to placing all or no patients in overflow beds.

Avoid Overflow Beds Range (Predicted Mortality > 42%)

The Avoid Overflow Beds range is identified as the range above 42%, where no net benefit is gained from placing all patients in overflow beds or from using the model. This suggests that patients with a predicted mortality outcome above 42% should not be placed in overflow beds due to the high associated risks, as no benefit was derived beyond this risk threshold.

The identified risk ranges require a practical translation to make the DCA results more clinically relevant to hospital staff. This is necessary because, for example, at the time of admission a patient's predicted risk is not known. It is therefore unclear where in the risk ranges a patient falls and thus difficult to determine whether the patient is relatively safe on an overflow bed or should be avoided. In addition, running the full prediction models requires patient information that is not always available at the point of admission and would be too time-consuming for each patient. Hospital staff therefore need to be provided with quick and accessible guidelines to assess the risk of overflow bed placements.

To address this, a practical patient classification of the "Relatively Safe" and "Avoid Overflow Beds" risk ranges was developed based on three parameters that are assumed to be always available and known at the time of admission: age, number of known comorbidities from the Charlson Comorbidity Index, and origin location before admission. In addition, these parameters are significant predictors of mortality risk, ensuring that these classification parameters are both clinically and statistically relevant.

This patient classification was created separately for each risk range in the form of coloured Heatmaps. These Heatmaps have been created by dividing the acute admission patient population into categories based on age group (x-axis) and number of comorbidities (y-axis). The boxes of these categories shown in the Heatmap indicate the percentage of all acute patients who fall into that particular risk range, based on their calculated mortality prediction.

To illustrate, the Heatmap for the "Relatively safe" range shows for each box which percentage of all acute patients in age group X with a number of Y comorbidities fall within the "Relatively safe" range (predicted mortality below 4%). If the box for patients aged 40-50 with one comorbidity, for example, shows a percentage of 90%, this means that 90% of acute admissions between the ages of 40 and 50 with one comorbidity fall within the "Relatively Safe" range.

A colour scheme was applied to the Heatmaps to visually indicate for which types of patients the vast majority (green) can be relatively safely placed on an overflow bed. As the percentage of a particular type of patient in the "Relatively Safe range decreases, the colour of the boxes is gradually turning red. This provides a visual classification of patient types, allowing a practical way of quickly determining whether these patient types are predominantly in the safe range (green) or less frequently (red). For the latter type of patient, it may therefore be less safe to place them on the overflow beds, requiring applying the prediction models to estimate their mortality risks or avoiding overflow bed placement at all.

These Heatmaps would make the decision-making regarding overflow beds more efficient and accessible while maintaining patient safety. The Heatmaps for the "Relatively Safe" range are presented separately for different origin locations before admission in Figure 20.

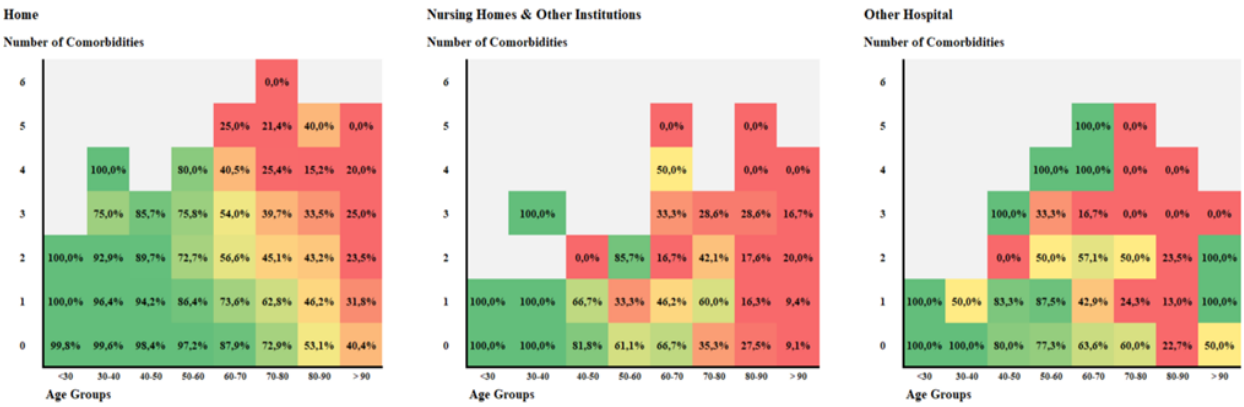

Figure 20: Heatmap classifying patients with the "Relative Safe" Range

The pattern that emerges from these Heatmaps reveals that patients under the age of 60 with no or minor Charlson Comorbidities can be admitted to overflow beds relatively safely, as the vast majority of these types of patients fall into the "Relatively Safe" risk range, as reflected in the green area on the left side of the Heatmaps. However, as age and the number of Charlson Comorbidities increase, the proportion in this low-risk group decreases sharply. These findings suggest that older patients with multiple comorbidities should not be considered safe for overflow beds, regardless of where they originate from.

This decline is even more pronounced for patients admitted from nursing homes or other hospitals, who are likely to be more frail and older, and therefore likely to be less suitable for overflow beds. In addition, the pattern for patients from other hospitals suggests that it may be safer to keep the patient in the other hospital in a clinically appropriate bed rather than admit them to an overflow bed.

In a similar way to how Heatmaps were developed for the "Relatively Safe" risk range, heatmaps can be developed for the "Avoid Overflow Beds" range. These Heatmaps will show the exact opposite, i.e. which types of patients are not safe for and should be avoided from overflow beds. The patterns found for the "Avoid Overflow Beds " Heatmaps suggest that older patients (>80) with multiple Charlson Comorbidity Index comorbidities (>2) should be avoided from overflow beds, with similar patterns identified for all origins before admission. The heat maps for the Avoid Overflow Beds range can be found in Appendix H - Decision Curve Analysis.

For those patient types that do not fall within these Relatively Safe or Avoid ranges, the application of the model can provide valuable insight by predicting the risk of mortality with and without exposure to overflow beds, as illustrated with a patient scenario in 5.3 Model Estimation.

These risk estimations can be compared to create a sense of the potential mortality risks associated with overflow beds. These quantified insights will enable the hospital staff to make more risk-informed clinical overflow bed decisions based on each patient's specific estimated risk profile. This could support them in deciding which patients to place in which overflow beds or help them to decide to take measures to prevent placing high-risk patients outside their clinically appropriate ward.

6.4 Summary of Research Phase 3

The third research phase aimed to answer:

SQ 3: ***"To what extent can the developed predictive models for 2022 accurately predict observed mortality for 2023?"***

SQ 4: ***"To what extent could the predictive models provide clinical usefulness to hospital staff?"***

Temporal validation showed that the final models retained strong discriminatory performance when applied to the 2023 data, discriminating well between mortality and survival outcomes. However, calibration deteriorated over time, with predictions particularly overestimated for high-risk patients relative to observed mortality rates. Therefore, model recalibration was conducted, which showed that with simple adjustments, model accuracy could be maintained over time and to new data.

The clinical usefulness assessment showed that the models could lead to better decisions than alternative strategies of placing all or no patients in overflow beds, over a wide range of predicted mortality. Within this range, the model can be used to provide staff with better insights into the risk of individual patients associated with overflow bed exposure. This analysis also provided more insight into the types of patients who can be relatively safely placed on overflow beds, typified as patients below 60, regardless of the number of comorbidities or admission location. Additionally, this risk classification showed that overflow beds should be avoided for older patients above 80 with multiple Charlson comorbidities,

7. Discussion

This chapter presents the discussion of the final research findings. Firstly, an overview of the key research findings is provided, together with a reflection on these findings by placing the findings within the existing literature. This is followed by a discussion of the limitations of the research, followed by a presentation of the scientific contributions of this study. Subsequently, recommendations for future research are provided. Next, a discussion of research implications is presented, structured in practical contributions and policy recommendations. The chapter concludes with a reflection on the researcher's position.

7.1 Overview and Reflection on Key Research Findings

This study aimed to assess the impact of patient exposure to overflow beds in hospital admissions on safety, operationalised in mortality. The key findings of this research on the impact of exposure to overflow beds on mortality could be derived from the predictive models. The predictive model development phase showed that the most statistical and clinically relevant predictions were made for acute admissions.

The key outcomes of this research will be discussed and placed within the current understanding of existing literature. In an attempt to explain the findings the framework of Goulding et al. (2012) is applied. Goulding et al. took a qualitative approach to identify 5 key themes that might lead to safety risks for patients in overflow beds. The framework of Goulding et al. is visually summarised in Figure 21. A more detailed version of this framework can be found in Appendix I – Framework of Underlying Safety Mechanisms

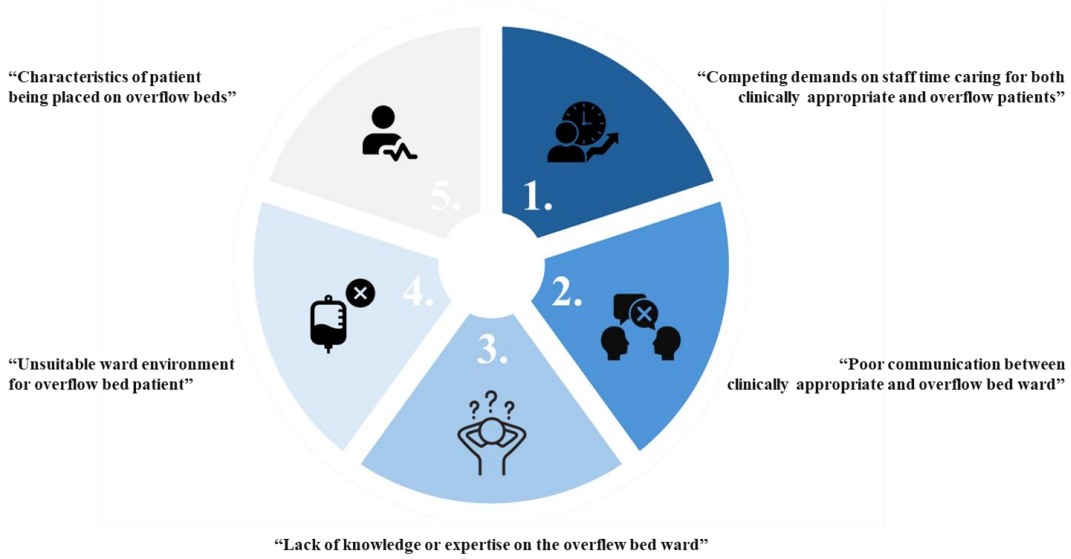

Figure 21: Visualisation of Goulding et al. (2012)'s framework of underlying mechanisms

Overall impact of overflow bed exposure

The findings of this research show that there is a statistically significant effect on the odds of mortality for patients exposed to overflow beds compared to those not exposed. The results indicate that the adjusted mortality odds are 1.65 times larger for exposed patients, indicating a 65% increase in mortality risks, compared to patients who were not exposed to overflow beds.

These findings align with most outcomes of existing literature indicating that there is an increase in mortality risks associated with overflow beds. These overall results are most comparable to those of Santamaria et al. (2014), as this study also included all hospital admissions and therefore observed the overall impact of overflow beds within a hospital. This study showed that the mortality rate for outlier patients was more than twice as high. Although odds are not the same as the mortality rates, the general indication aligns with this research's findings on an overall increase in mortality risk for exposed patients.

Impact of overflow bed location

The findings on the impact of the location of the overflow bed showed that the mortality odds compared to no exposure differed per location and type of patient. The largest increase in mortality risk was observed for mixed patients, with odds 4.6 times higher if placed in another mixed ward, 3.6 times if placed in surgical wards and 1.2 times higher if placed in medical wards, compared to no exposure.

These findings are difficult to relate directly to the existing literature because the classification of mixed wards is highly dependent on the organisational structure of the hospital and has not been specifically addressed in previous studies. A possible explanation for the increased risk for mixed patients, particularly for the combination of mixed patients to mixed wards, is the high variability of care within the mixed classification. The mixed classification covers a wide range of specialties and patient types, each requiring different expertise that may not be available in other settings. For example, a mixed patient (e.g. a neurology patient) on a mixed gastroenterology ward may be cared for by staff who are unfamiliar with the patient's condition, as these specialties may be considered to be completely different areas of expertise, while both were typed mixed. This unfamiliarity, as outlined in Goulding et al.'s framework (theme 3), could explain the increased mortality risks for especially these patients.

The results for medical patients admitted to surgical wards showed a significant increase in mortality risk, with odds doubled compared to non-exposed patients. These findings align with previous studies by Serafini et al. (1.8x), Perimal-Lewis et al. (1.4x), and Patry et al. (lower survival probabilities). This study contradicts Zannella et al., Stylianou et al., and Kohn et al., who found no effect. Interestingly, surgical patients placed in medical wards, which was not investigated before, also showed a significant increase in mortality risk (2.7x).

The observed increased mortality effects may be explained by Goulding et al's framework, where staff unfamiliarity (theme 3) with other patient types and an increase in the staff's workload to care for these unknown patients (theme 2) could lead to unrecognised deterioration of patient conditions or missed treatments that could explain increased risks. Communication barriers (theme 2) between wards could also hinder timely intervention, e.g., it could be questioned whether staff can communicate potential problems associated with certain types of patients if they do not recognise them. The mismatch in ward suitability may also limit access to necessary resources or equipment for other types of patients (theme 4). In conclusion, multiple mechanisms may explain the found effect of increased risks for patients placed outside their intended ward type.

The contradiction in findings compared to Zannella et al. and Kohn et al. may be explained by their multicentre study design, whereas this study was conducted in a single hospital. In studies covering multiple hospitals, the mortality effect impact may have been reduced due to wide variability between hospitals in managing overflow beds and associated underlying mechanisms. In addition, Stylianou et al. also included a much larger dataset spanning admissions from several years. A larger and more diverse dataset may have led to greater variability in patient population which may have influenced the observed effect of overflow bed exposure on mortality compared to these findings based on only one year of data.

Impact of duration of overflow exposure

The findings on the duration of overflow bed exposure showed that short-term exposure (<1.36 days) was associated with the highest risk increase, approximately 2.3 times compared to no exposure. Prolonged stays did not lead to significant increases in mortality odds. These findings suggest that the most critical period for patient safety is the initial phase of admission.

This is consistent with Bai et al., who reported that mortality risk is highest on admission (approximately three times higher than with no exposure) and decreases over time. While Bai et al. suggested that after 3 weeks the mortality risk is no higher than no exposure, this study found that after 1.36 days the risk is no longer significantly higher. One possible explanation is that the initial period of admission is crucial for monitoring patients, especially for detecting deterioration. If this is undetected, uncommunicated or delayed due to overflow bed exposure (Goulding et al.'s themes 1, 2 and 3), this may lead to a higher risk of mortality. The reason why the effect decreases over time may be due to high risk patients being repatriated to clinically appropriate wards or, in extreme cases, have died, eliminating the increased risk with prolonged exposure. In addition, it may be that the remaining patients with prolonged exposure to overflow beds are not as susceptible to the associated mortality risks and are therefore relatively safe on overflow beds, as these patients may already have a lower predicted risk and survive.

