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DEMAND AND CAPACITY IMBALANCE IN THE EMERGENCY DEPARTMENT, AND PATIENT OUTCOMES

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DEMAND AND CAPACITY IMBALANCE IN THE EMERGENCY DEPARTMENT, AND PATIENT OUTCOMES

THESIS FOR DOCTORAL DEGREE (Ph.D.)

By

Björn af Ugglas

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"There is a time in the life of every problem when it is big enough to see,
yet small enough to solve."

Michael O. Leavitt, United States Secretary of Health and Human Services 2005-2009

ABSTRACT

Background:

An emergency department (ED) is always open and continuously needs to balance the inflow and demand for emergency service with available capacity. When demand exceeds the available capacity of an ED, it is referred to as crowding. Crowding is a critical concern for EDs worldwide, and there is evidence that it is associated with increased mortality, morbidity, and an unsustainable working environment. One of the most critical factors impacting crowding is the access to hospital beds at the right level of care to allow for a timely admission of patients. The long-term trend across the OECD countries is that the number of hospital beds per capita is declining. This development is mainly positive and driven by improvements in diagnostics and clinical care, resulting in more efficient use of resources. However, reducing hospital beds without a concurrent innovation that leads to a reduction in the demand for inpatient care will likely lead to an increased bed occupancy that could result in crowding and poor outcomes for patients.

Aims:

This doctoral thesis aims to improve the knowledge of demand and capacity imbalance in the ED and how this impacts patient outcomes. More specifically:

1. Is hospital bed occupancy associated with increased mortality?
2. Is hospital bed occupancy associated with crowding?
3. Is crowding associated with increased mortality?

Methods:

The thesis includes four studies, three large retrospective cohort studies, analyzing around 2 million adult ED visits in each study using survival analysis. Hazard ratios are estimated using a cox proportional hazards model. The model is adjusted for potential confounding factors such as case-mix and arrival time. The model allows for differences between hospitals in the underlying risk, and seasonal trends are considered using calendar time as the underlying time scale. The remaining study is a descriptive study of the developments of crowding and key input, throughput, and output factors during the first wave of COVID-19 at a university hospital.

Results:

Aim 1: Study I found no statistically significant association between hospital bed occupancy and 30-day mortality.

Aim 2: In Study I, there was an association between bed occupancy and crowding. For each 10% increase in bed occupancy, the length of stay in the ED increased by 16 minutes for all patients and 28 minutes for admitted patients. In Study III, there was an association between emergency ward occupancy and crowding with an estimated correlation (95% CI) between mean ED LOS and mean emergency ward bed occupancy of 0.94 (0.55 – 0.99).

Aim 3: Study II identified a statistically significant association between crowding and 30-day mortality with an estimated HR (95% CI) of 1.08 (1.03-1.14) in the high category of crowding, which included the top 5% of ED visits most exposed to crowding. The study included visits from Stockholm County during 2012-2016. Study IV used the same methodology but included visits to 14 EDs in four counties during 2015-2019. The results were mixed, and only Stockholm county had robust associations between crowding and mortality. Estimated HRs for 30-day mortality in Stockholm county in the subgroup analysis for admitted patients was 1.06 (1.01-1.12) in the moderate category and 1.11 (1.01-1.22) in the high. During the study period, the average hospital bed occupancy in Stockholm was 101% compared to 92% in Skåne and 81% in Östergötland.

Conclusions:

A relative increase in hospital bed occupancy is not necessarily associated with increased mortality among patients seeking care at the ED. It is, however, associated with additional workload and increased crowding in the ED.

The association between crowding and mortality varies by hospital, and there are statistically significant associations in some, but not all. Since the association is not universal, it may potentially be avoidable.

An additional finding is that there are signs that a high hospital bed occupancy may modify and reinforce the association between crowding and mortality. If this would be the case, patients exposed to a combination of boarding and crowding may be at risk of poor outcomes. Investigating outcomes and mechanisms for this patient group should be a priority in future research.

Keywords:

emergency department, demand, capacity, crowding, hospital bed occupancy, boarding, mortality

LIST OF SCIENTIFIC PAPERS

I. Björn af Ugglas, Therese Djärv, Petter L. S. Ljungman, Martin J. Holzmann, **Association Between Hospital Bed Occupancy and Outcomes in Emergency Care**: A Cohort Study in Stockholm Region, Sweden, 2012 to 2016. *Ann Emerg Med.* 2020 Aug;76(2):179-190.

II. Björn af Ugglas, Therese Djärv, Petter L. S. Ljungman, Martin J. Holzmann, **Emergency department crowding associated with increased 30-day mortality**: a cohort study in Stockholm Region, Sweden, 2012 to 2016. *JACEP Open.* 2020;1-8.

III. Björn af Ugglas, Niclas Skyttberg, Andreas Wladis, Therese Djärv, Martin J. Holzmann, **Emergency department crowding and hospital transformation during COVID-19**, a retrospective, descriptive study of a university hospital in Stockholm, Sweden. *Scand J Trauma Resusc Emerg Med* 28, 107 (2020).

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CONTENTS

LIST OF ABBREVIATIONS

ACEM	Australasian college for Emergency Medicine
ACEP	American College of Emergency Physicians
CAEP	Canadian Association of Emergency Physicians
CI	Confidence interval
COVID-19	Corona virus disease 2019
ED	Emergency department
EDWIN	Emergency department work index
EHR	Electronic healthcare records
EMS	Emergency medical services
HR	Hazard ratio
LOS	Length of stay
LWBS	Left without beeing seen
NEDOCS	The national emergency department overcrowding scale
OECD	Organisation for Economic Co-operation and Development
PIN	Personal identification number
RCEM	The Royal College of Emergency Physicians
SARS-CoV-2	Severe acute respiratory syndrome coronavirus 2
SEAL	Skåne emergency department assessment of patient load
SI	International system of units
SVAR	The Swedish national quality register for emergency care
TAS	Telephone triage and advice service
UCR	Uppsala clinical research center

1 INTRODUCTION

Emergency departments (EDs) form an essential component of the healthcare system across the world.[1-3] For example, there are roughly 2 million adult ED visits per year in Sweden[4] in a population of 8 million adults[5], resulting in 25 visits per 100 persons and year. England has similar figures with 28 visits per 100 persons[6] indicating the importance of emergency care for society.

1.1 CROWDING

An ED is always open and continuously needs to balance the inflow and demand for emergency service with available capacity. When demand for emergency service exceeds the available capacity of an ED, it is referred to as crowding.[7-10] Crowding is a critical concern for EDs worldwide,[11] and there is evidence that it is associated with increased mortality,[12-15] morbidity,[16-18] and an unsustainable work environment.[19, 20] The earliest articles on ED crowding that I have been able to find dates back to 1990 in the United States.[21, 22]

However, already in the first volume of the Journal of the American College of Emergency Physicians from 1972, a study describes patients placed in “the holding area”[23]. From the article, we can conclude that ED crowding and waiting for an available inpatient bed (boarding)[24] was an issue already from the early days of Emergency Medicine.

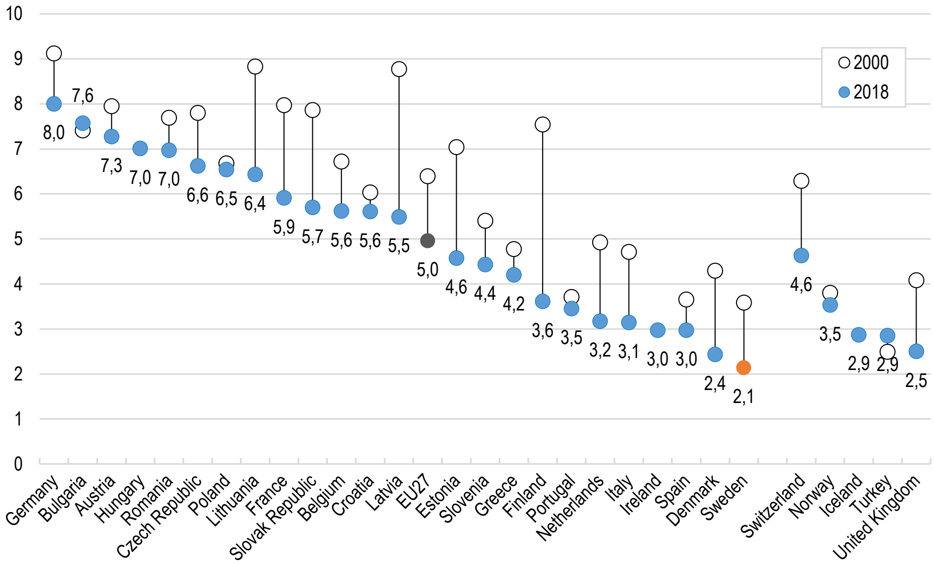
A proposed direction for future research in ED crowding is to develop measures of the problem, understand the causes of crowding, improve understanding of the relationship between crowding and the quality of care, and test interventions to improve crowding.[25] Another conclusion is that research needs to focus more on system-wide solutions to mitigate crowding.[26]

There are many articles available that have quantified the impact that a single or a few risk factors have on ED crowding. There are also systematic literature reviews available that gather and group different causes, characteristics, and outcomes.[26-29] The impact crowding has on mortality has been studied, but the quality is inconsistent, and further research is required.[29]

1.2 HOSPITAL BED OCCUPANCY

One of the most critical factors impacting ED capacity and the ability to avoid crowding is the access to inpatient hospital beds at the right level of care to allow for a timely admission of patients in need of inpatient care.[30] The long-term trend across the OECD countries is that the number of hospital beds per capita is declining. In the latest OECD-report,[31] all countries except Bulgaria and Turkey exhibit a decline from 2000 to 2018 (Figure 1).