7.2 Research Limitations

There are several limitations to this research that should be acknowledged. This section will reflect on the main limitations of the research and how it was attempted to limit the impact of these limitations on the research findings.

Quality of hospital data

First, this study was based on routinely collected hospital data from a single hospital over two consecutive years. As a result, the findings may not be generalisable to other types of hospitals with considerably different patient populations, such as academic medical centres or highly specialised hospitals providing different types of care.

In addition, routinely collected data are inherently subject to research limitations (Grzeskowiak et al., 2013; Hemkens et al., 2016). The data were not collected for research purposes and may contain inaccuracies due to administrative errors, bias or misclassification. These potential (systematic) errors could affect the results. For example, human bias may have influenced whether a patient was classified as acute, and data formatting or ward registration practices may have influenced the identification of overflow bed exposure. To manage these limitations, hospital staff were consulted to verify whether the identified overflow bed patterns were consistent with their perception of clinical reality. Margins of error were assessed to verify whether the created research data matched actual admission numbers, using additional data sources. Moreover, structurally misclassified overflow bed-exposed patient groups were adjusted to ensure more accurate data formatting

Generalisability of mixed ward classification

The specification of the location model was based on the classification of wards. Wards and patients were classified according to internal hospital guidelines, distinguishing between surgical, medical and mixed wards. These classifications were used to operationalise the effect of the type of care associated with a particular location compared to the type of care that is required for particular patients. While surgical and medical wards are common across hospitals and literature, the use of the mixed ward classification hinders generalisability and interpretation.

Mixed wards include a wide range of specialties and medical expertise, making it difficult here to identify specific patient groups that were particularly affected by overflow bed exposure. In contrast to medical and surgical wards, where the range of provided care is more clearly defined, the broad scope of mixed wards with both surgical and medical care elements complicates external comparison. The lack of a clear care profile for mixed wards limits the generalisability of these findings, as it remains unclear which specific (lack of) care elements drive the increased mortality risks for mixed wards.

Sample size and overfitting

The iterative model development process revealed that the most statistically and clinically relevant models were created for acute admissions, due to the low ratio of (mortality) events per variable in non-acute models. As a result, by considering only acute admissions and using one year of data (2022), the final development sample sizes for admissions and mortality outcomes were significantly reduced. This reduction may have led to some overfitting of the models, making the model coefficients too extreme (Ogundimu et al., 2016). Given the lack of additional data and the fact that widely accepted thresholds for events per variable were surpassed, the decision was made to continue with these models and sample sizes. However, the potential impact of the reduced sample size should still be acknowledged.

In addition, the model specification included dummy coded variables for all subcategories of each categorical predictor. This choice resulted in a large number of (low-frequency) variables relative to the sample size, which may have further contributed to overfitting (Steyerberg & Vergouwe, 2014). The grouping of patient types also resulted in low observed frequencies for certain variables, which affected calculations such as adjusted mortality rates. Although these calculations take into account the patient mix, the observed to expected mortality rate may have been disproportionately high if the overall sample size of the particular group was small. The decision to continue with these smaller sample size groups was mainly based on clinical relevance, as combining groups to increase the sample size would result in less recognisable and less clinically meaningful groups.

Long-term applicability of findings

Given potential model overfitting, the performance of the models over time and on new data may be limited (Efthimiou et al., 2024; Shipe et al., 2019). The temporal validation of this study revealed that the models were less well-calibrated for the 2023 validation set. In particular, predictions for high-risk cases were too extreme compared to observed mortality rates. Besides overfitting, this reduced performance may be due to changes in the data, as a consequence of the dynamic nature of healthcare. Changes in the hospital context or patient population could affect model fit, limiting the long-term applicability of the findings.

An example of this is the presence of COVID-19 in 2022, which may have influenced the patient population used for model development. Moreover, COVID-19 was assessed as a potential effect modifier between mortality and overflow bed exposure, no significant interaction was found. As a result, it was decided to include this diagnosis in the model. However, it had to be included as a separate sub-diagnosis due to the lack of a severity class classification. These modelling decisions around COVID-19 may have affected the long-term applicability of the models, as it is unlikely that COVID-19 will have a significant impact on future patient populations but did impact the current analyses.

In response to the observed calibration drift, model recalibration was conducted to update models to such changes. It was found that simple adjustments could considerably improve model calibration when applied to new data. While recalibration does not remove the initial potential limitation of overfitting, it provides a practical solution for improving prediction accuracy in such a dynamic research context.

Unaccounted variables

Finally, there may be variables not included in the models that could further explain the relationship between overflow bed exposure and mortality. These variables could improve the predictive power of the models or enhance their practical applicability. Examples of variables could be the potential risk associated with the transfer of patients, a factor highlighted in the literature (Goulding et al., 2012; Stylianou et al., 2017) or the time of admission, particularly at times outside regular day shift, such as evenings, nights or weekends, which was often mentioned by hospital staff. Both are not yet included in the model.

Nevertheless, the explanatory power of the model, as indicated by the Nagelkerke R^2, shows that the included variables already provide considerable meaningful clinical value Gupta et al. (2024). The practical applicability of the models is somewhat limited by the use and definitions of the LBZ variables. For example, current decision-making is often based on the patient's diagnosis or admission specialty, whereas in the models this is represented indirectly by the severity class, which may not be as intuitive for hospital staff.

7.3 Scientific Contribution to Knowledge Gaps

Three knowledge gaps were identified in previous literature regarding overflow bed exposure and potential mortality risks: 1) a lack of clear consensus on mortality implications, 2) limited generalisability and applicability of existing findings, and 3) a lack of explicit integration of safety risks in hospital capacity management. This section reflects on the scientific contributions of this research to these knowledge gaps, structured in specific contributions in the field of hospital safety science, hospital capacity management sciences, and methodological contributions to clinical prediction model research.

Scientific contributions to Hospital Safety Science

This study adds evidence to previous studies by supporting the notion that exposure to overflow beds increases the risk of patient mortality during hospital admission. The research findings validate previous research by confirming an overall increased risk of mortality but extend this current understanding of the safety implications by examining the risks across three clinically relevant dimensions: general exposure, location and duration.

It was demonstrated that the risk associated with overflow bed exposure is not uniform for all patients and is significantly different for specific types of patients placed in specific overflow bed locations and the degree of exposure. Whilst the addition of a single thesis is unlikely to lead to an academic consensus on the impact on mortality, this comprehensive research perspective and subsequent findings contribute to the science of hospital safety by extending the concept of overflow beds beyond simply admissions outside the clinically appropriate ward. It provides a more detailed understanding of the risks based on a clinically relevant framework of risk dimensions.

In addition, this study improves the generalisability of findings on overflow bed risk by providing new evidence for a Dutch hospital context that has not been studied before. Furthermore, it extends the previous literature, which mainly examined medical patients admitted to non-medical wards, by including a broader range of patients on medical, but also surgical and mixed wards. The results increase the external validity of previous findings for medical patients, but provide new evidence that increased mortality risks are not restricted to medical patients. This helps to strengthen current evidence in hospital safety science by providing more detailed findings that are applicable to wider hospital contexts and patient populations.

Scientific contributions to Hospital Capacity Management

This study contributes to the field of hospital capacity management by showing how clinical decisions in times of bed shortages can more explicitly incorporate safety considerations. Previous studies have identified safety risks associated with overflow beds and called for future research into tools, standards and guidelines to ensure a more safety-conscious approach to overflow beds. This study bridged this gap by demonstrating how the predictive modelling results can be translated into clinically relevant tools to support hospital staff.

Specifically, this study demonstrates this through the development of two decision-support tools; 1) visual guidelines that classify patients who can generally be relatively safely placed in overflow beds and those who should be avoided, and 2) a prediction-based tool that can estimate mortality risk for individual patients. By providing insights into these tools, this study contributes to scientific knowledge on how a more risk-informed and safe approach to hospital capacity management can be achieved. This complements previous literature by addressing practical measures that could help mitigate the identified increased mortality risks.

Methodological contributions to Clinical Prediction Modelling

This study advances the field of clinical prediction modelling from a methodological perspective by demonstrating the value of applying a Decision Curve Analysis (DCA) and model recalibration.

While the DCA is a well-established method for evaluating the benefits of clinical prediction models in, for example, guiding medical treatment and intervention decisions, it had not previously been applied in the context of overflow bed management. This study demonstrates how DCA can help determine safe and unsafe risk ranges for overflow bed placement, providing the methodological foundation to ensure that the predictive models are not only statistically significant but also clinically useful for hospital practices. This methodological contribution supports the broader application of DCA to translate clinical prediction model findings into actionable and more clinically relevant implications.

Finally, this study contributes methodological insights by demonstrating the value of model recalibration to improve the adaptability and longer-term applicability of clinical prediction models. It is often noted in the literature that strong external validation of clinical prediction models is difficult to achieve and is likely to reduce the accuracy of predictions due to differences in patient populations and hospital (organisational) contexts (Davis et al., 2020; Van Calster et al., 2023). This study has demonstrated how model recalibration could improve predictive accuracy when applied to new data. This provides a practical methodological contribution for researchers, but also other hospitals, to adapt existing models to contextual and patient population differences, rather than developing entirely new models.

7.4 Recommendations for Future Research

Several directions for future research can be recommended. These directions can be divided into future research aimed to address limitations and validate findings and new research that builds upon this study.

Future research recommendations to address limitations and validate findings

Given the limited sample size of acute admissions in the development of the prediction models, a replication of this study with a larger dataset across several years may provide more valid results. A model developed with data from multiple years with a larger number of admissions and mortality outcomes would allow validation of the 2022 results, helping to determine whether the predicted mortality impact was overestimated. This research has provided the methodology to prepare research data for future research, indicating how the provided hospital capacity data can be added to the annually available LBZ data, making future research more accessible.

A larger data set would also allow for more detailed models, including variables that are currently not accounted for. Future research could include the effect of patient transfers. Data on patient transfers can be derived by counting the different admission locations recorded for the admission segments (the basis of hospital capacity data) belonging to an individual admission. This would give an indication of the number of transfers a patient has experienced. Similarly, the time of admission can be added to the analyses. Each admission segment is classified into a day, evening or night shift. This allows the time of admission to be subtracted based on the recorded shift of the first admission segment of an individual admission, reflecting whether the patient was admitted during a regular day shift or a more irregular evening or night shift.

In addition, the research can be extended by detailing the effect of location at the specific wards of the hospital, rather than at the highly aggregated level of ward type. This avoids using a classification of mixed wards, which is difficult to generalise and interpret. A ward-based model allows direct quantification of the safety impact of being intended for a particular clinically appropriate ward but being placed in another overflow ward. In addition, this approach would align the results more closely with the actual hospital design, thereby increasing the practical use of the models by hospital staff. An important requirement for ward-based models would be a high level of data availability to avoid overfitting due to the need to include a large number of variables to include all wards independently in the models.

Future research could also be conducted in other hospitals with different patient populations and organisational contexts. This would serve as a validation to assess whether similar effects are observed in different hospital contexts. As the models are based on LBZ variables, future studies can easily adopt the methodology of this research. The DHD provides LBZ data for all hospitals in the Netherlands, making future research accessible. In addition, it could be investigated whether model recalibration proves to maintain the accuracy of the developed models when applied to data from different hospitals

Future research recommendations to build upon this research

Future research could examine the broader safety implications of overflow bed exposure by analysing two additional indicators included in the LBZ data: unexpected length of stay and readmissions. These metrics provide insight into whether overflow bed exposure leads to longer hospital stays or the need for readmission. These metrics require a different methodological approach due to interference with mortality and a survivor effect. Patients who die may have either short or prolonged hospital stays, making it difficult to determine whether overflow bed exposure truly impacts the length of stay. In addition, patients who die cannot be readmitted. As a result, the impact of overflow beds on these indicators may appear to be less pronounced than it actually is. Methodologically, this can be addressed by limiting future analysis to patients who survive their hospital stay.

In this way, future research would supplement the current study. While this study focuses on primary safety risks, specifically preventing patient mortality, future research could take a broader perspective by assessing the quality of care for those who survive. If patients who are exposed to overflow beds consistently have longer hospital stays or more frequent readmissions, this may indicate inefficiency and ineffectiveness of overflow bed care for example due to complications or delayed care. Broadening the scope would allow future studies to measure multiple dimensions of quality as defined in the IOM framework and to explicitly examine trade-offs between these dimensions. While the impact of overflow beds on safety would still be examined, future research could provide additional insights into the effectiveness and efficiency of care, reflected in prolonged hospital stays and increased readmissions.

Finally, interesting opportunities for future research arise from the simultaneously conducted qualitative study on overflow bed use and its safety implications. This study explored the current decision-making process for overflow bed placements, the challenges faced by staff and how they take safety considerations into account in these decisions.

The quantified risks and predictive models developed in this study, combined with the qualitative findings from the other study, provide an opportunity for mixed-methods research. An interesting area for future research could be to investigate how hospital staff decision-making changes when they have explicit knowledge of the risks and access to a tool for estimating patient-specific risks associated with overflow bed placement. One possible approach could be a discrete choice study in which decision-makers are presented with different patient scenarios and associated risks. By analysing their choices, such future research could provide new insights into the preferences, risk perceptions and trade-offs considered when making overflow bed placement decisions.

7.5 Research Implications

In times of increasing pressure on healthcare, society, and hospitals in particular, face growing challenges in ensuring the availability of high-quality care. The shifting demand for care, financial and political pressures, and resource limitations such as the availability of healthcare personnel put the Dutch healthcare system under pressure. As a result, hospitals are increasingly faced with capacity constraints that require a difficult balance between efficiency, high accessibility of care, and maintaining patient safety.

It is therefore likely that the use of overflow beds will continue to be necessary to manage bed shortages. Given the identified safety risk associated with overflow beds, this calls for a more efficient, but above all safe approach to hospital capacity management. These research implications provide a reflection on how the research findings can contribute to these challenges with more general practical contributions and policy recommendations focused on the hospital under study.

Practical Contributions

To discuss the practical contributions of this study to enhance the integration of safety considerations in overflow bed decisions, it is important to reflect on how safety implications arise. The perspective of Goulding et al. (2012) provided a useful perspective on safety by describing implications arising from the interaction between latent conditions (structural factors shaped by hospital planning, policies, or strategic decisions), underlying mechanisms (as presented in Figure 21), and an inadequate response to these factors. The practical research contributions are structured around these factors to indicate how hospitals could address these factors to mitigate safety implications related to overflow beds.

Mitigate latent conditions

Firstly, the results of this study could be used by hospitals to critically evaluate their bed allocation strategies. Capacity allocation norms - the occupancy and refusal rates - could be reassessed to determine whether they, besides anticipating historical, seasonal and expected patterns in the demand for care, also adequately address patient safety considerations. For example, if current bed allocation plans consistently result in overflow placements associated with high safety risks, it may be appropriate to adjust refusal norms to reduce these placements and ensure more space for admission to the clinically appropriate ward, even if this results in a small increase in the number of empty beds. The clinically relevant EDA results are of particular interest for this purpose, as they indicate areas of the hospital where the measured absolute risks were significantly higher compared to others. Explicit integration of these findings could reshape bed allocation strategies, reducing the need for overflow beds at the forefront.

Raising awareness of underlying mechanisms

Although this study did not directly examine the underlying mechanisms explaining why overflow bed placement is associated with increased mortality risk, it provides quantified evidence that these risks exist. Awareness of these risks is therefore a critical first step in mitigating the impact.

By increasing awareness of these risks among hospital staff, hospitals could set up targeted interventions. Examples based on Goulding et al. (2012)'s framework could include providing additional training for nursing staff on wards that frequently host particular overflow patients or participating in temporary rotations on these associated clinically appropriate wards to improve familiarity with specific required care. Similarly, if clinically responsible teams are made more aware of the increased risks associated with overflow placement, they could take a more proactive role in monitoring and clinical review of overflow bed patients, preventing delayed care.

Strengthening the response to using overflow beds

When capacity constraints make the use of overflow beds unavoidable, hospitals need to ensure that safety risks are well considered in their associated bed allocation decision-making process. Currently, in this research context, the placement of patients in overflow beds is the primary responsibility of a patient flow coordinator. The management of overflow beds is now primarily driven by capacity-deficit protocols and daily bed allocation meetings between wards and is informally influenced by the clinical judgement of clinicians. However, this decision-making process lacks structured, quantified insight into the risks associated with these decisions. This study directly contributes to improving this decision-making process by providing practical guidelines and a risk prediction tool to assist patient flow coordinators in integrating explicit safety considerations into the overflow bed decision.

The practical guidelines enable hospitals to assess the risk of mortality at the point of admission (at the ED or Acute Medical Unit) based on routinely available patient characteristics, including age, Charlson Comorbidity Index and the origin location before admissions. By integrating these guidelines into existing hospital admission workflows and daily bed allocation strategies, patient flow coordinators can make more informed decisions about which patients are relatively safe for overflow placement and which should be prioritised for admission to the clinically appropriate ward.

In addition, the prediction tool could help hospitals and patient flow coordinators make better decisions by assessing the individual safety risks of incoming patients along three dimensions: the general risk of overflow beds, the specific location of the overflow bed, and the length of stay in an overflow bed. By entering all relevant (LBZ) patient variables, the tool can estimate the mortality risk for both exposure and non-exposure scenarios. This provides patient flow coordinators with a clear, quantified overview of a patient's risk profile when placed in an overflow bed, thereby enhancing the sense of patient safety. In addition, this individual patient's risk profile could also be used to increase clinical awareness for a particular patient. In response, the clinically responsible team and nursing staff could initiate, for example, more frequent reviews or closer communication with the clinically responsible ward.

The practical contributions of these guidelines and tools should be recognised as being limited to comparable hospitals in terms of hospital context, approach to hospital capacity management and patient population. These hospitals may adopt these tools. Hospitals that have a different perspective on hospital capacity management, and therefore may have a different policy or process around overflow beds, or hospitals that have a very different patient population, for example, due to specialised care (such as academic medical centres), are recommended to first recalibrate the models to their own data. To achieve predictive accuracy to new data, this study provided the methodological contribution of model recalibration.

This study should be considered a first exploratory step in increasing awareness of the safety implications related to overflow beds. By integrating risk awareness and practical risk-informed tools into bed management strategies, hospitals can take proactive steps to improve patient safety. Based on addressing the conditions that contribute to patient safety risks—latent conditions, underlying mechanisms, and response strategies—this research provides hospitals with practical contributions to work toward a more efficient and, more importantly, safer approach to managing hospital capacity shortages in a time of increasing societal healthcare pressures.

Policy Recommendations

The policy recommendations are structured across a strategic, tactical, and operational level, aligning with levels of decision-making in current hospital capacity management.

Strategic Research Implications

The strategic decision-making level is considered the longer-term vision of the hospitals and policies that affect the entire organisation, The strategic level is executed by hospital support management.

- **Initiate a Hospital-Wide Discussion on Safety Risks of Overflow Beds**

A broad discussion across medical, nursing and supporting staff should be initiated on the findings of this study, to share the results on the mortality risks associated with overflow bed exposure. The clinically relevant EDA highlighted hospital areas with higher adjusted mortality rates, providing a starting point for these discussions. The predictive models added a quantified translation to these risks. These insights can enhance hospital-wide awareness, resulting in a more risk-informed perspective on overflow bed use. This perspective could initiate small, practical adjustments, such as more frequent medical rounds for overflow patients and earlier escalation of concerns by nursing staff, to help mitigate risks. Check-in on the overflow bed patients should become a habit, a culturally integrated part of daily hospital operations.

- **Introduction of additional education for hospital staff in relation to overflow beds**

It is recommended to invest in the introduction of educational programmes for hospital staff concerning the management of overflow beds. An initial training programme could include increasing the familiarity of ward nursing staff with the care that needs to be provided to the types of patients for whom that particular ward is the first overflow alternative according to the capacity-deficit flowcharts. This can be achieved, for example, through temporary rotations or observations so that staff gain a better understanding of what skills are required to care for this type of patient.

In addition, educational workshops on the use of the provided practical guidelines and risk prediction tool can be organised. By engaging with e.g. patient flow coordinators and ward managers, on how these models can be used in their work processes, they can intuitively learn to use them. This would also help to increase the acceptance of the tools by indicating the potential added value of these applications.

- **Multidisciplinary Hospital Design**

As a long-term recommendation, the hospital could explore the use of multidisciplinary wards to address capacity constraints. Instead of concentrating care, a more centralised approach could be considered. This study showed that for similar types of patients, the use of overflow beds did not significantly increase risks. By adopting these findings to a hospital-wide approach with multidisciplinary wards, the issues of overflow beds may become less relevant as the concept of clinically appropriate wards is broadened. However, this alternative view of hospital design should be further explored to assess whether increased capacity and accessibility could outweigh reduced specialist care.

Tactical Research Implications

The tactical decision-making level is considered the monthly revision in hospital capacity management and is more tailored to specific wards. The tactical level is organised around ward-level management.

- **Re-evaluate Current Overflow Bed Decision Flowcharts**

Current decision flowcharts for overflow bed placements should be reassessed based on the identified risks. This study suggests prioritizing placement within the same ward type where possible to minimize safety concerns, except for mixed patients. In the long term, if ward-level prediction models are developed, these flowcharts can be further refined based on more-detailed risk calculations to determine the safest alternative wards for overflow placements.

- **Monitor Overflow Bed Usage for Model Updates**

It is recommended to review the use of overflow beds regularly. This will help to assess whether the models are still consistent with actual hospital practice. This review is important to monitor whether the models need to be updated. Reasons for model recalibration could include structural changes in hospital capacity management that affect overflow beds, abrupt changes in the patient population due to e.g. the possible emergence of serious epidemics, or the attraction of the hospital to provide additional or new specialist care. In the longer term, it is recommended to update the models to correct for inherent gradual changes in the patient population.

Operational Research Implications

The operational decision-making level is considered to be the daily decision-making process regarding overflow bed placement for incoming urgent individual patients. This decision is made at the ED or Acute Medical Unit by the patient flow coordinator and/or discussed in the daily bed allocation meeting.

- **Adopt the Practical Guidelines and Risk-Prediction Tool**

It is recommended to consider the Heatmaps provided in 6.4 Clinical Usefulness and the Excel tool provided in Appendix J - Dashboard for Risk Predictions in the current decision-making regarding overflow bed placement. While it should be emphasized that these guidelines and tool should not replace clinical judgment, they could contribute to more risk-informed guidance to the patient flow coordinator and daily bed allocation meetings in making safer overflow bed placement decisions as described earlier.

To facilitate practical use, the risk-prediction tool could be further improved into a more clinically relevant dashboard where more clinically relevant and easily available patient data can be entered. Such improvement can be developed by integrating more interactive applications such as an app or AI-driven tools that quickly assess risks and suggest optimal admission locations for each individual patient.

- **Consider Regional Patient Allocation**

When bed capacity is limited, it is not always possible to avoid overflow beds or to choose the most-safe ward alternative, patients must ultimately be admitted to wherever space is available. In such cases, these tools can also support regional patient allocation. The heatmaps indicate that for patients over 70 coming from another hospital, overflow bed placement is not considered relatively safe. Instead, it may be safer for these patients to remain in a clinically appropriate bed at their original hospital. Conversely, the hospital can consider transferring less acute incoming patients to a nearby hospital if it enables admission to a clinically appropriate bed, as it might outweigh the risk of an overflow bed placement. These insights could provide a basis for the hospital to initiate patient transfers or to decline high-risk takeovers, ensuring safer admission decisions across the regional network of hospitals

7.6 Reflection on Researcher's Position

As a researcher, it is important to reflect on how the study was approached and how personal perspectives may have influenced the research. The results may have been shaped by my background, observations and assumptions.

With a background in Engineering and Policy Analysis, I approached this research with a data-driven and socio-technical systems perspective. Before this study, I had little knowledge of medical or hospital organisation. This allowed me to remain open and objective in my approach. Expectations of possible outcomes were initially based on the relevance of the study, as the hospital under study had indicated a need for insight into the quality implications of overflow bed use. Intuitively, I considered it plausible that admitting a patient to a ward other than the one where its specialist care is located could affect the quality of care. This hypothesis was supported after I conducted an exploratory literature search on the concept of overflow beds and underlying safety mechanisms.

Considerable attention was paid at the start of the research to understanding the socio-technical context of overflow beds. Observing hospital-wide operations provided me insight into the complexity of overflow bed management, which is influenced by both social and technical factors. On the one hand, human decision-making plays a subjective role in bed allocation; on the other hand, more technical aspects such as strategic planning, physical space and hospital design also shape capacity decisions. In addition, overflow beds involve multiple stakeholders - including patients, hospital staff making strategic capacity decisions, nurses providing care, and doctors with clinical responsibility. Given these complexities, this research therefore focused not only on quantifying safety risks but also on ensuring a clinical relevance to hospital practice, to contribute to improvements in hospital safety.

Consequently, my research perspective relied on the expertise of hospital staff to assess clinical relevance. Throughout the research process, clinical staff were constantly consulted to determine how the findings could be translated into practice. An example of this is the development of the risk dimension framework, which served as the basis for structuring the study and was based on factors considered important by staff involved in making decisions about overflow beds.

The focus on clinical relevance may have influenced methodological choices, some of which may have statistical implications. For example, grouping patients into clinically relevant categories may have reduced the sample size, potentially increasing the risk of overfitting. In addition, clinical relevance is inherently context-dependent, as it may vary between hospital settings and staff perspectives. To mitigate these risks and ensure academic integrity, predictive modelling and validation approaches were based on established literature. A balance was found between clinical and statistical relevance, reflected in decisions such as the inclusion of variables such as COVID-19 diagnosis and socioeconomic status - factors that were less clinically relevant but improved statistical accuracy and consistency. Ultimately, this study represents a co-creation between the clinical expertise of the hospital staff and the academic objectivity and critical approach of the researcher.

The results of the study are consistent with my initial intuitive expectations and fit within the broader existing literature. Through the systematic application of validated methods and the focus on clinical applicability, I would argue that the findings are credible, valid and provide valuable insights for improving overflow bed management. As such, I hope that this study will be a real step forward for hospitals in managing bed shortages in times of increasing pressure on care.

8. Conclusion

This study investigated the extent to which patient exposure to bed capacity shortages during hospital admission leads to safety implications. This has been explored by assessing an increased risk of mortality based on patient exposure to an overflow bed, instead of being admitted to the intended clinically appropriate ward. The main research question that was aimed to be addressed in this study was:

*"To what extent does **patient exposure to bed capacity shortages during hospital admission** increase the **risk of mortality**?"*

Patient exposure to overflow beds during hospital admission is associated with an increased risk of mortality, reflected both in an increased absolute risk (4.0% vs 2.6%) and a relative risk of 1.65 times higher odds of mortality for patients exposed to overflow beds compared with those not exposed.

This study demonstrated that these mortality risks are not uniform for all patients and significantly differ across three risk dimensions: the general risk of exposure to overflow beds, associated with the location of overflow bed admission and associated with the duration of exposure. In addition, increased risk levels varied by patient type and characteristics. This conclusion was based on three research phases:

Initial Exploration of Mortality Risks

It could be concluded from the initial clinical Exploratory Data Analysis that the observed mortality rates, adjusted for patient mix, were consistently higher across the three risk dimensions:

- **General Exposure:** the adjusted mortality rate for patients placed in an overflow bed had higher adjusted mortality rates than those who were not. Also, these findings showed that older patients, urgent admissions, with more severe diagnoses, and more often a presence of comorbidities were more frequently placed in overflow beds.
- **Location of Exposure:** elevated adjusted mortality rates were particularly observed for patients being placed outside the type of their clinically appropriate wards, indicating higher mortality rates for surgical, medical and mixed patients admitted to different typed wards. In addition, for mixed patients to mixed wards also a considerably higher adjusted mortality rate was observed.
- **Duration of exposure**: the observed adjusted mortality rate followed a wave-like pattern over time, increased at the initial start of admission, stabilizing over time, and rising again after one week of overflow bed exposure.

Effect-size of Overflow Bed Exposure on Mortality

The predictive models confirmed the initial patterns and provided a quantified effect-size of the mortality risks associated with overflow bed exposure. It could be concluded for the three risk dimensions that:

- **General Exposure**: exposure to an overflow bed results in a 65% higher mortality risk than an admission without overflow bed exposure
- **Location of Exposure:** patients intended for mixed wards admitted to any other wards have the highest estimated increase in mortality odds compared to no exposure. In addition, medical patients placed to surgical patients have doubled mortality odds, while surgical patient patients placed to medical wards will experience almost tripled mortality odds, compared to no exposure. The location of the overflow bed thus matters for the extent of mortality risks

- **Duration of the exposure:** it can be concluded that the duration of the exposure matters for the extent of increased mortality risks. Only significant mortality odds of about 2 times higher compared to no exposure were found for the first 34 hours of admission

The Extent of Increased Risks Translated to Patient Types

It can be concluded that the findings on the extent of mortality risks of this study can be used to determine more practical guidance to identify low and high-risk patients to support decisions on overflow bed placement. The concluding findings for these patient types are:

- **Relatively Safe patients**: Patients under 60 years of age were found to be at relatively low risk, suggesting that overflow bed placement is generally safe for this group.
- **Avoid Overflow Bed patients**: Patients over 80 years of age with multiple comorbidities had the highest mortality risk, indicating that overflow bed placement should be avoided for them.