Figure 1. Hospital beds per 1,000 population, 2000 and 2018, by OECD country

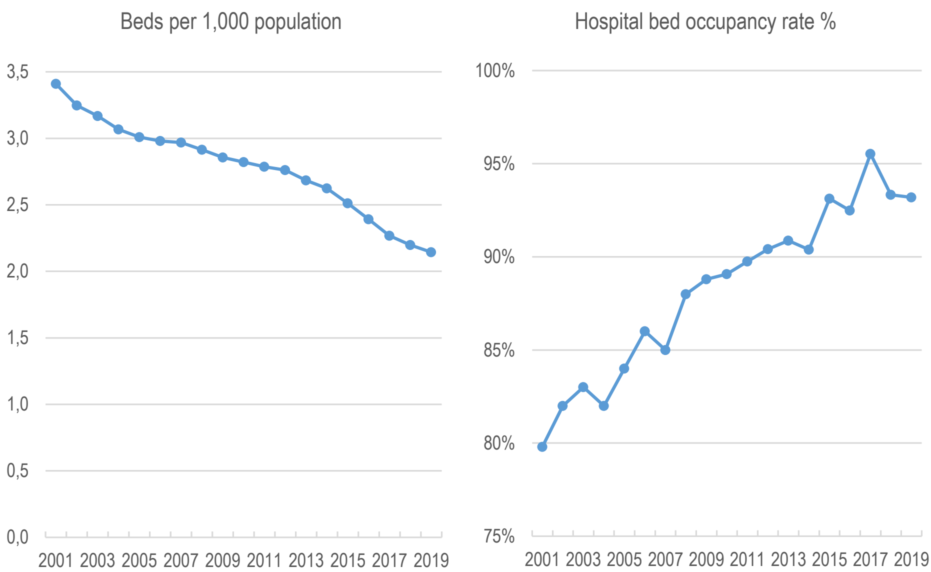


This development is mainly positive and driven by improvements in diagnostics and clinical care, resulting in more efficient use of healthcare resources. One good example is the introduction of high-sensitive troponin that can rule out potential myocardial infarctions that previously required admission to inpatient care for surveillance.[32] Other significant trends are the shift of open surgery to laparoscopic[33] and endovascular[34] interventions that reduce hospital LOS for many patients. These and many more clinical practice innovations have reduced the need for hospital beds and free up substantial resources for society.

However, reducing the number of hospital beds per capita without a concurrent innovation that leads to a reduction in the demand for inpatient care is not a workable solution. For example, a healthcare system's inability to educate, recruit, and retain nurses is not a sustainable reason to reduce inpatient care capacity. Instead, it will likely lead to an increase in the hospital bed occupancy rate which may be associated with increased mortality.[35-37]

Sweden leads this development towards fewer hospital beds and has the lowest number of beds per capita in the OECD comparison with 2.1 hospital beds per 1,000 population, down from 3.6 beds per 1,000 population in 2001.[31] During the same period, the hospital bed occupancy rate in the country increased from 80% in 2001 to 93% in 2019[38, 39] (Figure 2). This bed occupancy level exceeds the 90% threshold where EDs may no longer efficiently deliver care.[40] The crowding situation also deteriorated, with the median ED LOS increasing from 148 minutes in 2010 to 224 minutes in 2019.

Figure 2. Hospital beds per 1,000 population, and hospital bed occupancy rate in Sweden 2001-2019



There are no signs that the trend towards fewer hospital beds, increased bed occupancy rates, and higher crowding levels have reached an end. Even if there already exists evidence that this development is associated with negative consequences, it has not yet reached a point where politicians, policymakers, and hospital management teams together have been able to stop the growing imbalances in the ED.

2 LITERATURE REVIEW

This literature review starts with a motivation of why healthcare is a service and how services research can help us better understand crowding. It continues with an introduction to queuing theory that can help us understand critical elements in balancing demand and capacity. Furthermore, crowding is defined and then structured by combining two existing perspectives of crowding.

2.1 HEALTHCARE IS A SERVICE

To effectively balance demand and capacity in the ED, it is important to understand that healthcare is a service. The specific characteristics that services have compared to goods and products were discussed already by the classic economist Adam Smith in the Wealth of nations in 1776, who highlighted the "perishability" of services.[41] Later, in 1803, the French economist Jean-Baptiste Say used healthcare as an example of a service. He concluded that physician advice is an immaterial product. Additionally, he highlighted the "intangibility" and "inseparability" of services.[42] A fourth characteristics of services is "heterogeneity", and was first introduced in the early 1930s. These characteristics have been discussed and refined within the field of service marketing, and the conclusion is that there are many types of services, and you need to view every type of service separately in relation to the four characteristics (intangibility, heterogeneity, inseparability, and perishability).[43]

2.1.1 Service characteristics of emergency department care

The service characteristics relevant for balancing demand and capacity in emergency care are heterogeneity, inseparability, and perishability:[43]

1. **Heterogeneity** – healthcare services are hard to standardize. They include a high level of variation due to individual patient-related factors. Additionally, there is also variation from the provider, as healthcare services are labor-intensive.[43]
2. **Inseparability** – the production and consumption of healthcare services cannot be separated. There is a required interaction and co-production taking place between patient and provider.[43]
3. **Perishability** – it is impossible for healthcare service providers to store their production and buffer capacity by holding inventories to better match demand.[43]

Together, these three characteristics are likely to create challenges in matching demand and capacity in emergency care. The individual variation in both patient and provider is difficult to quantify and manage. Additionally, the inseparability and perishability characteristics mean that demand and capacity need to be balanced continuously to avoid delays or high costs.[43]

2.1.2 Strategies for balancing capacity and demand in a service setting

Due to the above characteristics, balancing demand and capacity in EDs becomes both difficult and important. There are two basic groups of strategies[44] proposed for balancing capacity and demand in service organizations. In practice, organizations use different combinations in various situations.[44-46]

- **Demand-driven** – adjust capacity to match demand as close as possible (chase demand)
- **Resource-driven** – manage and influence demand against a fixed capacity (level capacity)

The average demand for ED-services often follows a predictable daily, weekly and seasonal pattern.[47, 48] One common demand-driven strategy is to implement variable staffing levels by hour, weekday, and season to better match demand. Another example is planning capacity to immediately take care of patients with the highest priority in specially equipped resuscitation rooms with designated staff.[49] Here, the capacity is adjusted to meet demand through dedicated resources and preemptive prioritization. An indirect method of improving ED capacity is by improving the hospital bed capacity. For example, active discharge planning can lower hospital LOS and increase capacity.[50]

Influencing demand for ED care is usually challenging, at least for an individual ED and the main resource-driven strategy is triage and medical prioritization.[51-54] The need to be timely assessed by a physician is evaluated in the triage-process, and patients with lower priority will have to wait until a physician is available. In the physician assessment, the physician decides the surveillance-level and the re-evaluation interval for each patient.[55] Physicians may also prioritize diagnostic resources like imaging based on medical priority.[56] This inventorying of demand for patients with lower priority often results in an extended length of stay for these patients but secures the quality of service for patients with the greatest medical needs. On a system level, it is also possible to shift demand from the EDs towards urgent care centers and primary care through public information campaigns and telephone triage and advice service (TAS).[57-59]

However, when these planned strategies are not enough to balance capacity and demand, there is a need for coping strategies to manage and control the reduction in service levels. A coping strategy aims to maintain the core service quality while still achieving resource targets/constraints and could be focused on adjusting either capacity or demand.[60] One example of a coping strategy used in some emergency care systems to reduce demand is ambulance diversion.[61] Another is to refer low priority patients arriving at the ED to other care providers.[62] Coping strategies that increase capacity include bringing in additional staff with short notice or make existing staff stay longer in case of severe imbalances. Another critical component to increase ED capacity is to open up more inpatient beds by temporary allowing lower staff-to-patient ratios or adding temporary staff. A final strategy that can be used is to postpone elective interventions that are not imperative.[63] In extreme events like a mass-casualty incident, pandemic outbreak, or other disasters, the hospital can establish a Hospital Command Group[64] according to predefined protocols[65] to mobilize all hospital resources. In these events, the hospital can combine strategies to maximize the total capacity. An overview of examples grouped by type of strategy can be seen in Table 1.

Table 1. Examples of strategies to balance capacity and demand in EDs

	Demand-driven – increase capacity	**Resource-driven – manage demand**
Planned strategies	• Plan staffing according to historical inflow and workload patterns • Secure capacity for critically ill patients taking inflow variability into account when planning • Active discharge planning to reduce inpatient LOS and increase hospital bed capacity	• Triage and medical prioritization – inventorying demand for patients with lower priority to secure the quality of service to patients with the most urgent medical need • Shift demand from low severity patients to urgent-care centers and primary care through public information campaigns and central call center
Coping strategies	• Process and compensation system for bringing on additional staff with short notice • Opening additional inpatient beds in the hospital by adding staff or temporary allowing lower staff-to-patient ratios • Cancel elective interventions to free up additional inpatient beds in the hospital • Establish a hospital command group according to predefined guidelines to mobilize all the hospital's resources.	• Ambulance diversion • Diversion of low severity patients to other care providers or self-care at ED registration

2.2 QUEUEING THEORY

Queueing theory is a mathematical theory used within the field of operations research. It has also been leveraged in many healthcare areas[66-69] to model and better understand the relationship between input and outcomes in demand/capacity problems. Compared to other methods like simulation,[70] queueing theory is less complicated and requires fewer data points.[71] However, the details are still confusing enough for non-mathematicians, and some of the necessary assumptions may not hold in practice.[69] Regardless of the challenges of detailed modeling of clinical processes, queueing theory gives us an understanding of the fundamental relationships between different factors when balancing capacity and demand.[66-72]

2.2.1 Little's law

Little's law is a simple formula that shows how the number of patients in the system is related to the arrival rate and length of stay.[73] In an ED context, this means that the average number of patients in the ED equals the average arrival rate multiplied by the average length of stay. If the average inflow increases, the average number of patients in the ED will grow unless the average length of stay is reduced. Similarly, if the average length of stay increases by 10%, the average number of patients in the ED will grow by 10% if the average inflow is unchanged. The formula is attractive due to its simplicity, but it is essential to understand its limitations and that the relationship only holds for averages.