Between these high and low-end patient types, the study findings and predictive models provide benefits to estimate and compare the risks of individual patients for exposure to no exposure to overflow beds. This could contribute to a better understanding of the risks associated with patient-specific decisions regarding overflow bed placement.

Concluding Remarks

This research provides a better understanding of the safety implications associated with patient exposure to bed shortages during hospital admissions. By identifying and quantifying the effect of exposure to overflow beds on mortality, the findings of this study could help to raise awareness among hospital staff of the potential safety implications. This research provided practical insights and recommendations that could help hospitals make more risk-informed decisions to manage hospital capacity in times of capacity constraints.

Society and healthcare systems will increasingly face the pressure of increasing demand for care against limited resources, and the concept of overflow beds is expected to persist. The balancing act for hospitals to manage capacity constraints while maintaining high quality care will become increasingly difficult. This research has contributed an additional step in addressing this complex societal challenge by providing new insights into how to more proactively and explicitly consider safety implications, ultimately leading to a more future-proof, efficient, but most importantly, safe approach to managing hospital capacity shortages.

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Appendix A – LBZ Variables

This appendix provides a brief overview of all LBZ variables included in this study. The LBZ variables were used in exactly the same way as they were provided by the hospital and initially by the DHD. No adjustments or modifications were made. Therefore, in the application of these variables, their definitions were derived from the descriptions provided by the DHD in *Naslagwerk LBZ-indicatoren* (Bosman & Hekkert, 2024) and CBS in *HSMR 2023 Methodological Report* (CBS, 2024)

Age

Age at point of admission

Gender

Male or Female

Urgency

Acute or Non Acute

An admission is considered urgent if the admission cannot be delayed because the care must be provided within 24 hours. The required care could be immediate observation, investigation and/or treatment. The 24 hours within which this care is essential is determined by the time a specialist assesses the patient and decides that urgent admission is necessary.

Severity Class of the Main Diagnosis

The severity class of the main diagnosis represents an indication of the severity of a patient's recorded main diagnosis. The severity class is determined by the ICD-10 diagnosis codes, which are widely used in international medical contexts. The CBS has classified all ICD-10 codes into severity classes based on mortality rate categories. Mortality rates for each ICD-10 code were determined by calculating the mortality rate over 6 years of historical LBZ data and then classified into the ranges 0, .01, .02, .05, .1, .2, .3, .4 and 1.

Two additional severity classes were used; 'other' for diagnoses for which no accurate severity was available, and a separate severity class for all ICD-10 codes related to COVID-19. COVID-19 was still relatively new and unknown in 2022 and 2023, so there was insufficient data to determine an accurate severity and severity class. Therefore, the COVID-19 subdiagnosis was considered separately for severity classes.

Origin Location before Admission

The origin location before admission for Mortality and HSMR data is classified and grouped into three categories: home, nursing homes or other institutions (such as rehabilitation centre, psychiatric institutions or hospices) or other hospitals

Social Economic Status

The Social Economic Status (SES) of a patient is determined based on the postal code of the patient's residence. To determine the SES of postal codes, another CBS scoring method was used based on household data including welfare indicators, education levels and labour participation.

Comorbidities

The Comorbidities of the Charlson Comorbidity Index are included in the LBZ data. The LBZ registered the presence of a particular comorbidity for an admission based on corresponding ICD-10 codes. The included comorbidities of the Charlson Comorbidity Index are provided in the table below.

Charlson Comorbidity Index
1 Acute Myocardial Infarction
2 Heart Failure
3 Peripheral Arterial Disease
4 Cerebrovascular Diseases
5 Dementia
6 Chronic Pulmonary Diseases
7 Connective Tissue Disease
8 Peptic Ulcer Disease
9 Liver Disease
10 Diabetes Mellitus
11 Diabetes Complications
12 Paraplegia and Other Paralyses
13 Kidney Disease
14 Cancer
15 HIV
16 Metastases
17 Severe Liver Disease

Admission Month

Admission Month was based on the admission date

(Year of Admission)

Originally, the year of admission was also included in the LBZ data. For this research purposes, the year of admission was considered irrelevant as the discharge date was used to determine to which year an admission should be registered. LBZ uses the same definitions but year of admission was not specifically included in any analysis.

Appendix B – Clinically Relevant EDA

Adjusted Mortality Rates

The following table presents the observed and expected mortality values that have been used to calculate the Adjusted Mortality Rate for each risk dimension and underlying sub-categories. The observed mortality rate for 2022 was 3.1%. The following formula was employed to calculate the Adjusted Mortality Rates:

$$Adjusted\ Mortality\ Rate\ (X) = Observed\ Mortality\ Rate\ (3{,}1\%) * \frac{\sum Observed\ Mortality\ (X)}{\sum Expected\ Mortality\ (X)}$$

	N [Population]	Observed Mortality	-	Observed Mortality Rate
Observed Mortality	15101	465	-	3,1%
	N [Group]	**Observed Mortality**	**Expected Mortality**	**Adjusted Morality Rate**
Dimension 1 – General Exposure				
No Exposure to Overflow Bed	13775	360	425,84	2,6%
Exposure to Overflow Bed	1326	105	82,15	4,0%
Dimension 2 - Location				
Surgical Patient to Surgical Ward	25	0	0,29	0,0%
Medical Patient to Medical Ward	351	22	26,31	2,6%
Mixed Patient to Mixed Ward	55	6	2,62	7,1%
Surgical Patient to Medical Ward	102	6	1,99	9,4%
Medical Patient to Surgical Ward	314	37	24,96	4,6%
Surgical Patient to Mixed Ward	53	4	2,35	5,3%
Medical Patient to Mixed Ward	220	15	14,65	3,2%
Mixed Patient to Surgical Ward	71	5	2,39	6,5%
Mixed Patient to Medical Ward	132	10	6,52	4,8%
Dimension 3 - Bed Duration				
0 – 0,75 Day Exposed	265	29	15,20	5,9%
0,76 – 1,36 Days Exposed	265	16	10,38	4,8%
1,37 – 6,99 Days Exposed	663	45	44,51	3,1%
> 6,99 Days Exposed	133	15	12,05	3,9%

Structural Differences Analysis

The following tables presents the results of a Structural Difference Analysis for the distribution of the admissions groups exposed and not exposed to overflow beds. The statistical tests employed to determine statistical significant differences included the t-test for age and the chi-squared test or Fisher's exact (*) test for other variables. The Fisher's exact test was executed when the number of expected values was below five, for which employing a Chi-squared test is not considered suitable. Statistically

	Not Exposed to Overflow Bed	Exposed to Overflow Bed	P-value
Admissions (N,%)	13775 (91,2 %)	1326 (8,8 %)	
Age (Mean, Standard Deviation)	64,88 (18,43)	69,70 (17,20)	< 0.001
Gender (N Male, % Male)	7126 (51,7 %)	673 (50,8 %)	0,496
Urgency (% Acute)	9189 (66,7 %)	1208 (91.1%)	< 0.001
Severity Class Main Diagnosis (N, %)			
[0,0.01)	6477 (47,0%)	363 (27,4%)	< 0.001
[0.01,0.02)	1920 (13,9%)	164 (12,4%)	0.113
[0.02,0.05)	3129 (22,7%)	336 (25,3%)	0.030
[0.05,0.1)	1634 (11,9%)	213 (16,1%)	< 0.001
[0.1,0.2)	162 (1,2%)	23 (1,7%)	0.077
[0.2,0.3)	115 (0,8 %)	13 (1,0%)	0.581
[0.3,0.4)	41 (0,3%)	10 (0,8%)	0.012*
[0.4,1]	6 (0,0%)	1 (0,1%)	0.475*
COVID-19_subdiagnosis	246 (1,8%)	200 (15,1%)	< 0.001
Other	45 (0,3%)	3 (0,2%)	0.797*
Comorbidities (N, %)			
1 Acute Myocardial Infarction	937 (6,8%)	103 (7,8%)	0.185
2 Heart Failure	888 (6,4%)	112 (8,4%)	0.005
3 Peripheral Arterial Disease	986 (7,2%)	101 (7,6%)	0.537
4 Cerebrovascular Diseases	140 (1,0%)	22 (1,7%)	0.030
5 Dementia	280 (2,0%)	74 (5,6%)	< 0.001
6 Chronic Pulmonary Diseases	1243 (9,0%)	182 (13,7%)	< 0.001
7 Connective Tissue Disease	243 (1,8%)	21 (1,6%)	0.632
8 Peptic Ulcer Disease	21 (0,2%)	6 (0,5%)	0.027*
9 Liver Disease	82 (0.6%)	22 (1,7%)	< 0.001
10 Diabetes Mellitus	1866 (13,5%)	258 (19.5%)	< 0.001
11 Diabetes Complications	241 (1,7%)	26 (2,0%)	0.577
12 Paraplegia and Other Paralyses	77 (0,6%)	10 (0,8%)	0.370
13 Kidney Disease	912 (6,6%)	163 (12,3%)	< 0.001
14 Cancer	924 (6,7%)	111 (8,4%)	0.022
15 HIV	3 (0,0%)	0 (0,0%)	1.000*
16 Metastases	945 (6,9%)	77 (5,8%)	0.145
17 Severe Liver Disease	31 (0,2%)	7 (0,5%)	0.045*
Origin location before admission (N,%)			
Home	12821 (93,1%)	1180 (89,0%)	<0.001
Care home, nursing home, and other institutions	377 (2,7%)	112 (8,4%)	<0.001
(Other) Hospital	577 (4,2%)	34 (2,6%)	0.004
Social Economic Status (SES) (N,%)			
Lowest SES	3832 (27,8%)	459 (34,6%)	<0.001
Under Average	833 (6,0%)	62 (4,7%)	0.043
Average	2280 (16,6%)	215 (16,2%)	0.752
Above Average	3238 (23,5%)	287 (21,6%)	0.126
Highest SES	3558 (25,8%)	293 (22,1%)	0.003
Unknown	34 (0,2%)	10 (0,8%)	0.004*
Admission Month (N,%)			
January	1167 (8,5%)	115 (8,7%)	0.802
February	1041 (7,6%)	77 (5,8%)	0.020
March	1196 (8,7%)	123 (9,3%)	0.465
April	1139 (8,3%)	112 (8,4%)	0.822
May	1125 (8,2%)	98 (7,4%)	0.322
June	1104 (8,0%)	99 (7,5%)	0.481
July	1093 (7,9%)	100 (7,5%)	0.612
August	1083 (7,9%)	111 (8,4%)	0.512
September	1191 (8,6%)	114 (8,6%)	0.952
October	1148 (8,3%)	126 (9,5%)	0.144
November	1269 (9,2%)	112 (8,4%)	0.355
December	1219 (8,8%)	139 (10,5%)	0.047

	Not Exposed to Overflow Bed	Exposed to Overflow Bed	P-value
Admission Specialty			
Anaesthesiology	23 (0,2%)	0 (0,0%)	0.258*
Cardiology	1.738 (12,6%)	85 (6,4%)	<0.001
Surgery	3.138 (22,8%)	116 (8,7%)	<0.001
Internal Medicine	2.513 (18,2 %)	579 (43,7%)	<0.001
Otorhinolaryngology (ENT)	483 (3,5%)	22 (1,7%)	<0.001
Clinical Geriatrics	1 (0,0%)	1 (0,1%)	0.168*
Pulmonology	1.038 (7,5%)	232 (17,5%)	<0.001
Gastroenterology	954 (6,9%)	152 (11,5%)	<0.001
Oral and Maxillofacial Surgery	41 (0,3%)	3 (0,2%)	1.000*
Neurosurgery	5 (0,0%)	0 (0,0%)	1.000*
Neurology	1.644 (11,9%)	67 (5,1%)	<0.001
Ophthalmology	4 (0,0%)	0 (0,0%)	1.000*
Orthopaedics	361 (2,6%)	41 (3,1%)	0.309
Plastic Surgery	178 (1,3%)	3 (0,2%)	0.001
Rheumatology	8 (0,1%)	0 (0,0%)	1.000*
Urology	1.202 (8,7%)	19 (1,4%)	<0.001
Obstetrics and Gynaecology	444 (3,2%)	6 (0,5%)	<0.001

Appendix C – Coding of Predictors

The following tables provide a detailed overview of the candidate predictors. For each categorial candidate predictor, the associated sub-categories and defined reference categories are indicated.

Exposure Candidate Predictors
Model – General Exposure
No Exposure (reference) Exposure to Overflow Bed
Model – Location
No Exposure (reference) Surgical Patient to Surgical Ward Medical Patient to Medical Ward Mixed Patient to Mixed Ward Surgical Patient to Medical Medical Patient to Surgical Ward Surgical Patient to Mixed Ward Medical Patient to Mixed Ward Mixed Patient to Surgical Ward Mixed Patient to Medical Ward
Model – Duration
No Exposure (reference) 0 – 0.75 Day Exposed 0.76 – 1.36 Days Exposed 1.47 – 6.99 Days Exposed > 6.99 Days Exposed

LBZ Candidate Predictors	
Age	Comorbidities
Numerical	Acute Myocardial Infarction
Gender	Heart Failure
Male (reference)	Peripheral Arterial Disease
Female	Cerebrovascular Diseases
Urgency	Dementia
Non-Acute (reference)	Chronic Pulmonary Diseases
Acute	Connective Tissue Disease
Severity Class of Main Diagnosis	Peptic Ulcer Disease
[0,0.01) (reference)	Liver Disease
[0.01,0.02)	Diabetes Mellitus
[0.02,0,05)	Diabetes Complications
[0.05,0.1)	Paraplegia and Other Paralyses
[0.1,0.2)	Kidney Disease
[0.2,0.3)	Cancer
[0.3,1)	HIV
COVID-19 subdiagnosis	Metastases
Other	Severe Liver Disease
Origin Location before Admission	Admission Month
Home (reference)	January (reference)
Nursing homes and other institutions	February
Other Hospital	March
Social Economic Status (SES)	April
Lowest SES (reference)	May
Under Average	June
Average	July
Above Average	August
Highest SES	September
Unknown	October
	November
	December

Appendix D - Model Estimations

The following tables present the model estimations for the three final predictive models for acute admissions. Each table displays the significant predictors included in the final models, after a model development process following a stepwise backwards selection with a P-value of <0.05. For each variable, the coefficient β, P-value, log-odds and its associated (95%) confidence intervals are presented.