2.2.2 The flaw of averages

The variation in inflow and healthcare services' heterogeneity means that capacity models based on averages will not be accurate enough. Both the variation in inflow and the variation in service time will increase delays (if utilization is unchanged).[71, 72] This means that if averages are used in calculations, the service levels will be lower than desired. Target ratios commonly used in healthcare, such as utilization targets of 85% bed occupancy or nurse to patient ratios of 1:6, are based on averages and do not consider the system's size and the variation in arrival rate or service time.[71, 72]

2.2.3 Instability

When utilization in a system increase towards 100%, the average delay increases exponentially towards infinity, assuming everything else is equal. This relationship translates to rapidly reducing service levels when the system is getting close to its maximum capacity. A system where the average total capacity is less than average demand is "unstable, and the queue will continue to grow".[71] This instability when utilization increases mean that we need to be careful when assuming linearity when studying the outcomes of demand and capacity imbalances. There will likely be threshold effects and exponential relationships when utilization is getting close to its maximum.

2.2.4 Economies of scale

The size of the system impacts the service level. Larger units have a higher service level at the same utilization rate as a smaller unit, everything else equal.[71] This means that merging departments or ED flows could be an excellent way to increase operational efficiency. Ideally, this also means that a larger system can maintain the same service level at higher utilization. However, having separated ED flows may add other benefits like a higher degree of specialization. Increasing the size too much may also result in a loss of overview and control and may require additional resources to manage the patient flow. It could also lead to other logistical challenges coming from having too many patients in one unit.

2.3 DEFINING AND STRUCTURING THE CONCEPT OF CROWDING

2.3.1 Definitions of crowding

Definitions of crowding vary slightly across the world (Table 2). The common theme in all definitions is that demand for ED services exceeds available capacity. The definitions in Canada, UK, and Australasia detail that it is a state when the ED's function is limited, and in Canada and UK, the medical associations highlight the ability to provide timely and safe/qualitative care. Another common characteristic in all four definitions is that crowding is defined as a state and a "situation" that "occurs".

Table 2. Definitions of crowding, and overcrowding

Country / Medical association	Definition of crowding/overcrowding
United States American College of Emergency Physicians (ACEP, 2019)	"Crowding occurs when the identified need for emergency services exceeds available resources for patient care in the ED, hospital, or both."[7]
Canada Canadian Association of Emergency Physicians (CAEP, 2013)	"Emergency department overcrowding is defined as a situation where the demand for emergency services exceeds the ability of an ED to provide quality care within appropriate time frames."[8]
Australasia Australasian College for Emergency Medicine (ACEM, 2019)	"Emergency department overcrowding refers to the situation where ED function is impeded because the number of patients exceeds either the physical and/or staffing capacity of the ED, whether they are waiting to be seen, undergoing assessment and treatment, or waiting for departure."[9]
United Kingdom The Royal College of Emergency Medicine (RCEM, 2015)	"Crowding is the situation where the number of patients occupying the emergency department is beyond the capacity for which the emergency department is designed and resourced to manage at any one time. This results in an inability to provide safe, timely and efficient care to those patients, and any subsequent patients who attend the department."[10]

However, to define crowding as a state is problematic. How would you, for example, determine the threshold for when the quality of care is impacted? Is it when a young, healthy patient in need of a suture for a minor wound must wait, or when vital parameters for one (or many) unstable patients are not reevaluated according to guidelines? The diversity of the ED patient population will make it very difficult to articulate this threshold.

The benefits of defining crowding as a state is that it simplifies communication of the issue and satisfies the human and epidemiological desire to divide a complex reality into a few categories. To have a broad consensus of a definition of an absolute level of crowding that is relevant and works in different types of EDs in many countries would be ideal. Such a definition would enable us to communicate with policymakers and decision-makers to develop guidelines and set relevant targets to avoid crowding.

In this thesis, I will use the American definition of crowding "crowding occurs when the identified need for emergency services exceeds available resources for patient care in the ED, hospital, or both"[7] as a starting point.

The definition has a clear focus on the imbalance between demand and capacity in the ED and highlights the role of the entire hospital's capacity. Even if it describes crowding as something that "occurs", it does not attempt to define more precisely when it occurs, making it more flexible.

Maybe, we should allow the term crowding to be a continuum? It would cover the entire spectrum of demand/capacity imbalance, ranging from low levels where queues are starting to form in various parts of the ED process to extreme levels where demand is much higher than the available capacity, reaching a disaster scenario.

Viewing crowding as a relative scale instead of a state may open the path towards a standard definition. To clarify, let's take an example from the research area of road safety. The definition of "inappropriate speed" is "driving too fast for the conditions, which relates to the driver, vehicle, road and traffic mix".[74] This helps discuss the concept but has similar challenges as the definitions of crowding as it is expressed as a loosely defined state. On the other hand, the vehicles' average speed is very explicit and can be derived from the International System of Units (SI)[75] length and time. By using the well-defined but relative measure of speed, we can relate this to outcomes. For example,
"1% increase in speed results approximately in 2% change in injury crash rate, 3% change in severe crash rate, and 4% change in fatal crash rate."[76, 77]

Similarly, it may help to move towards measuring crowding on a relative but well-defined scale. From this stable position, we can then explore how different crowding levels are related to different outcomes. Low levels of crowding are likely to be associated with increased length of stay and low patient satisfaction but not serious patient outcomes. In contrast, a very high crowding level is expected to be associated with increased morbidity and mortality.

2.3.2 Causes, characteristics, and outcomes of crowding

As discussed, there is no agreed definition of crowding, neither a consensus on how to best measure it nor an established threshold. To structure the crowding concept, it is helpful to clarify and separate the distinctions between causes, characteristics, and outcomes of crowding.[78] In the following sections, I will list examples of fundamental causes, characteristics, and outcomes related to crowding.

Figure 3. Causes, characteristics, and outcomes of crowding

2.3.3 The input, throughput output model of crowding

The ED system is complex and multi-layered, and causes, characteristics, and outcomes of crowding may appear in different parts of the system simultaneously.[11, 27] This complexity and how the emergency care system often is organized make it challenging to identify and prioritize which risk factors to address. A clear definition of the emergency care system helps navigate the topic. Asplin et al. introduced a conceptual model[79] that partitions the emergency care system into three components: input, throughput, and output. The model is widely spread with almost 500 citations in Web of Science[80] and provides a practical framework to better structure the work to understand and develop potential solutions to crowding.[79]

Figure 4. High level components in the conceptual model of emergency care

2.3.4 Causes (or mitigators) of crowding

There are several potential risk factors that together cause (or prevent) crowding. Crowding is a multivariable problem, and the relative impact and relationship between causes need to be quantified. In addition to this, there are soft factors influencing performance such as competence, leadership, processes, and working methods that have a substantial impact but are difficult to measure.

Input – the arrival intensity is a critical factor, but also the variation in arrival intensity has an impact on service levels and crowding.[67, 72] The case-mix is also related to crowding as more complex patients require more time. Additionally, the variation in case-mix is also a factor since a broad range of chief complaints requires medical staff with a broad competence or multiple servers with expertise in separate areas together with a reliable sorting process.

Throughput – the most crucial factor is the medical staff competence and the number of resources.[27, 29] Efficient work methods and processes and strong teamwork also help mitigate crowding.[26] In addition to this, the ED needs a high service level from diagnostic resources like lab and imaging to prevent crowding.[26, 27, 29]

Output – the timely access to inpatient care is a critical component to avoid crowding and poor outcomes.[26, 27, 29] Available inpatient beds within the right specialty and care-level are vital to avoid that patients requiring inpatient care are treated for an extended period at the ED while waiting for a bed (boarding)[24], as these patients are resource-intensive and at risk of poor outcomes.[13, 24, 81] It is also essential to have developed care pathways[82] for elderly patients with common geriatric syndromes like delirium, dementia, and polypharmacy. This patient group is both challenging and vulnerable, which may lead to both resource issues in the ED and inadequate outcomes for patients.[82, 83]

2.3.5 Characteristics of crowding

The main characteristics of crowding are that when demand exceeds capacity, queues form in various parts of the system. Combined, these extended wait times leads to increased ED length of stay (ED LOS) and more patients present in the ED (ED census).[26, 27, 29, 72] Different service level metrics based on ED LOS such as share of patients with ED LOS less than 4 or 8 hours could also be used. Another marker of crowding is if the combined workload triggers an ambulance diversion. Diverting ambulances limits the inflow of seriously ill patients until the ED can recover the balance between demand and capacity.[26, 27, 29] When the waiting time to the first physician assessment increase too much, it may trigger patients to leave the ED. This is called left without being seen (LWBS) and is together with the waiting time to physician another marker of crowding.[26, 27, 29] A further option is to capture the staff perception of crowding as a marker of crowding[84], and several multivariable measures have been developed that combine variations of the above characteristics and other as a composite metric like EDWIN,[85] NEDOCS,[85] or SEAL.[86]

2.3.6 Outcomes of crowding

A commonly studied outcome of crowding is mortality.[26, 27, 29] The reason for this is that it is both important and definitive. However, mortality is hard to study as it is strongly related to disease severity, and I will discuss this challenge in detail later in this thesis. However, mortality is only the tip of the iceberg, and many other outcomes are valuable to study. For example, morbidity is crucial and could for example be indicated by acquired comorbidities and adverse events,[16-18] admission to intensive care, revisits to the ED, readmission to inpatient care, and extended hospital LOS, all indicating a deterioration of the patients health.

A well-studied group of outcomes are delays to diagnosis or treatment of time-critical interventions.[26-29] Other outcomes that are more difficult to quantify include nursing care left undone[87] and indirect effects like staff burnout and compassion fatigue.[88]

2.3.7 A proposed model for structuring crowding

By combining the two approaches with causes, characteristics, and outcomes[78] and Asplin's model of input, throughput, and output[79], we can construct an overview table of crowding that helps navigate the topic (Table 3).