Model – General Exposure

Model variant 1: Exposure vs No Exposure	**Acute Admission [N=10397] – Stepwise Backwards [P<0.05]**				
	β	***p-value***	***Exp(β)***	***CI: lower***	***CI: upper***
Overflow Bed Exposure					
No Exposure (reference)					
Exposed to Overflow Bed	0,501	< 0,001	1,651	1,274	2,139
Age	0,043	< 0,001	1,044	1,035	1,054
Severity Class Main Diagnosis					
[0,0.01) (reference)					
[0.01,0.02)	0,938	0,001	2,555	1,471	4,439
[0.02,0.05)	1,588	< 0,001	4,896	3,122	7,677
[0.05,0.1)	2,271	< 0,001	9,692	6,216	15,112
[0.1,0.2)	2,803	< 0,001	16,489	8,930	30,447
[0.2,0.3)	2,944	< 0,001	18,998	9,580	37,676
[0.3,1]	4,876	< 0,001	131,144	64,826	265,309
COVID-19_subdiagnosis	2,468	< 0,001	11,796	7,043	19,756
Other	2,576	< 0,001	13,141	3,698	46,699
Comorbidities					
1 Acute Myocardial Infarction					
2 Heart Failure	0,341	0,019	1,406	1,057	1,872
3 Peripheral Arterial Disease					
4 Cerebrovascular Diseases	-1,143	0,057	0,319	0,098	1,035
5 Dementia					
6 Chronic Pulmonary Diseases					
7 Connective Tissue Disease					
8 Peptic Ulcer Disease	2,331	< 0,001	10,284	3,318	31,881
9 Liver Disease	0,979	0,013	2,662	1,228	5,771
10 Diabetes Mellitus					
11 Diabetes Complications					
12 Paraplegia and Other Paralyses					
13 Kidney Disease	0,550	< 0,001	1,734	1,319	2,278
14 Cancer					
15 HIV					
16 Metastases	0,878	< 0,001	2,405	1,751	3,305
17 Severe Liver Disease	1,126	0,048	3,082	1,011	9,398
Origin location before admission					
0 Home (reference)					
1 Nursing homes and other institutions	0,449	0,015	1,566	1,089	2,253
4 Other Hospital	0,634	0,008	1,885	1,182	3,005
Social Economic Status					
1 Lowest SES (reference)					
2 Under Average					
3 Average					
4 Above Average					
5 Highest SES					
6 Unknown	1,145	0,028	3,143	1,132	8,725
Admission Month					
January					
February	0,508	0,004	1,662	1,179	2,344
March					
April					
May					
June					
July					
August					
September					
October					
November					
December	0,462	0,005	1,587	1,153	2,185
Constant (intercept)	-8,406	< 0,001			

Model - Location

Model Variant 2: Location Exposure Groups	**Acute Admission [N=10395] – Stepwise Backwards [P<0.05]**				
	β	***p-value***	***Exp(β)***	***CI: lower***	***CI: upper***
Overflow Bed Exposure					
No Exposure (reference)					
Surgical Patient to Surgical Ward					
Medical Patient to Medical Ward					
Mixed Patient to Mixed Ward	1,523	0,002	4,586	1,769	11,889
Surgical Patient to Medical Ward	0,993	0,043	2,7	1,034	7,049
Medical Patient to Surgical Ward	0,733	< 0,001	2,082	1,392	3,115
Surgical Patient to Mixed Ward					
Medical Patient to Mixed Ward					
Mixed Patient to Surgical Ward	1,287	0,019	3,62	1,24	10,568
Mixed Patient to Medical Ward	0,957	0,012	2,603	1,230	5,507
Age	0,045	< 0,001	1,046	1,036	1,055
Severity Class Main Diagnosis					
[0,0.01) (reference)					
[0.01,0.02)	0,961	0,001	2,614	1,506	4,538
[0.02,0.05)	1,594	< 0,001	4,924	3,139	7,724
[0.05,0.1)	2,311	< 0,001	10,083	6,462	15,734
[0.1,0.2)	2,861	< 0,001	17,484	9,453	32,341
[0.2,0.3)	3,008	< 0,001	20,237	10,189	40,195
[0.3,1]	4,904	< 0,001	134,761	66,389	273,549
COVID-19_subdiagnosis	2,587	< 0,001	13,285	7,938	22,233
Other	2,628	< 0,001	13,844	3,883	49,359
Comorbidities					
1 Acute Myocardial Infarction					
2 Heart Failure	0,372	0,011	1,451	1,089	1,932
3 Peripheral Arterial Disease					
4 Cerebrovascular Diseases	-1,169	0,053	0,311	0,095	1,016
5 Dementia					
6 Chronic Pulmonary Diseases					
7 Connective Tissue Disease					
8 Peptic Ulcer Disease	2,438	< 0,001	11,451	3,707	35,374
9 Liver Disease	1,158	0,002	3,185	1,508	6,728
10 Diabetes Mellitus					
11 Diabetes Complications					
12 Paraplegia and Other Paralyses					
13 Kidney Disease	0,507	< 0,001	1,661	1,263	2,184
14 Cancer					
15 HIV					
16 Metastases	0,893	< 0,001	2,442	1,777	3,356
17 Severe Liver Disease					
Origin location before admission					
0 Home (reference)					
1 Nursing homes and other institutions					
4 Other Hospital	0,552	0,020	1,737	1,089	2,770
Social Economic Status					
1 Lowest SES (reference)					
2 Under Average					
3 Average					
4 Above Average					
5 Highest SES					
6 Unknown	1,190	0,024	3,288	1,168	9,257
Admission Month					
January (reference)					
February					
March					
April	-0,366	0,060	0,693	0,474	1,015
May					
June					
July					
August	-0,632	0,007	0,531	0,335	0,843
September	-0,480	0,030	0,619	0,401	0,956
October	-0,459	0,032	0,632	0,415	0,961
November					
December					
Constant (intercept)	-8,246	< 0,001			

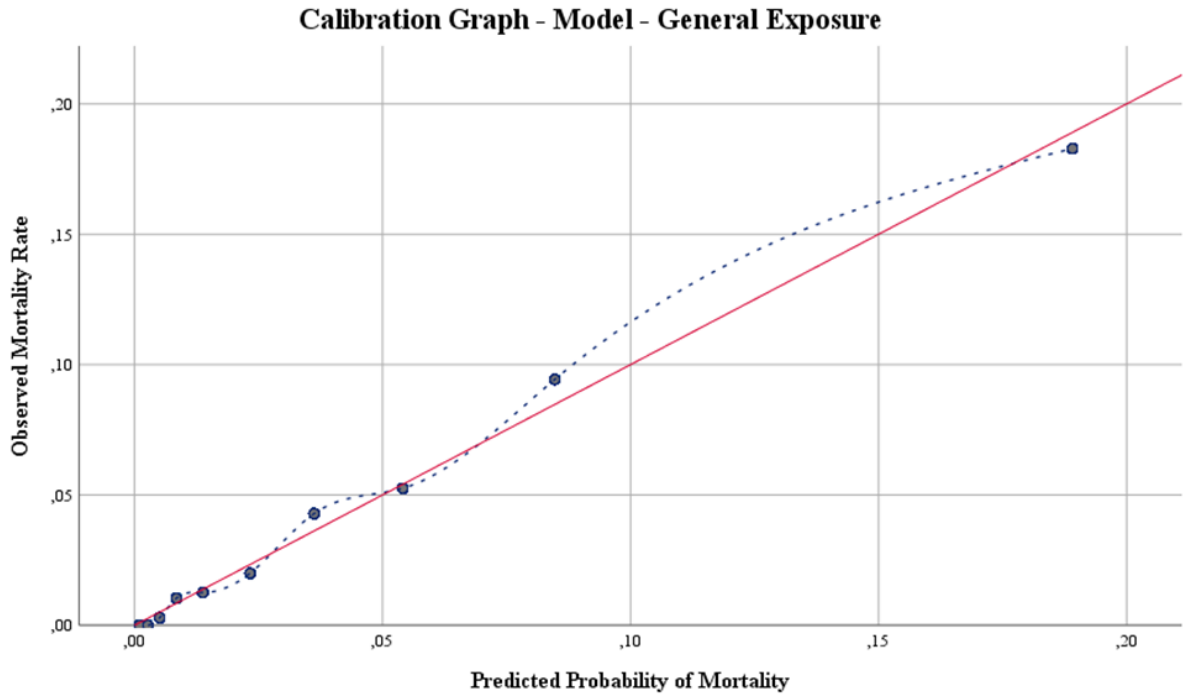
Model – Duration

Model Variant 3: Duration Exposure Groups	**Acute Admissions [N=10397] – Stepwise Backwards [P<0.05]**				
	β	***p-value***	***Exp(β)***	***CI: lower***	***CI: upper***
Overflow Bed Exposure					
No Exposure (reference)					
0 – 0.75 Day Exposed	0,873	< 0,001	2,394	1,497	3,828
0.76 – 1.36 Days Exposed	0,855	0,003	2,351	1,341	4,122
1.37 – 6.99 Days Exposed					
> 6.99 Days Exposed					
Age	0,044	< 0,001	1,045	1,036	1,055
Urgency					
Non Acute (reference)					
Acute					
Severity Class Main Diagnosis					
[0,0.01) (reference)					
[0.01,0.02)	0,952	0,001	2,591	1,490	4,503
[0.02,0.05)	1,590	< 0,001	4,904	3,125	7,696
[0.05,0.1)	2,276	< 0,001	9,733	6,234	15,195
[0.1,0.2)	2,824	< 0,001	16,839	9,127	31,070
[0.2,0.3)	2,893	< 0,001	18,049	9,063	35,944
[0.3,1]	4,873	< 0,001	130,698	64,222	265,981
COVID-19_subdiagnosis	2,607	< 0,001	13,558	8,161	22,523
Other	2,567	< 0,001	13,029	3,658	46,413
Comorbidities					
1 Acute Myocardial Infarction					
2 Heart Failure	0,318	0,030	1,374	1,031	1,832
3 Peripheral Arterial Disease					
4 Cerebrovascular Diseases	-1,167	0,053	0,311	0,096	1,014
5 Dementia					
6 Chronic Pulmonary Diseases	0,279	0,041	1,321	1,012	1,726
7 Connective Tissue Disease					
8 Peptic Ulcer Disease	2,273	< 0,001	9,712	3,142	30,019
9 Liver Disease	0,964	0,017	2,622	1,190	5,777
10 Diabetes Mellitus	-0,272	0,049	0,762	0,582	0,999
11 Diabetes Complications					
12 Paraplegia and Other Paralyses					
13 Kidney Disease	0,597	< 0,001	1,816	1,378	2,395
14 Cancer					
15 HIV					
16 Metastases	0,875	< 0,001	2,399	1,745	3,300
17 Severe Liver Disease	1,130	0,049	3,096	1,005	9,540
Origin location before admission					
0 Home (reference)					
1 Nursing homes and other institutions	0,499	0,007	1,647	1,144	2,369
4 Other Hospital	0,658	0,006	1,931	1,209	3,083
Social Economic Status					
1 Lowest SES (reference)					
2 Under Average					
3 Average					
4 Above Average					
5 Highest SES					
6 Unknown	1,181	0,024	3,258	1,172	9,058
Admission Month					
January (reference)					
February	0,507	0,004	1,661	1,178	2,341
March					
April					
May					
June					
July					
August					
September					
October					
November					
December	0,452	0,006	1,571	1,140	2,166
Constant (intercept)	-8,445	< 0,001			