Table 3. A model for structuring crowding including examples of causes, characteristics and outcomes

	Causes	Characteristics	Outcomes
Input	• High arrival intensity • Case-mix with complex and resource-intensive patients • High level of variation in arrival intensity / case-mix	• Extended length of stay • Increased ED census • Ambulance diversion • Patients leaving before being seen by a physician (LWBS) • Long wait time to first assessment by the physician • Staff perception of crowding • Multivariable measures that indicate crowding (EDWIN, NEDOCS, SEAL)	• Increased mortality • Increased morbidity – Acquired comorbidities and adverse events – Admission to intensive care – Revisits to ED – Readmission to inpatient care – Extended hospital LOS • Delay of time-critical interventions • Nursing care left undone • Staff burnout and compassion fatigue
Throughput	• Low staff competence • Low staff resourcing • Poor processes and teamwork • Low service level from diagnostic resources (lab, imaging)		
Output	• Limited access to inpatient care • Ineffective care pathways for frail elderly		

2.3.8 COVID-19 and the impact on crowding

The current COVID-19 pandemic may impact many elements of the proposed model of crowding. The underlying SARS-CoV-2 virus is highly contagious, and COVID-19 is potentially deadly, especially for elderly patients with specific comorbidities.[89] At the same time, hospitals are adapting quickly by establishing command groups[64] to mobilize all relevant resources. Altogether, COVID-19 may impact both arrival intensity and case mix,[90] processes, resourcing, and competence in the ED[91] as well as the hospital bed capacity.[92] This means that COVID-19 may also result in unique opportunities to study rapid shifts in conditions and crowding as large changes and interventions are implemented in a short timeframe.

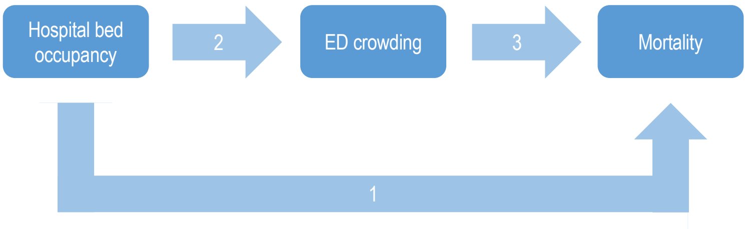
3 RESEARCH AIMS

This doctoral thesis aims to improve the knowledge of demand and capacity imbalance in the ED and how this impacts patient outcomes.

More specifically, the research aims of this thesis are to answer the following research questions:

1. Is hospital bed occupancy associated with increased mortality?
2. Is hospital bed occupancy associated with crowding?
3. Is crowding associated with increased mortality?

Figure 5, Specific research aims of the thesis



4 METHODS

4.1 STUDY DESIGN

The studies included in the thesis all contribute to the overall aim, as shown in Table 4. The table links the individual studies to the specific aims in the thesis.

Study I was a retrospective cohort study with the primary aim to investigate the association between hospital bed occupancy and mortality and links directly to the first specific aim in the thesis. As a secondary aim, the study assessed bed occupancy's effect on admission rates to inpatient care, and ED LOS, which is an indicator of crowding and links to the second specific aim in the thesis.

Study II and IV are also retrospective cohort studies where the aims are directly aligned with the thesis's third aim to investigate the association between crowding and mortality. Study IV builds on the learnings from Study II and more recent data and includes a more heterogeneous group of EDs.

Study III is a descriptive study of the transformation of a university hospital during the first period of COVID-19 in Stockholm. A primary aim was to investigate how crowding and important output factors like bed occupancy developed in the different phases of the crisis and contributes to the second specific aim in the thesis to answer if hospital bed occupancy is associated with crowding.

Table 4. Link between the specific aims in the thesis, and the four included studies

Study / Aim	**Thesis aim #1:** Is hospital bed occupancy associated with increased mortality?	**Thesis aim #2** Is hospital bed occupancy associated with crowding?	**Thesis aim #3** Is crowding associated with increased mortality?
Study I: The aim of this study is to evaluate the associations between bed occupancy and 30-day mortality, in-hospital mortality, readmissions for inpatient care within 30 days, and revisits to the ED within 7 days. In addition, we aimed to assess the effect of bed occupancy on admission rates to inpatient care and patient lengths of stay in the ED.	Primary aim to evaluate the association between bed occupancy and 30-day mortality	Secondary aim to assess the effect of bed occupancy on admission rates to inpatient care and ED LOS	-
Study II: The aim of this study is to investigate the association between crowding and 30-day mortality.	-	-	Primary aim to investigate the association between crowding and 30-day mortality
Study III: The aim is to describe how the Huddinge site at the Karolinska university hospital (KH) responded to the COVID-19 crisis, and how crowding, and important input, throughput and output factors for crowding developed at KH during a 30-day baseline period followed by the first 60 days of the COVID-19 outbreak in Stockholm Region.	-	Primary aim to describe how crowding and important output factors (including bed occupancy) developed	-
Study IV The aim of this study is to investigate the association between ED crowding and all-cause mortality within 7 and 30 days from the ED visit, and the potential differences between three counties in Sweden.	-	-	Primary aim to investigate the association between crowding and all-cause mortality within 7 and 30 days from the ED visit

4.2 SETTING

The four studies included visits from 16 EDs in four counties in Sweden. The EDs covered a range from the smallest ED in Ystad with 17 thousand visits in 2016 to the largest inner-city ED, Södersjukhuset in Stockholm, that had 107 thousand visits during the same period. The studies included a large private ED and five university hospital EDs (Table 5).

The Swedish emergency care system is in a period of transformation. A recent government report on emergency care in Sweden[93] highlights the lack of inpatient beds, and insufficient primary care capacity as critical concerns for EDs. Sweden introduced Emergency Medicine as a secondary specialty for physicians in 2006 and as a primary specialty in 2015.[94] There is an ongoing effort to reform primary care with the aim to increases availability, continuity, and enable more personalized care.[95]

Table 5. Included hospitals, by study

County	Hospital	Type	Year 2016 volume[96]	Study I	Study II	Study III	Study IV
Stockholm	Norrtälje	Public	22,030	X	X		
	Danderyd	Public	84,976	X	X		X
	Karolinska Solna	University hospital	63,394	X	X		X
	Capio S:t Göran	Private	81,099		X		
	Södersjukhuset	Public	107,244	X	X		X
	Karolinska Huddinge	University hospital	68,133	X	X	X	X
	Södertälje	Public	32,430	X	X		X
Skåne	Helsingborg	Public	46,185				X
	Kristianstad	Public	35,260				X
	Lund	University hospital	52,771				X
	Malmö	University hospital	61,905				X
	Ystad	Public	17,828				X
Örebro	Örebro	University hospital	67,970				X
Östergötland	Motala	Public	18,181				X
	Linköping	University	34,255				X
	Norrköping	Public	34,915				X

4.3 STUDY POPULATION

Study I, II, and IV were all cohort studies, including more than 2 million observations in each study from multiple EDs over five years. In the studies, all adult patients seeking care at one of the included EDs were the starting point in defining the study population. Patients seeking care at specialized EDs that were physically or organizationally separated from the general ED were excluded. Examples of this are patients seeking specialized psychiatric, gynecologic, or obstetric care in some of the hospitals.

All patients who had a valid arrival and discharge time were included in the crowding exposure calculation. To evaluate more detailed patient characteristics and mortality outcome it was necessary to have a valid personal identification number (PIN) for each visit. Patients without a correct PIN were excluded. The reasons for not having a valid PIN could be that the patient is a foreign national, that the identity is protected or unknown for other reasons during the visit. Patients who were dead on arrival were also removed from the dataset together with patient visits that were missing information required in the regression models.

- Study I included visits to the six public EDs in Stockholm County during 2012-2016.
- Study II included visits to all seven EDs in Stockholm County during 2012-2016.
- Study IV included visits to 14 EDs in four counties across Sweden during 2015-2019.

Study III was a descriptive study of all visits during 90 days at a university hospital ED. The study described the transformation during the first wave of COVID-19 in Huddinge, the southern site at the Karolinska University Hospital in Stockholm (KH). The department for infectious diseases at KH is the largest in the country, and the hospital is the primary receiver of patients with suspected highly infectious diseases in the region. During this period, the hospital rapidly grew its intensive care capacity and was a critical component in the regional care of patients with severe COVID-19. We included all adult patient visits to the ED except a few cases where triage priority, sex, or ED LOS were missing.

- Study III included all ED visits to KH in the first wave of COVID-19 during a 30-day baseline period followed by the first 60 days of the first wave of COVID-19 in Stockholm county.

4.4 DATA SOURCES

Study I and II used the same underlying database. Data from all ED visits where gathered for each of the seven hospitals in Stockholm. The data included information about each ED visit and the PIN of each patient. The data was compiled into one dataset and given to the National Board of Health and Welfare that added information from the National Patient Register,[97] the Swedish Prescribed Drug Register,[98] and the Cause of Death Register[99] using the PIN. The combined dataset was then pseudonymized and returned to us.

For Study I, we also gathered historical information on the number of staffed beds and the number of admitted patients for each ward and hour during the study period. This information was only available for the six public hospitals using the EHR TakeCare, so Capio S:t Göran hospital could only be included in Study II. Using this detailed information on individual ward level, we were able to ensure data quality, remove wards that were not relevant for our research, and calculate the hospital bed occupancy for each hour during the study period.

Study III relied on standard management reports from the Karolinska University Hospital. Crosstabs of daily data from the management data warehouse was delivered to us with Tableau Desktop 2018.3.0.

In Study IV, the data source was the Swedish national quality register for emergency care (SVAR).[100, 101] The register included all data necessary to perform the study, and text-files, including pseudonymized data, were delivered to us from the Uppsala Clinical Research center (UCR).[102]

4.5 EXPOSURES AND OUTCOMES

The exposure in Study I was hospital bed occupancy, and the primary outcome was 30-day mortality. The study also included several secondary outcomes to investigate how the hospital bed occupancy impacted patients and the emergency care process. Study II and IV investigated the exposure ED census compared to the expected ED census as a proxy measure for crowding. Study II's outcome was 30-day mortality, while Study IV also evaluated 7-day mortality. Study III had instead crowding as the outcome and used mean ED LOS as a proxy. The key exposures investigated were the number of ED visits per day, the proportion of imaging performed, and emergency ward bed occupancy (Table 6).

Table 6. Exposures and outcomes, by study

Study	Primary exposure(s)	Primary outcome(s)	Secondary outcomes
Study I:	Mean hospital bed occuopancy during the 24-hour period preceding and including the hour the patient arrived at the ED.	• 30-day mortality	• In-hospital mortality • Readmission for inpatient care within 30 days of hospital discharge • Revisits to the ED within 7 days of being discharged directly home from the ED • Admission rate • ED LOS
Study II:	Mean hourly ED census during the shift that the exposed patient arrived, divided with the expected ED census for this shift. The expected ED census was estimated using a separate linear model for each hospital with year, weekend/weekday, and shift as predictors	• 30-day mortality	-
Study III:	Input: Number of ED visits per day (mean) Throughput: Proportion of imaging performed (%) Output: Emergency ward bed occupancy (%)	• Crowding, defined as mean ED LOS	-
Study IV	Mean hourly ED census during the shift that the exposed patient arrived, divided with the expected ED census for this shift. The expected ED census was estimated using a separate linear model for each hospital with year, weekend/weekday, and shift as predictors	• 30-day mortality • 7-day mortality	-

4.6 VARIABLES

Study I, II, and IV included patient characteristics that were used to control for confounding. The database used in Study I and II incorporated information from national registers such as prior hospital care and socioeconomic data. In Study I, we found that the socioeconomic data did not add much value to the model, so we removed it in Study II. In Study II we also realized that neither comorbidities nor historical inpatient care impacted the association between crowding and mortality, so these covariates were not included in Study IV. Study III only had distributions of age, sex, and arrival mode but no individual data (Table 7).

Table 7. Included patient characteristics variables, by study

Variable	Comment	Study I	Study II	Study III	Study IV
Age	Age in full years	X	X	(X)	X
Sex		X	X	(X)	X
Arrival mode	Arrival by emergency medical services (EMS) or other		X	(X)	X
Triage priority	1 (resuscitation), 2 (unstable), 3-4 (stable) or 5 (no need to triage)	X	X		X
Chief complaint	Top chief complaints by the number of total deaths within 30 days. Top 12 complaints included in Study II and top 25 in Study IV.		X		X
Comorbidities	Previous stroke, previous myocardial infarction, chronic obstructive pulmonary disease, previous heart failure, diabetes, active cancer, chronic kidney disease	X			
Arrival year			X		X
Arrival on weekday/weekend	Weekday: Monday 7 AM–Friday 5 PM Weekend: Friday 5 PM–Monday 7 AM	X	X		X
Arrival hour or shift	Day: 7 AM – 3 PM Evening: 3 PM – 11 PM Night: 11 PM – 7 AM	X	X		X
Hospital stays last year	Prior inpatient care episode last 365 days: none, 1, 2, 3, or more	X			
Marital status	Married, divorced, never married, widowed	X			
Length of education	<10, 10-12, >12	X			

(X) only distribution, no individual data

4.7 STATISTICAL METHODS

Study I, II, and IV used similar survival analysis methods, while Study III was a descriptive study using basic distribution tables, graphs, and correlation analysis.

4.7.1 Study I, II, and IV

Baseline data on patient characteristics were presented as absolute numbers, proportions, and means with standard deviations (SD) or as medians together with values for quartile 1 and 3 as an alternative measure of dispersion.

Crude incidence rates were presented, and adjusted hazard ratios (HR) for the outcome with a 95% confidence interval were estimated for each exposure category. The statistical model was a cox proportional hazards model stratified by hospital and using calendar time as an underlying time dimension.

That the model is stratified means that it allows for independent baseline hazards between hospitals but assume that the HR is the same for all hospitals. Calendar date was chosen as the underlying time dimension to handle seasonal effects like flu-season, holidays, and other known or unknown seasonal influences that may otherwise introduce bias.

In the primary analysis of mortality, follow-up started at the ED visit date and ended at death, or the end of the follow-up period at 7 or 30 days following the visit. A person could have more than one visit within the 30-day period. If so, the later visits were ignored until the date after the previous 30-day period ended (left-truncated), ensuring that no patient contributed with risk time more than once for each date.

Different sensitivity and subgroup analyses were performed in the three studies to improve the validity of the findings. In studies I and II, we performed sensitivity analysis with alternative definitions of bed occupancy and crowding exposures. Furthermore, in Study I, subgroup analysis for the highest priority, by hospital, and by age group was performed. In Study IV, an additional model excluding the triage priority was evaluated. Subgroup analyses for three counties and only for admitted patients were also made in Study IV to investigate differences between counties and by admission status.

The proportional hazards model's assumptions were checked by calculating annual HRs of the risk factors to check that there were no trends or systematic patterns in the estimates over time. Additionally, we also inspected the survival curves stratified by exposure category to check for crossed or diverging lines.

Data management of the combined database and the analysis of Study I was made using SAS software 9.4, SAS Institute Inc. Data management and analysis in Study II and IV were performed with R version 3.6.1 using RStudio 1.1.463.

4.7.2 Study III

Study III was a descriptive study that visualized the hospital bed capacity transformation and described the development of crowding and factors usually associated with crowding. Mean ED LOS with a 95% confidence interval was estimated for each phase. Key factors known to be associated with crowding were described in tables showing distributions, means, and proportions. Pearson correlations with P-value and 95% confidence intervals were estimated between the outcomes crowding and critical input, throughput, and output factors. (average visits per day, the proportion of imaging performed, and bed occupancy in the emergency wards). Development of staffed inpatient beds and the average number of patients were visualized in line graphs by the type of ward, phase, and date. To create the summary tables and figures, we used R version 3.6.1 and RStudio 1.1.463.

4.8 ETHICAL CONSIDERATIONS

Study I and II are retrospective register-based cohort studies including data from substantial populations of almost one million individual patients. Study IV also includes visits from slightly more than one million individual patients. In studies I and II, the data was also linked to national registers' medical and socio-economic background data. The reason for needing so many observations is that we are studying a rare outcome and a rare exposure that require vast amounts of high-quality data.

The data used in the studies have been gathered in the electronic healthcare records for other purposes. We have obtained ethical approval from the regional ethical review board in Stockholm for Study I-II and from the Swedish Ethical Review Authority for Study IV to access the data. Study III was based on standard reports on an aggregate level and did not include any individual patient health information, so it did not require ethical approval.

Data for Study I and II were pseudonymized as soon as matching with national registers was performed, and data for Study IV was delivered in a pseudonymized state from the beginning. Pseudonymization is defined as "the processing of personal data in such a manner that the personal data can no longer be attributed to a specific data subject without the use of additional information".[103] Psudonymization "can reduce the risks to the data subjects concerned".[103]

However, data was not anonymized such that the "data subject is not or no longer identifiable".[103] Data could still potentially be identifiable with access to the key that is protected by the National Board of Health and Welfare, or by linking data with information from the EHR that is protected by the caregivers, or by using brute force and similar algorithms.[104]

The data has been stored securely in line with Karolinska University Hospital policy, and we have fulfilled the data security requirements stated in the applications to the ethical review boards.

Informed consent is not feasible to obtain from the patients for these types of extensive retrospective studies. Information that patient data may be used for research is available in the reception and waiting room of the ED, and the ethical review boards removed the requirement to get written informed consent for these studies.

The Helsinki declaration[105] sets the principles for research performed on human subjects. Our studies' primary concern is protecting personal information and confidentiality, as stated in section 24, and the situation where informed consent is impossible or impractical, as described in section 32. As a researcher, I should respect the principles of autonomy, integrity, and right to privacy.[106] In the Helsinki declaration section 5, it is also stated that there will be limited medical progress without research on human subjects.[105] Autonomy and integrity are essential rights, but they need to be weighed against other people's and society's interests and rights.[107]

My view is that society's benefit outweighs the risk of failing to protect the data from individuals included in the studies. The risk is reduced through pseudonymization and research findings in these studies could lead to policy changes in Sweden and other countries worldwide that could lead to increased patient safety in emergency departments. This risk/utility trade-off needs to be performed by an ethical committee, and all three studies that included individual patient data were approved.

5 RESULTS

5.1 THESIS AIM #1 – HOSPITAL BED OCCUPANCY AND MORTALITY

This thesis's first specific aim is to investigate if hospital bed occupancy is associated with increased mortality. The association was investigated in Study I.

The study included 2,084,554 visits by 816,832 individual patients to the six public EDs in Stockholm county 2012-2016. The included visits represented 84% of all ED visits to all seven EDs in Stockholm county during the period.

In total, there were 28,112 deaths within 30 days of the visit to the ED. In all bed occupancy categories, the incidence rate was 19 to 20 deaths per 100 person-years, except for patients in the highest occupancy group. For this group of patients that arrived at the ED when the hospital bed occupancy was greater than 104%, the incidence rate was 22 deaths per 100 person-years. None of the bed occupancy categories demonstrated statistically significant associations with 30-day mortality in the multivariable model (Table 8).

The estimated HR in the group with the highest bed occupancy greater than 104% was 1.10 (95% CI 0.96 to 1.27). The subgroup analysis that only included visits with the highest acuity level showed similar non-significant results. This was also the case for subgroup analyses by hospital and age-group and the sensitivity analysis using a different definition of the exposure.

Table 8, Association between hospital bed occupancy, and 30-day mortality in Study I

	< 85%	85% - 89%	90% - 94%	95% - 99%	100% - 104%	> 104%
Number of deaths	3,109	5,160	8,376	8,789	2,413	265
Person-years at risk	15,573	26,402	42,211	44,532	12,829	1,231
Incidence rate, (deaths/100 person-years)	20	20	20	20	19	22
Adjusted model*, HR (95% CI)	1.01 (0.97–1.06)	1 (reference)	1.01 (0.97–1.05)	1.00 (0.96–1.05)	0.96 (0.90–1.02)	1.10 (0.96–1.27)

*Adjusted model included age, sex, comorbidities, number of hospital-stays in the year preceding the index visit, marital status, length of education, and weekday/weekend timing of the visit.

5.2 THESIS AIM #2 – HOSPITAL BED OCCUPANCY AND CROWDING

The second specific aim was to evaluate if hospital bed occupancy is associated with crowding. In Study I, the associations between hospital bed occupancy and ED LOS as a proxy for crowding and admission rate to inpatient care as an indicator of workload for the ED were evaluated. In Study III the association between emergency ward bed occupancy and ED LOS as a proxy for crowding was investigated.