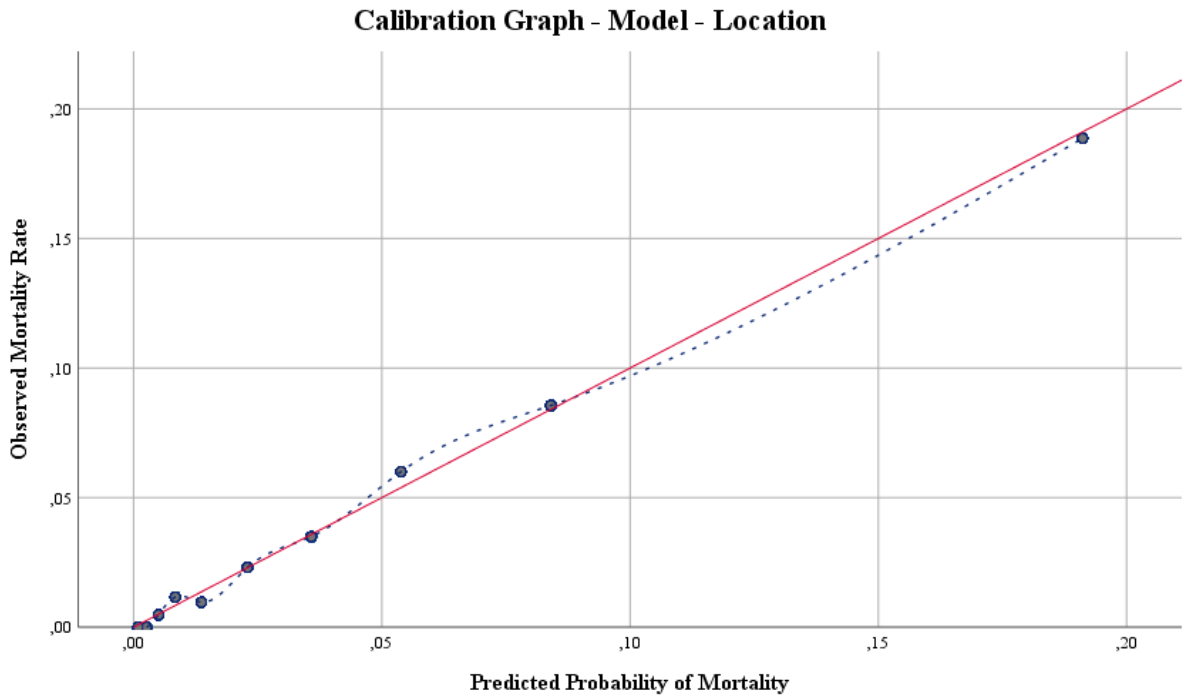
Appendix E - Model Performances

Calibration Graphs

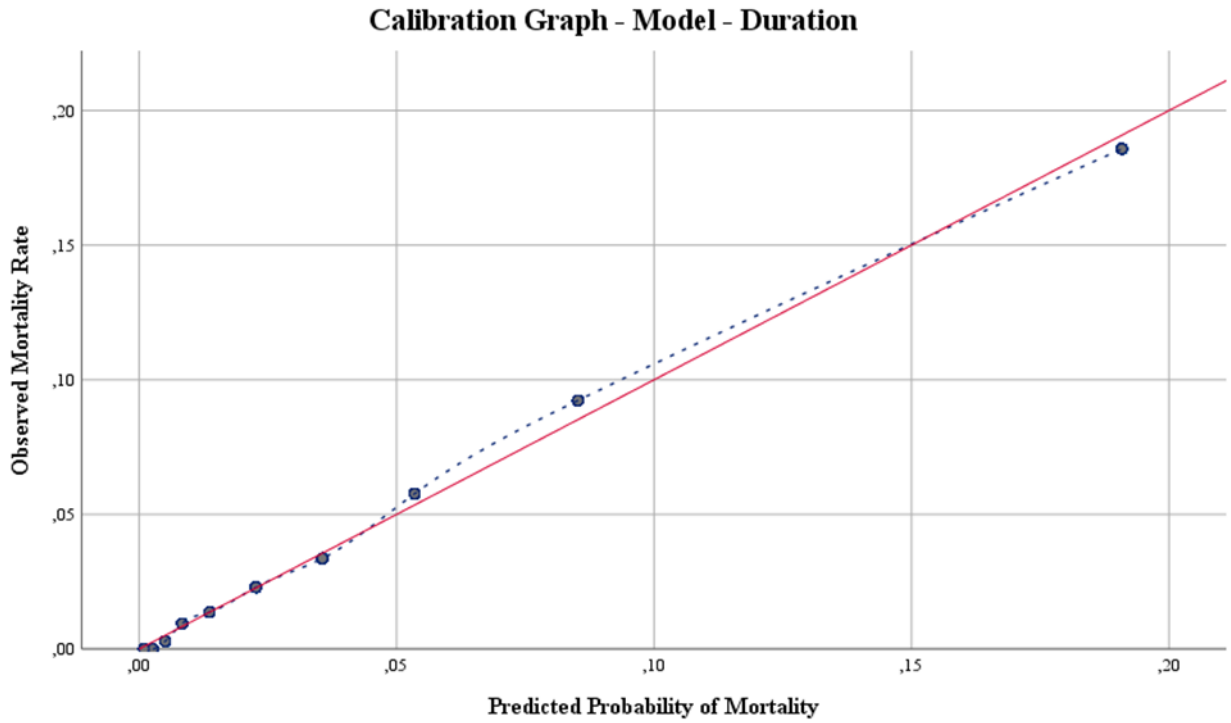
Model - General Exposure



Model – Location

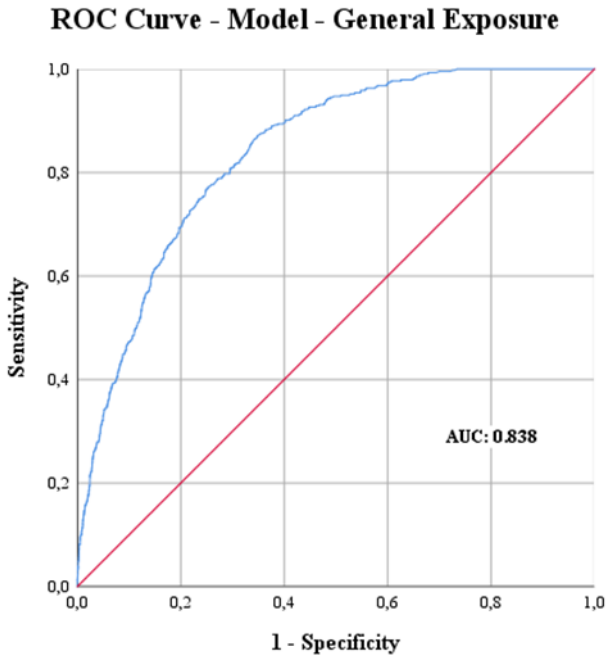


Model – Duration



ROC-Curves

Model – General Exposure



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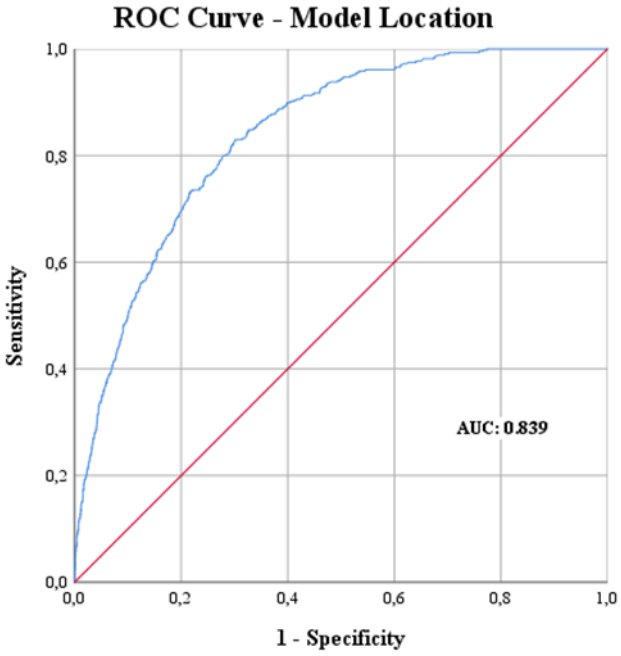

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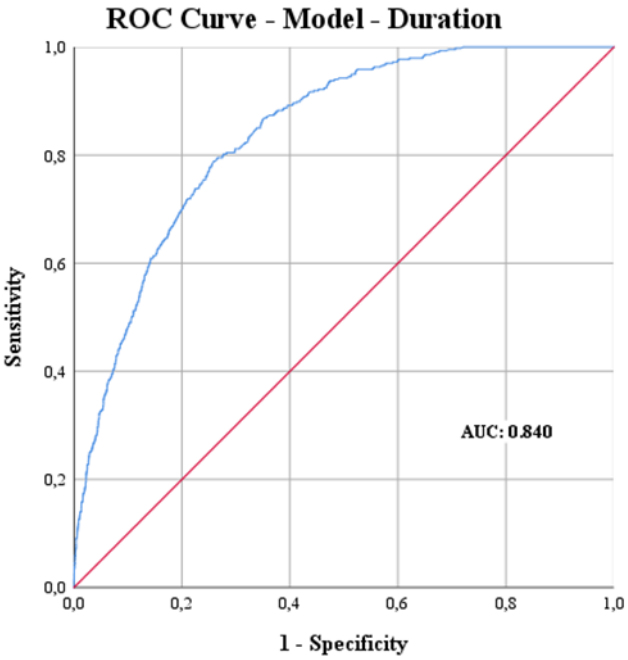
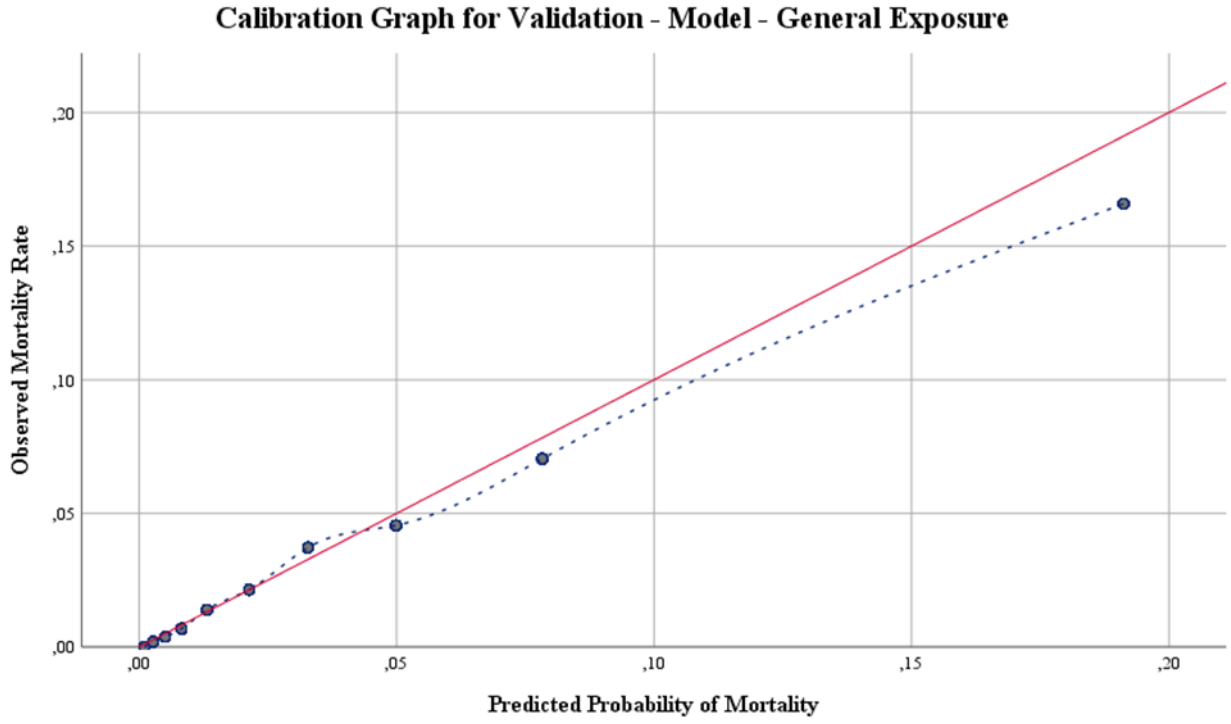


Appendix F - Model Validation

Calibration Graphs for Validation

Model – General Exposure



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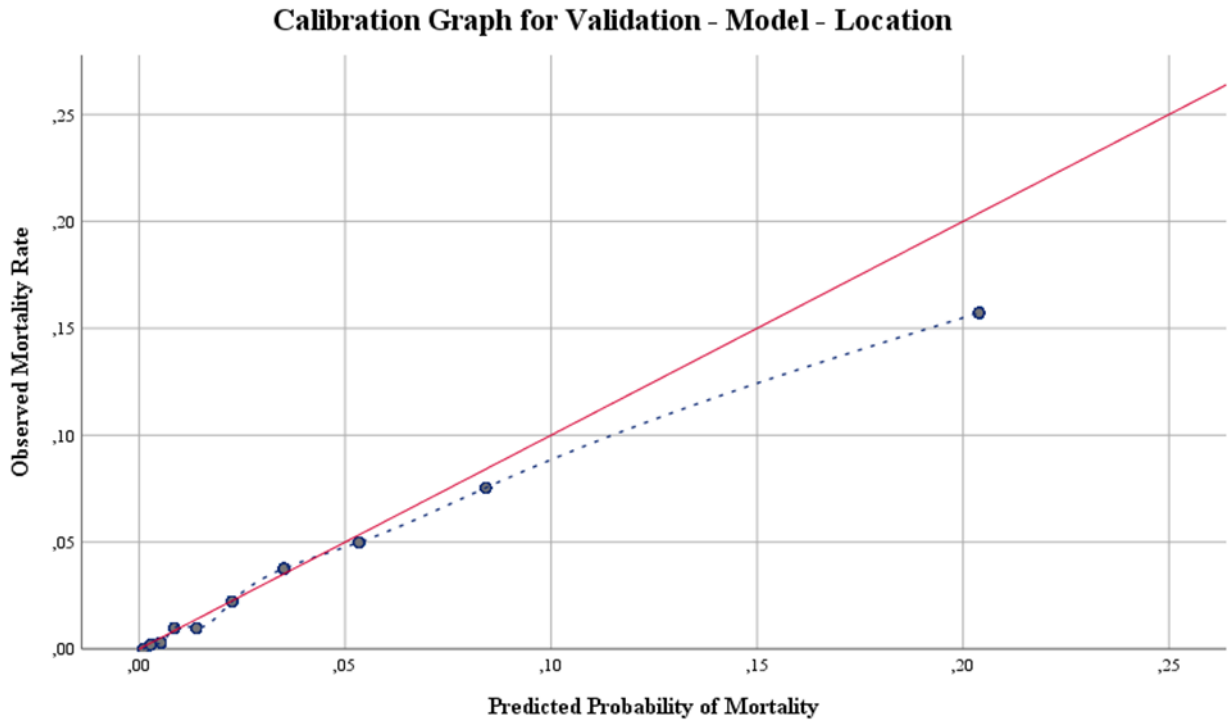
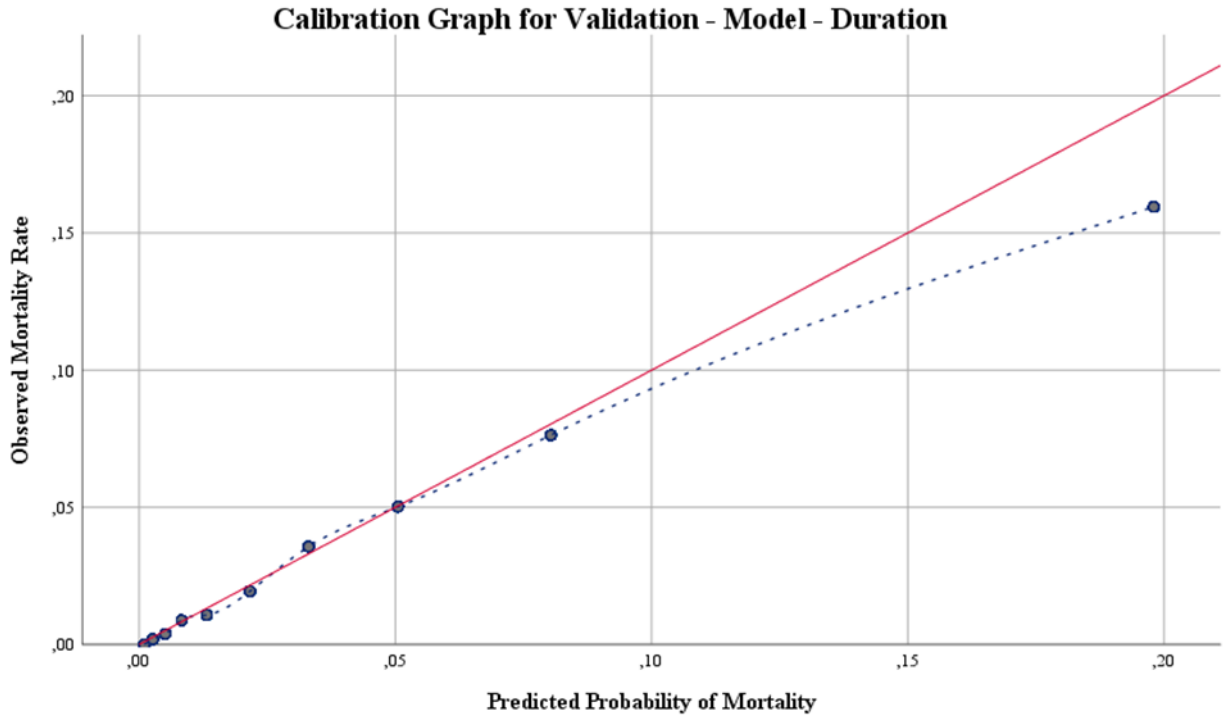
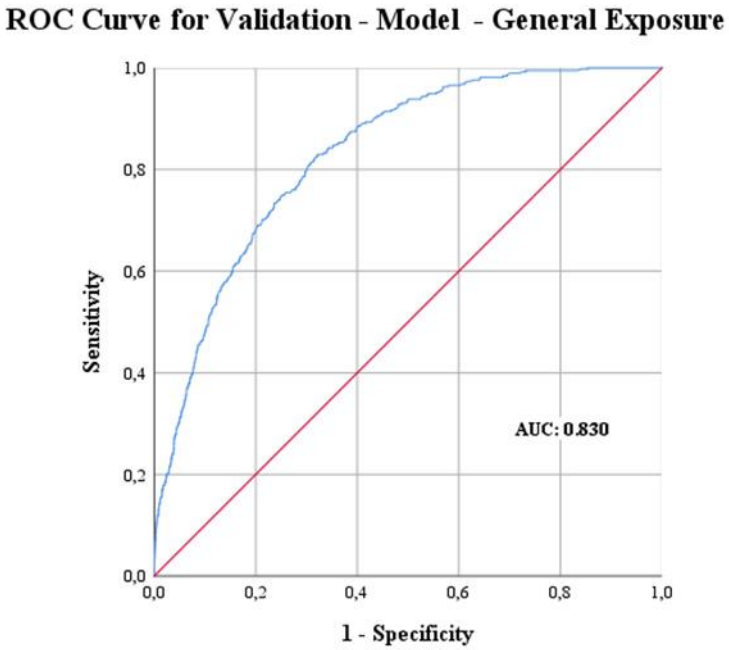