5.2.1 Hospital bed occupancy and ED LOS in Study I

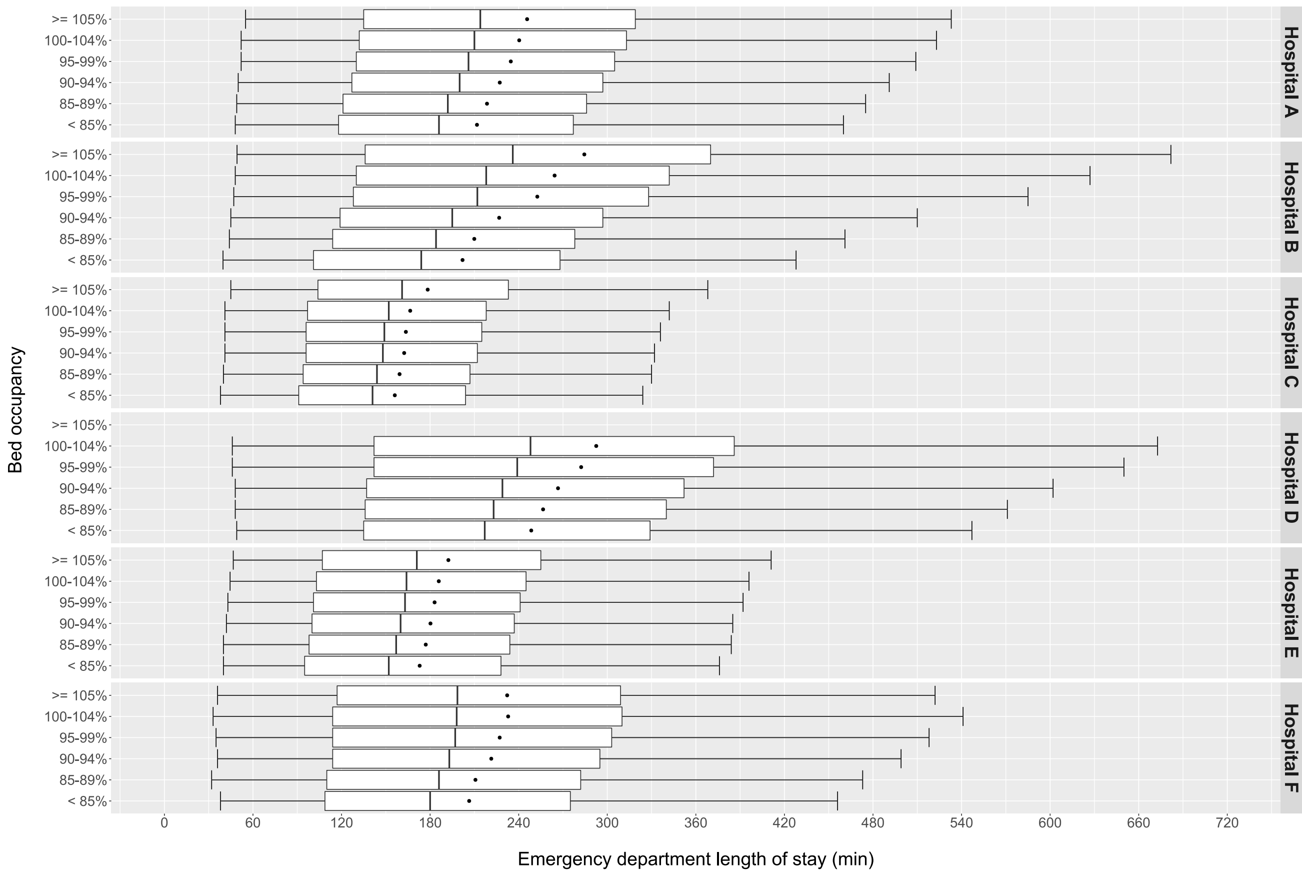
The mean (SD) ED LOS for all hospitals was 234 (163) minutes ranging from 162 (93) to 260 (178) minutes between the hospitals. ED LOS increased in all hospitals as bed occupancy was higher. (Table 9, Figure 6)

This pattern was most apparent for patients who were admitted for inpatient care. For each 10% increase in bed occupancy, the length of stay in the ED increased by 16 minutes (95% CI: 16–17) for all patients, by 28 minutes (95% CI: 27–29) for admitted patients, and by 9 minutes (95% CI: 9–10) for discharged patients.

Table 9, ED LOS by hospital, and category of hospital bed occupancy in Study I

ED LOS, Mean (SD)	All patients	<85%	85-89%	90-94%	95-99%	100-104%	>104%
Total	234 (163)	226 (151)	232 (157)	232 (160)	238 (171)	237 (175)	216 (146)
Hospital A	228 (146)	212 (132)	218 (138)	227 (143)	234 (151)	240 (158)	245 (160)
Hospital B	248 (182)	202 (142)	210 (134)	227 (155)	253 (186)	265 (204)	285 (223)
Hospital C	162 (93)	156 (90)	159 (92)	162 (93)	164 (93)	167 (96)	178 (103)
Hospital D	260 (178)	248 (162)	256 (171)	267 (186)	282 (207)	293 (221)	-
Hospital E	180 (111)	173 (107)	177 (109)	180 (111)	183 (113)	186 (116)	192 (116)
Hospital F	225 (160)	207 (137)	211 (141)	221 (153)	227 (162)	233 (175)	232 (168)

Figure 6, ED LOS by hospital, and category of hospital bed occupancy in Study I



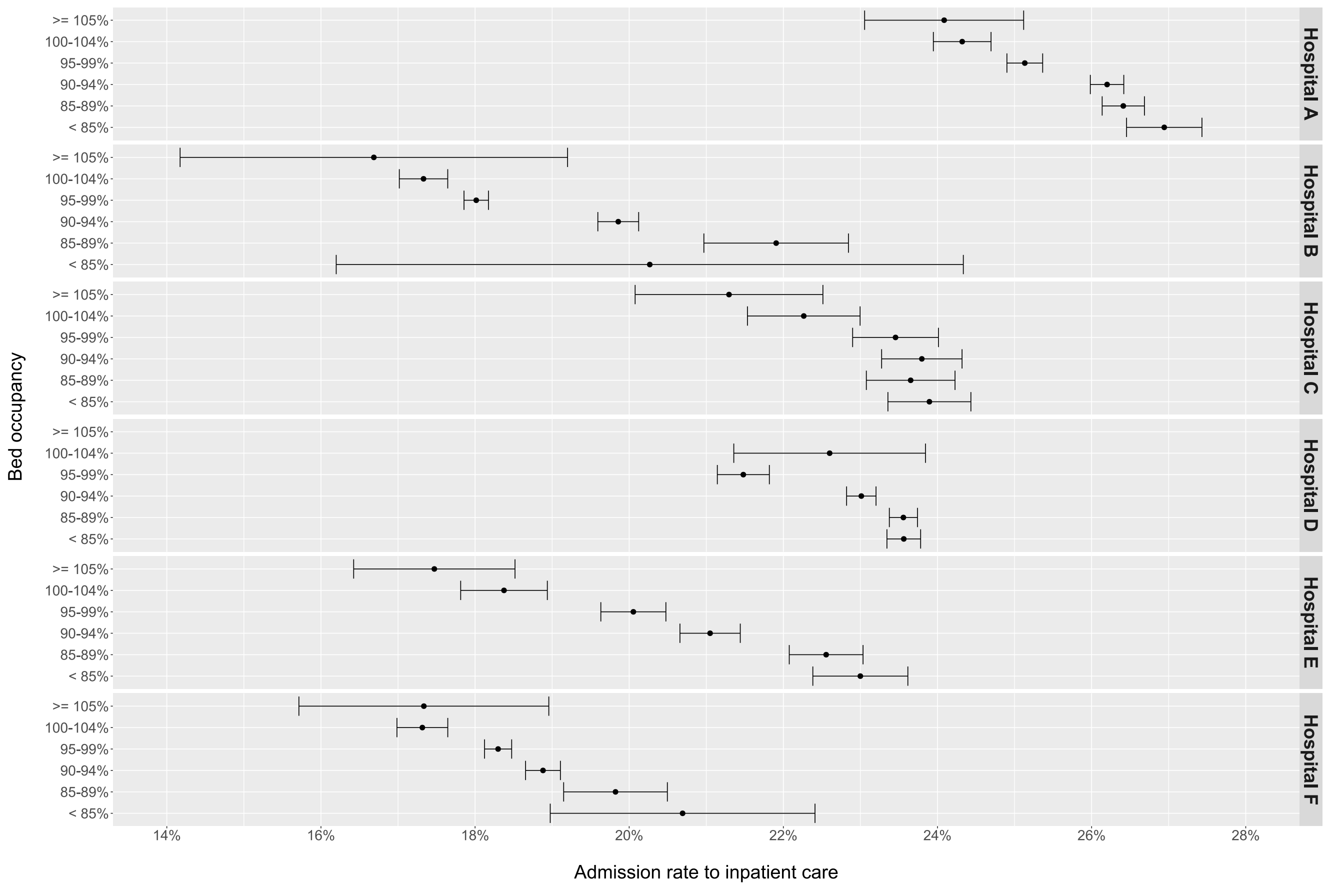
5.2.2 Hospital bed occupancy and admission rate in Study I

The mean admission rate for inpatient care was 21.9%. The admission rate varied between hospitals from a minimum of 18.4% to a maximum of 25.8%. In all hospitals, admission rates declined as bed occupancy increased (Table 10, Figure 7). A 10% increase in bed occupancy was associated with 1.9 percentage points (95% CI: 1.7–2.0) decrease in admission rate.

Table 10, Admission rate to inpatient care, by category of hospital bed occupancy in Study I

	All patients	<85%	85-89%	90-94%	95-99%	100-104%	>104%
Total	21.9	24.0	24.1	22.5	20.1	19.7	20.6
Hospital A	25.8	27.0	26.4	26.2	25.2	24.3	24.1
Hospital B	18.4	20.3	21.9	19.9	18.0	17.3	16.7
Hospital C	23.4	23.9	23.6	23.8	23.5	22.3	21.3
Hospital D	23.2	23.6	23.6	23.0	21.5	22.6	-
Hospital E	20.9	23.0	22.6	21.0	20.1	18.4	17.5
Hospital F	18.4	20.7	19.8	18.9	18.3	17.3	17.3

Figure 7, Admission rate by hospital, and category of hospital bed occupancy in Study I



5.2.3 Emergency ward occupancy and ED LOS in Study III

In the third study, the development of the first wave of COVID-19 was divided into six phases separated by five significant events that changed the ED's conditions. The five events were defined retrospectively by the research team. The first event was when patients with COVID-19 started to arrive at the ED. The next major event was the implementation of new working methods to cope with this. The last three events were based on sudden ambulance inflow changes due to the diversion of ambulances from other hospitals, following regional decisions.

A total of 9,754 ED visits during the 90-day study-period from February 1 to April 30 were initially included in the study. 407 visits (4%) were excluded due to missing information, leaving 9,347 visits (96%) included in the study.

The emergency wards' mean bed occupancy declined from 90% in the baseline phase 1 to 85% in phase 2 and to 66% in phase 3. Emergency ward occupancy then increased to 71% in phase 4 and 79% in phase 5, before it declined again to 70% in phase 6 (Table 11).

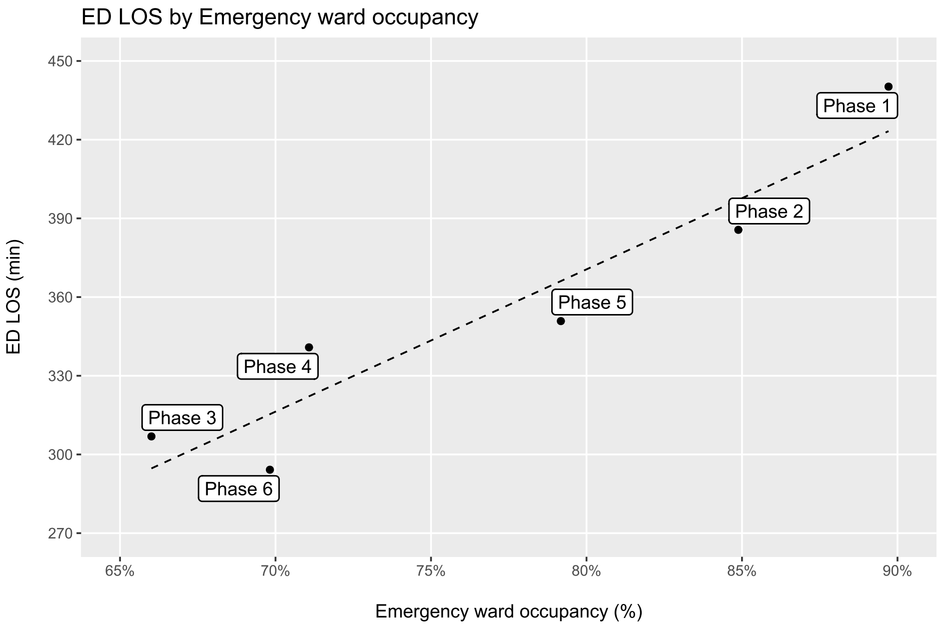
Mean ED LOS was 440 minutes in the baseline phase 1 and declined to 386 in phase 2 and 307 in phase 3. It then increased to 341 in phase 4 and 351 in phase 5, declining to 294 minutes in the final phase 6. All phases following the implementation of new working methods in phase 3 had a statistically significantly lower mean ED LOS than the earlier phases (Table 11).

Pearson correlation (95% CI) between mean ED LOS and mean emergency ward bed occupancy for each phase was 0.94 (0.55 – 0.99) with P = 0.005 (Figure 8)

Table 11, Emergency ward occupancy, and ED LOS, by phase in Study III

	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
Emergency ward, bed occupancy, %	90%	85%	66%	71%	79%	70%
ED LOS, Mean, minutes	440	386	307	341	351	294
ED LOS, Confidence interval, 95%	431 - 449	373 - 399	297 - 317	321 - 360	336 - 366	287 - 302

Figure 8, Correlation between emergency ward occupancy, and mean ED LOS, by phase in Study III



5.3 THESIS AIM #3 – CROWDING AND MORTALITY

The thesis's final specific aim was to evaluate if crowding is associated with increased mortality, which was investigated in Study II and IV.

5.3.1 Crowding and mortality in Study II

The final study population included 2,252,656 visits by 884,228 patients to the seven EDs in Stockholm county during 2012-2016. The crowding exposure was defined as the ED census vs. expected during the shift that the patient arrived and categorized into low, moderate, and high levels of crowding. Patient characteristics were mostly similar between the categories of crowding, but there were some exceptions. The proportion of visits with missing information on triage priority was higher in the higher categories of crowding, and the proportion of visits in the highest groups of crowding was higher during the night and lowered during the day. Crowding was also more common during weekdays and varied slightly between different years.

There were 32,720 deaths within 30 days of the visit to the ED, and the overall incident rate was 20.9 cases/100 person-years. The incidence rates were 20.9 in the reference category 0-75%, 20.6 in the category 75-95%, and 21.4 in the category 95-100%. The estimated adjusted HR (95% CI) was 1.00 (0.97-1.03) in the moderate crowding category 75-95% and 1.08 (1.03-1.14) in the high 95-100% category. The model was stratified by hospital and adjusted for age, sex, priority, weekend, hour, arrival mode, chief complaint, prior hospital admissions, and comorbidities (Table 12).

Results were similar when using the alternative exposure based on mean shift ED LOS vs. expected and when removing adjustments for comorbidities and prior hospital admissions.

The average hospital bed occupancy in Stockholm during the study period 2012-2016 was 94%[39]

Table 12, Association between crowding category, and 30-day mortality in Study II

Crowding category	0-75%	75-95%	95-100%
Number of deaths, n	24,551	6,482	1,687
Person-years at risk, n	117,540	31,423	7,872
Incidence rate, cases/100 person-years	20.9	20.6	21.4
Adjusted* HR (95% CI)	Reference	1.00 (0.97-1.03)	1.08 (1.03-1.14)

*Stratified by hospital, adjusted for age, sex, priority, weekend, hour, arrival mode, chief complaint, prior hospital admissions, and comorbidities

5.3.2 Crowding and mortality in Study IV

The final study population included 2,440,392 visits by 1,142,631 patients to 14 EDs in four counties in Sweden during 2015-2019. The crowding category was based on ED census vs. expected during the shift that the patient arrived. Patient characteristics were mostly similar between the groups of crowding, but there were some exceptions. The proportion of patient visits with the two highest acuity levels was slightly more common in the high crowding category with 17.7% of visits compared to 15.3% in the lowest reference category. The proportion of visits arriving during night shifts and weekends were higher in the high crowding category.

There were 41,737 deaths within 30 days of the visit to the ED, equaling 1.7% of total visits, and the overall incident rate was 24.0 cases/100 person-years. The incidence rates were 23.8 in the reference category 0-75%, 24.2 in the moderate category 75-95%, and 25.4 in the high category 95-100%. The estimated adjusted HR (95% CI) was 1.02 (1.00-1.05) in the moderate crowding category with a p-value of 0.08 and 1.01 (0.96-1.05) in the high category. The model was stratified by hospital and adjusted for age, sex, priority, weekend, hour, arrival mode, and chief complaint (Table 13).

The alternative analysis of the association with 7-day mortality had slightly higher HR estimates, with a statistically significant HR of 1.05 (1.00-1.09) and p-value 0.04 in the moderate category.

Subgroup analysis by county and for admitted patients showed differences by county. Stockholm had significant associations between crowding and 30-day mortality with an estimated HR 1.06 (1.01-1.11) in the moderate category and 1.08 (0.98-1.18) in the high and was the only county with statistically significant results, when including all patients. In the subgroup analysis by county for admitted patients, the estimated HR for Stockholm was 1.06 (1.01-1.12) in the moderate category and 1.11 (1.01-1.22) in the high. Skåne had mixed results, while Östergötland had no statistically significant associations (Table 14).

The associations were more robust in the subgroup analysis for admitted patients. Furthermore, the county with the highest average hospital bed occupancy[39] of 101% had clear associations between crowding and mortality. The county with 92% bed occupancy had mixed results, while the county with 81% bed occupancy did not have any association between crowding and mortality.

Table 13, Main analysis – association between crowding category, and 30-day mortality, in Study IV

Crowding category	0-75%	75-95%	95-100%
Number of deaths, n	31,098	8,434	2,205
Person-years at risk, n	130,547	34,789	8,681
Incidence rate, cases/100 person-years	23.8	24.2	25.4
Adjusted[1] HR (95% CI)	Reference	1.02 (1.00-1.05)[2]	1.01 (0.96-1.05)

[1] Stratified by hospital and adjusted for age, sex, priority, weekend, hour, arrival mode, and chief complaint
[2] p-value 0.08 (non-significant)

Table 14, Subgroup analysis by county and admission status – association between crowding category and 30-day mortality, in Study IV

County	Admission status	0-75%	75-95%	95-100%
Skåne	All patients, adjusted[1] HR (95% CI)	Reference	1.03 (0.99-1.06)	1.01 (0.95-1.07)
	Admitted patients, adjusted[1] HR (95% CI)	Reference	1.04 (1.00-1.08)[2]	1.01 (0.94-1.08)
Stockholm	All patients, adjusted[1] HR (95% CI)	Reference	1.06 (1.01-1.11)	1.08 (0.98-1.18)
	Admitted patients, adjusted[1] HR (95% CI)	Reference	1.06 (1.01-1.12)	1.11 (1.01-1.22)
Östergötland	All patients, adjusted[1] HR (95% CI)	Reference	0.99 (0.93-1.06)	0.97 (0.86-1.10)
	Admitted patients, adjusted[1] HR (95% CI)	Reference	1.03 (0.96-1.12)	1.02 (0.88-1.17)

[1] Stratified by hospital and adjusted for age, sex, priority, weekend, hour, arrival mode, and chief complaint
[2] p-value 0.03 (significant)

6 DISCUSSION

6.1 METHODOLOGICAL CONSIDERATIONS

Many studies on different aspects of crowding have been written. There are also several literature reviews that summarize these studies.[27, 29, 108-111] Original research that evaluates the association between crowding and mortality is less common. The reason is probably due to methodological challenges and lack of access to large amounts of high-quality data. Even if it is clear that crowding is associated with poor outcomes for patients, the association between crowding and mortality may not be as established as perceived,[29] and further research is warranted. There are, however, many methodological challenges, and I identified eight studies[12, 14, 15, 18, 112-115] that I analyzed in detail to learn from. In the following sections, I will discuss different methodological challenges and how we decided to address these. The focus is on Study II and IV, but there are also examples from Study I.