Model – Duration



ROC-Curves for Validation

Model - General Exposure



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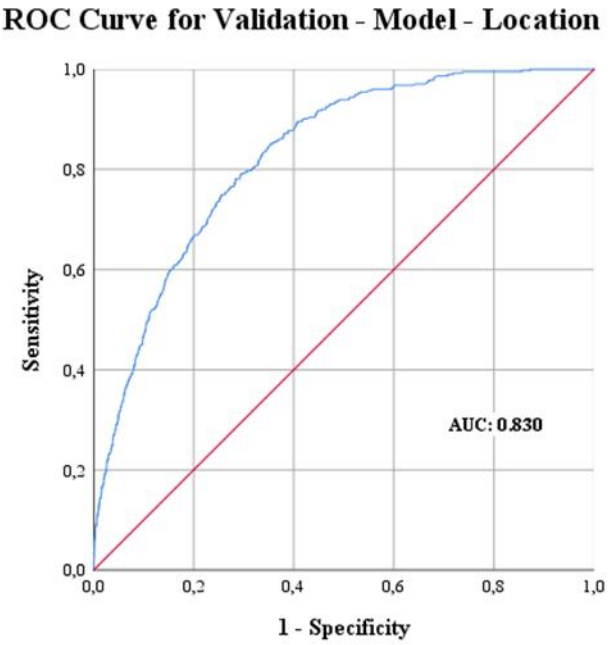

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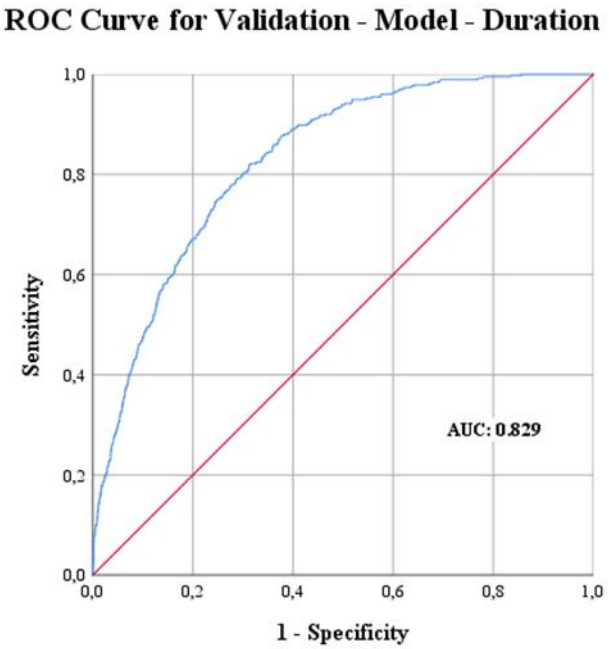
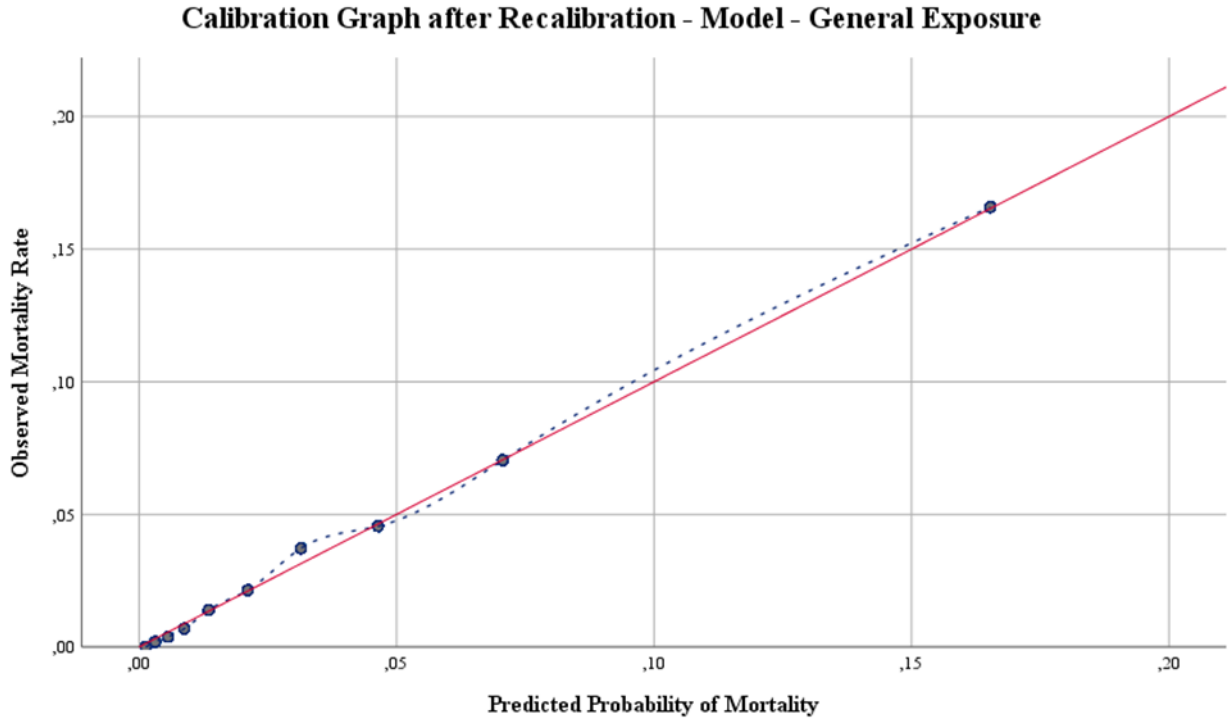


Appendix G - Model Recalibration

Calibration Graphs after Recalibration

Model – General Exposure



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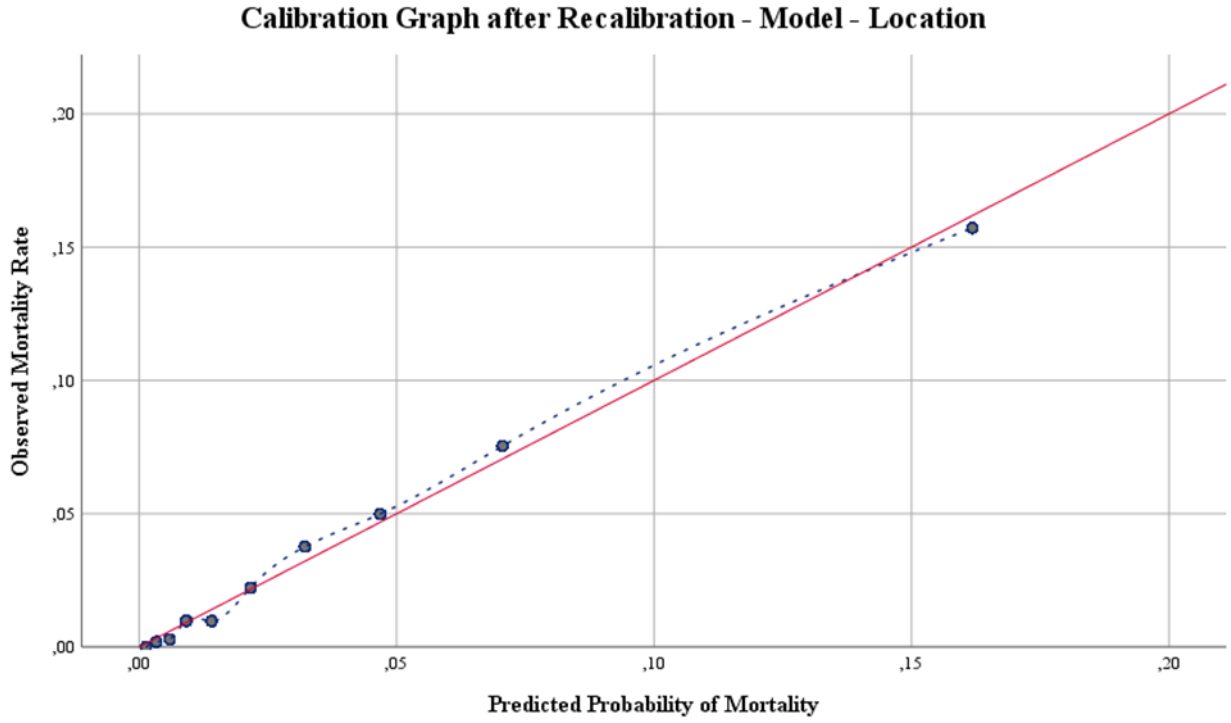
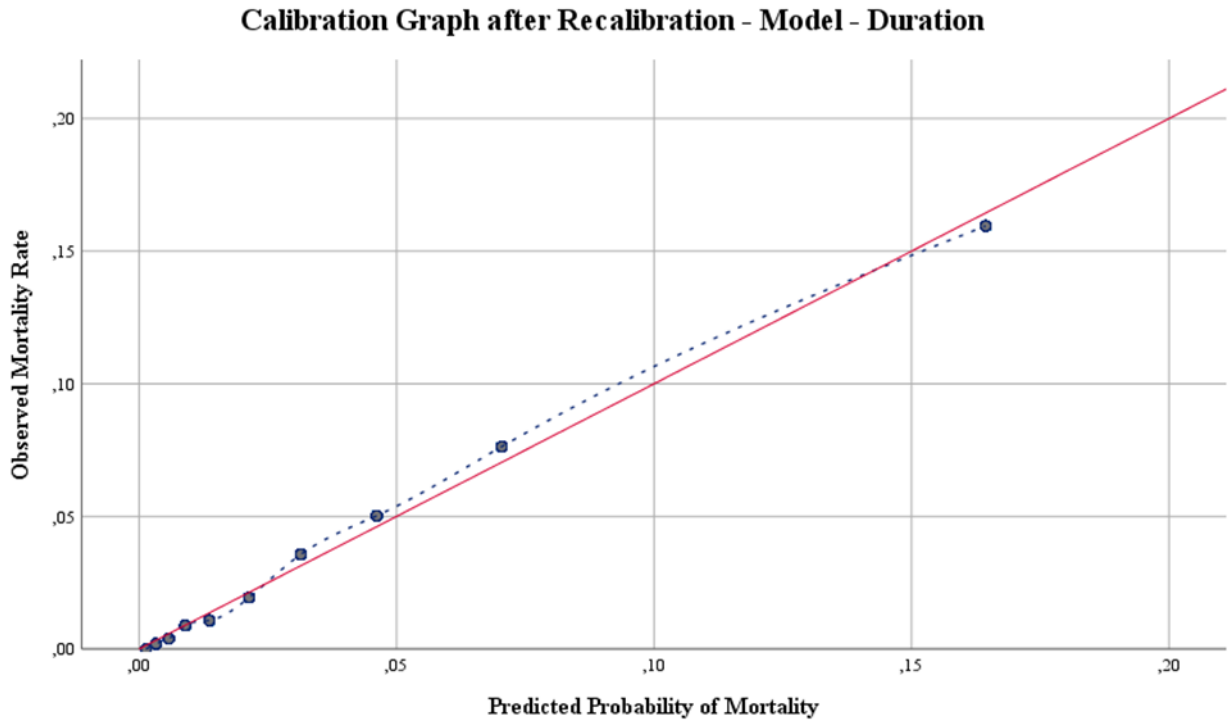
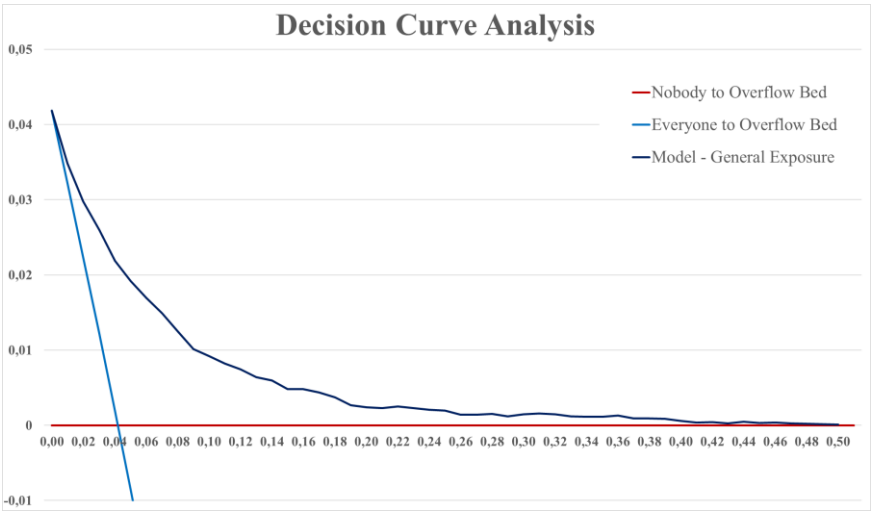


Model – Duration

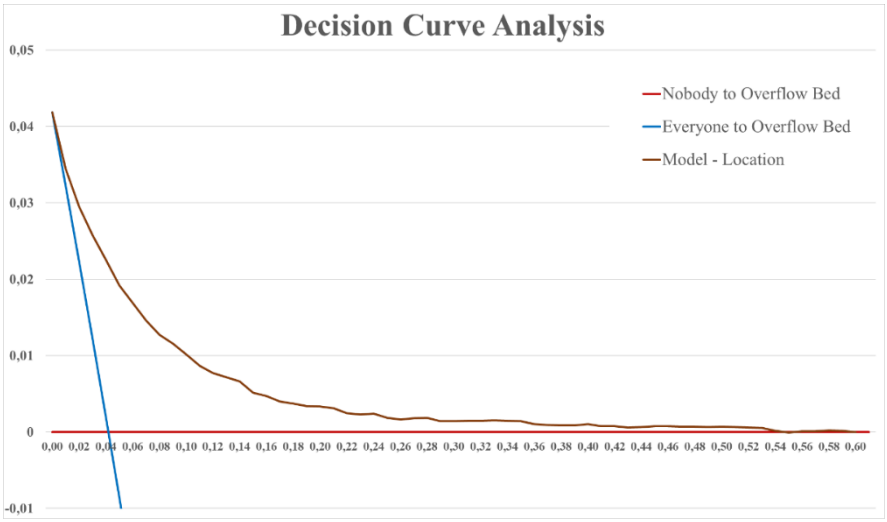


Appendix H - Decision Curve Analysis

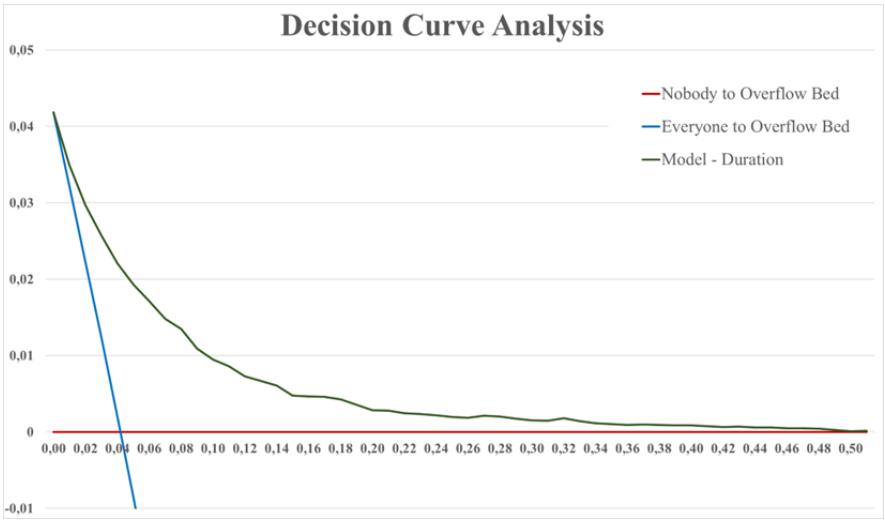
Model – General Exposure



Model – Location



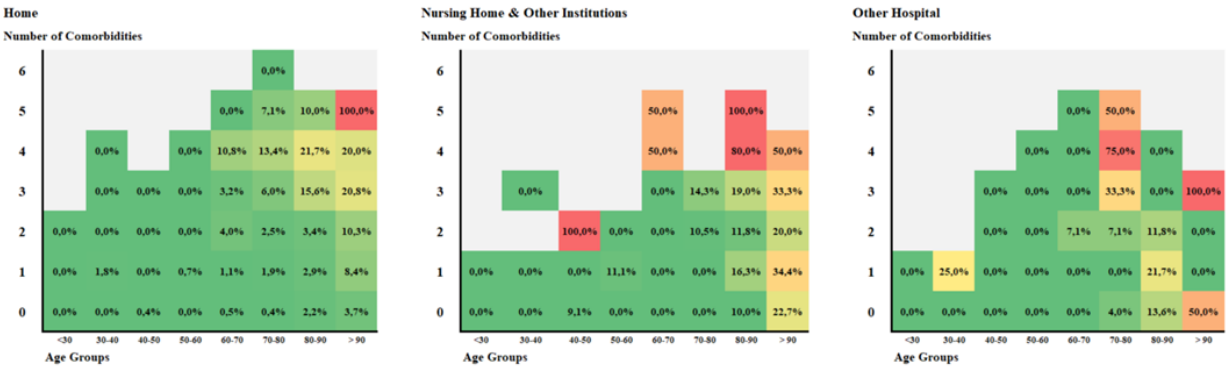
Model - Duration



Heatmap for the "Avoid Overflow Bed" risk range

The figure below shows the Heatmaps developed for the "Avoid Overflow Bed" risk range. These Heatmaps were constructed similar to the Heatmaps of the "Relatively Safe", as detailed in 6.4 Clinical Usefulness. These Heatmaps reflect the proportion of all acute patients with a predicted mortality risk falling into the "Avoid Overflow Bed" range, divided in boxes of age groups (x-axis) and Charlson Comorbidity Index comorbidities (y-as).

This classification of high-risk patients could be used to determine which patients should be kept out of overflow beds. It is important to note that these heatmaps follow a different colour pattern to the 'relatively safe' heatmaps. The decision was made to colour in red the boxes for which placement in an overflow bed should be avoided. It was considered more intuitive to use these colour patterns to indicate that these patients should not be placed in an overflow bed.



Appendix I – Framework of Underlying Safety Mechanisms

The literature highlights a range of potential factors that may explain the association between overflow bed exposure and safety risks. To evaluate the underlying factors, the framework developed by Goulding et al. (2012) can be used. Goulding et al. took a qualitative approach to identify 5 key themes that might lead to safety risks for patients in overflow beds.

The table below summarises Goulding et al.'s framework, outlining the five main themes and related mechanisms identified to explain safety risks due to overflow bed exposure.

Theme	Underlying Mechanisms
1. "Competing demands on staff time by hosting overflow bed patients and clinically appropriate patients to care for"	a. Difficult for staff to care for a mixture of patients with different needs b. Delayed medical reviews, causing a chain of delayed care and subsequent increased length of hospital stay c. Delayed medical review may lead to missed diagnosis, with risks for further deterioration patient's condition
2. "Poor communication between clinically appropriate ward and overflow bed ward"	a. Reduced (informal) communication between clinically appropriate medical staff and overflow ward staff b. Difficulties in communicating a deterioration of the patient's condition to the medical specialist c. Difficulties in communicating important information during care-handovers, leaving the receiving care-takers inadequately prepared to take over the care
3. "Lack of knowledge or expertise on the overflew bed ward"	a. Nursing staff lacks the knowledge and expertise required for optimal care for overflow bed patient b. Nursing staff face difficulties with dosing the right medication due to unfamiliarity c. Nursing staff might not recognize patient deterioration, due to unfamiliarity with patient's condition d. Overflow bed patients are more often reviewed by junior medical staff members, who may lack the required skills to make the right clinical diagnosis and decisions
4. "Unsuitable ward environment for overflow bed patient"	a. Geographical distance between overflow and clinically appropriate ward causes medical review delays and limits access to (small) medical resources b. Lack of adequate care equipment at the overflow ward, such as unavailable required medication c. Infectious patients being placed to overflow beds, putting receiving ward patients at infection risks
5. "Characteristics of patient being placed on overflow beds"	a. Overflow bed patients are perceived as the most medically fit and stable patients, and therefore (potentially wrongly) perceived as a lower priority. b. Patients in overflow beds are more frequently experiencing transfers that can contribute to patient disorientation, falls, and other risks associated with patient movement.

To provide an overview of the potential mechanisms mentioned by the reviewed literature related to overflow beds, the literature can be synthesized according Goulding et al.'s framework. This will contribute more comprehensive understanding of what factors might cause safety risks for patients exposed to overflow beds.

1. *Competing demands on staff time by hosting overflow bed patients and clinically appropriate patients to care for*

Several reviewed studies suggest that the use of overflow beds increases staff workload and may delay critical aspects of patient care, particularly initial medical contact, monitoring and timely intervention. Overflow placement has been associated with delayed clinical review, extended ward rounds that take up clinical time, and reduced patient monitoring due to physical distance from the appropriate medical teams. These effects are particularly pronounced in the early stages of admission, when medical review for diagnosis and monitoring for deterioration may be essential. The competing demands on staff time can lead to delays in care, which may disrupt the timely recognition of patient deterioration or complications, increasing the risk of mortality.

2. *Poor communication between clinically appropriate ward and overflow bed ward*

Communication difficulties are often cited between overflow wards and clinically appropriate teams, disrupting care coordination and continuity. A lack of structured communication has been linked to delays in medication administration and medical assessments, as well as reduced frequency and quality of interaction between the overflow and the medical responsible ward. Also, concerns have been raised about less well-established relationships between the overflow wards and the medical responsible teams. These may impact the ease of communication as the staff is not very well adjusted to each other. These communication disruptions can delay communication of patient deterioration and necessary interventions, potentially increasing the risk of compromised care and mortality.

3. *Lack of knowledge or expertise on the overflew bed ward*

All reviewed studies indicate that the overflow ward staff may lack familiarity with the specific needs of overflow patients, which could pose safety risks. There is a consistent notion that overflow staff may not have the necessary knowledge and expertise to meet the clinical requirements of patients in overflow beds, which could lead to compromising the safety of care and increased mortality risks.

4. *Unsuitable ward environment for overflow bed patient*

Several studies point to potential challenges created by physical separation between overflow wards and the clinically appropriate medical teams, which can limit the availability of resources and timeliness of the provided care. It was highlighted how geographic distance could reduce the frequency and duration of patient contact and medical review, resulting in care delays and reduced monitoring.

5. *Characteristics of patients being placed on overflow beds*

This theme was less frequently addressed within the reviewed studies. It was however noted that overflow patients are sometimes perceived as medically "fit", which may reduce their priority in providing care and delay necessary interventions. Additionally, frequent transfers between wards can lead to patient stress and reduced continuity of care, further impacting their safety and mortality risks.

Appendix J - Dashboard for Risk Predictions

This appendix contains screenshots of the risk prediction tool developed for the hospital under study. This tool was developed in Excel and translates the predictive models into a dashboard that could be used by hospital staff, such as patient flow coordinators or ward managers, to estimate a quantified risk profile for individual patients.

To use the tool, patient information can be entered based on the LBZ variables used, while hospital information could also be detailed by selecting the intended clinically appropriate ward for the particular patient and the overflow bed ward. Although improvements could be made to translate the LBZ variables into more clinically relevant variables available at the point of admission, this tool could already provide an initial sense of patient risk associated with overflow beds based on the three risk dimensions of general exposure, location and duration.

The screenshots show the application of dashboard to predict the mortality rates of the illustrative patient scenario described in 5.3 Model Estimation

Dashboard - Risk Predictions for Overflow Bed Placements

This dashboard can be used as tool to predict mortality risks related to overflow bed exposure for individual patients

Patient Characteristics

What is the age of the patient?	**72**
What is the gender of the patient?	**Female**
Severity Class of Main Diagnosis	
ICD10 Code	**J101**
Severity Class	**[0.02,0.05)**
Does the patient have known Comorbidities of the Charlson Comorbidity Index?	
Acute Myocardial Infarction	**No**
Heart Failure	**No**
Peripheral Arterial Disease	**No**
Cerebrovascular Diseases	**No**
Dementia	**Yes**
Chronic Pulmonary Diseases	**Yes**
Connective Tissue Disease	**No**
Peptic Ulcer Disease	**No**
Liver Disease	**No**
Diabetes Mellitus	**No**
Diabetes Complications	**No**
Paraplegia and Other Paralyses	**No**
Kidney Disease	**No**
Cancer	**No**
HIV	**No**
Metastases	**No**
Severe Liver Disease	**No**
What is the origin location of the patient before admission?	**Home**
What is the patient's postal code (to determine SES)	
Numbers of Postal Code	**2622**
Social Economic Status	**Average Social Economic Status**
What is the date of admission?	
date (dd/mm/yyyy)	**1-2-2025**

Location

What is the clinically appropriate ward where the patient should be admitted?

Ward	**Pulmonary Care**
Associated Type of Ward	**Medical**

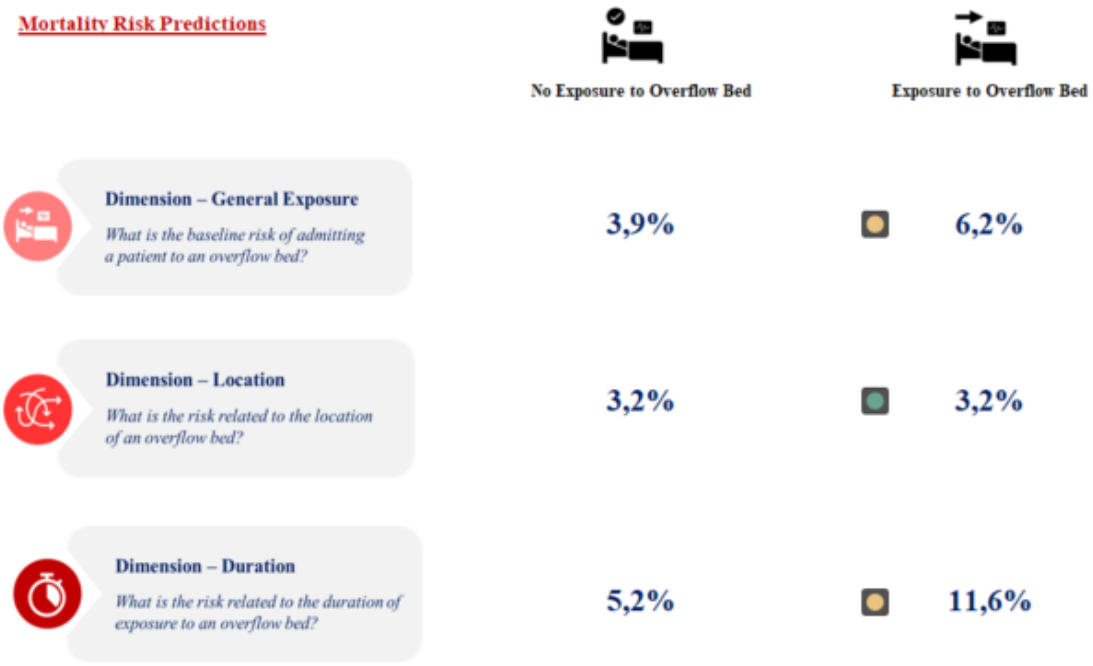
What is the overflow ward where the patient is to be admitted?

Ward	**Gastroenterology Care**
Associated Type of Ward	**Mixed**

Duration

How long is the patient expected to stay on an overflow bed?

Duration [hours]	**18**



The traffic lights displayed near the predicted mortality rates of Exposure to Overflow Beds are aligned with the risk ranges identified for each model in 6.4 Clinical Usefulness. Green indicates the “Relatively Safe” range, yellow the “Apply Model”, while red represents the “Avoid Overflow Beds” risk range.