6.1.1 Including multiple EDs

The first learning was to make an effort to add multiple ED's of different types.[12, 14, 15, 114] It is desirable to add as many EDs of different characters as possible to improve external validity and get enough observations. It also meant that we could perform subgroup analysis by ED and identify differences between counties in Study IV.

6.1.2 Studying a rare outcome and a rare exposure

Fortunately, mortality is a relatively rare outcome. For example, in Study IV, only 1.7% of ED visits were followed by death within 30 days. This number is easy to understand but can be misleading since patients may have multiple visits during the 30-day follow-up period. A more relevant but less intuitive number is the incidence rate with 24 cases/100 person-years in the same study.

From the section on queueing theory, we have learned that queueing systems exhibit instability and rapidly deteriorating service levels when the utilization is getting close to its maximum. This instability implies that the impact of crowding or high bed occupancy levels on patient outcomes is likely to be non-linear and most challenging in the highest levels of crowding. In studies II and IV, we choose to define the crowding categories based on our crowding measure's relative value. 0-75% of observations were classified as a normal state and served as reference, 75% - 95% of observations were defined as moderate crowding, and the top 5% were defined as a high level of crowding.

Altogether, these two findings mean that we may be dealing with both a rare exposure (5%) and a rare outcome (1-2%). To gain a statistical power of 90% and a certainty of 95% with an expected mortality of 1.5%, we estimated that 1,434,291 visits were needed to identify a hazard ratio (HR) of 1.10. We had sufficient power in all studies, but the high requirements for observations mean that studies of crowding and mortality need to be designed carefully. The ability to perform detailed subgroup analysis will also be limited.

6.1.3 Creating subgroups may introduce confounding-by-severity

Another learning is that there is a risk in selecting only a part of the population. This stratification may introduce confounding if the exposure is associated with the variable used to create the subgroups. In Study I, we found that a 10% higher bed occupancy is associated with 16 minutes longer ED LOS and almost two percentage points lower admission rate. These findings mean that the threshold for admissions may be higher when there is crowding. If you only include admitted (or discharged) patients, the risk is that you introduce confounding-by-severity. The rationale is that even if the total population is unchanged, the average severity of illness is higher in both subgroups when the threshold for admission is increased during crowding. As pointed out by Madsen et al. in their limitations: “patients whose conditions are not particularly severe might not be admitted during periods of severe bed shortage, which could have biased our results”.[35] Since follow-up information for discharged patients was available, we could include all patients in our studies.

6.1.4 Choosing and defining a proxy-crowding measure

In section 2.3.1, I decided to use the American definition of crowding as the situation when “the need for emergency services exceeds available resources.”[7] I also added that we should view crowding as a continuous variable and not a binary state. Even with this definition, crowding is still an intangible concept. It is necessary to define a proxy-variable that indicates crowding's presence to be able to study it.

From queueing theory, we can learn that ED census and ED LOS type metrics increase as demand exceeds capacity, so these are obvious candidates. Another option would be to use an indicator of overflow in the system, for example, ambulance diversion.[15] Additionally, we could measure the perception of crowding among the ED staff.[84] Finally, a composite multivariable measure like EDWIN,[85] NEDOCS,[85], SEAL[86], or new, more advanced measures based on machine learning could be developed.[116] All measures have benefits and drawbacks as listed in table 15.

Table 15. Benefits and drawbacks of different types of crowding measures

Type of measure	Benefit	Drawback
ED census	• Easy to understand • High availability in EHR systems • Can be measured in real-time to develop early warning systems	• Do not capture differences in case-mix • Natural variation during the day and within the week • Depends on the size of the ED
ED LOS	• Captures case-mix difference to some extent • High availability in EHR systems	• Sometimes difficult to understand. The Individual ED LOS cannot be used as it would introduce a high level of confounding-by-severity, so the measure becomes a bit more complicated. • Lagging indicator, so it can not be used in real-time • Depends on the structure of the ED
Staff perception	• Easy to understand • Has the potential to capture the complexity of crowding as it factors in multiple dimensions	• Subjective measure, challenges with interrater reliability, and that physicians and nurses experience crowding differently • Requires a manual collection of data, do not scale and therefore low availability • Can not be used in real-time
Ambulance diversion	• Easy to understand • More objective measure than staff perception • Has the potential to capture the complexity of crowding as it factors in multiple dimensions	• The level of ambulance diversion is very different in different healthcare systems
Composite measures	• Higher precision than a single metric • Can be used in real-time to develop early warning systems • Can be made objective if derived from an objective measure of crowding	• Difficult to understand, • No transparency, “black-box” system • Higher data requirements, may need prospective data collection or advanced EHR-systems. This makes it difficult to collect large amounts of data historically and across different hospitals

This thesis's primary purpose is to investigate the association between the crowding and bed occupancy measure and a rare outcome, so a critical parameter is the availability of many historical observations across multiple EDs. This rules out measuring staff perception and composite measures due to data availability. Ambulance diversion is used very conservatively in Sweden, so there are not enough ambulance diversion periods available to be useful. These conclusions leave measure based on ED LOS and ED census, which is also the preferred choice of many of the prior studies investigating the association between crowding and mortality (Table 16)

Table 16. Crowding exposure definitions in selected studies

Author	Type of measure	Definition
Af Ugglas et al Study II and IV	• ED census • ED LOS	• The primary exposure in both studies was defined as the mean hourly ED census during the shift that the exposed patient arrived, divided by the expected ED census for this shift. The expected ED census was estimated using a separate linear model for each hospital with year, weekday/weekend, and shift as predictors. • In the sensitivity analysis of Study II, the exposure was defined as the mean length of stay for all other patients arriving during the same shift as the exposed patient, divided by the expected mean length of stay for these other patients. The expected length of stay for the other patients is estimated using a linear model with hospital, year, shift, age, sex, triage priority at arrival, arrival mode, and chief complaint as predictors.
Berg et al	• ED LOS • ED census (EDOR)	• ED LOS was defined as the mean length of stay of all patients presenting at that ED during that shift and had the same triage acuity level. Exposure was categorized in 1h intervals • ED census was defined as the average number of patients during the interval of each visit, divided by the number of treatment beds (EDOR). Exposure was categorized into quartiles.
Guttmann et al	• ED LOS	• ED LOS was defined as the mean length of stay of all patients who presented at that ED during that shift and had the same triage category (priority 1-3 or 4-5). Exposure was categorized in 1h intervals
Jo et al	• ED census (EDOR)	• ED census was defined as the number of patients at the arrival of the exposed patient, divided by the number of licensed treatment beds (EDOR). Exposure was categorized into quartiles.
Mataloni et al	• ED LOS • ED census	• ED LOS was defined as the ED LOS of the exposed patient. Exposure was categorized into four categories. (<1h, 1-2h, 2-5h, >5h) • ED census was defined as the ED census at the arrival of the exposed patient. The exposure was categorized into three categories (0-75%, 75%-95% or 95%-100%) depending on how ED census compared to the historical distribution of ED census for that ED, and shift (08:00–15:59, 16:00–23:59 or 00:00–07:59)
McCusker et al	• ED census	• ED census exposure was defined as the average daily ED census divided with the average annual ED census at the same ED. ED census was calculated for patients that needed a bed vs. only waiting room separated into two different measures
Sun et al	• Ambulance diversion	• Exposure was defined as the number of ambulance diversion hours during the day of admission of the exposed patient. Days within the top quartile of daily ambulance diversion hours for a specific facility were categorized as crowded.
van der Linden et al	• ED census (EDOR)	• ED census was defined as the average number of patients at the arrival of the exposed patient, divided by the number of ED beds (EDOR). EDOR > 1.0 was categorized as crowding
Verelst et al	• ED census	• ED census was defined as the average ED census from the period 4 hours before ED admission of the exposed patient until 4 hours after admission. The exposure was categorized into four quartiles, where Q4 was defined as crowded.

We identified two fundamental requirements that should be fulfilled when choosing the proxy measure of crowding:

1. There should be no link between the exposed patients and the measure of crowding to avoid confounding-by-severity
2. The measure should capture the intraday variation of the exposure and handle natural variations of the exposure that is not related to crowding

An example of a breach of the first requirement would be if crowding were defined as the exposed patient's ED LOS. Since complex patients both tend to have longer ED and higher mortality, it will lead to confounding-by-severity. One example of this can be found in one of the most quoted articles[117] on the association between ED boarding and mortality. The authors acknowledge the problem in their limitations but still conclude that a statistically significant association was identified despite no illness severity adjustments. Great care must be taken when defining crowding exposure as it is easy to introduce confounding-by-severity, which may be challenging to adjust for in the analysis phase.

Despite the random nature of emergency care, the second requirement is also essential as history seems to repeat itself every week. Patient inflow and case-mix together with staffing and mortality outcomes systematically vary across weekdays and hours. However, many of the underlying factors are still unknown.[118, 119] These variations are substantial enough to distort the results, so it is vital to consider these factors' impact carefully. For ED census type measures, the number of patients is generally at the lowest level when the day shift starts in the morning and increases through the day and evening shifts until it declines again. This recurring intraday variation is often higher than the variation between days[120], so we want to capture this effect in our proxy-measure of crowding. Additionally, both ED census and staffing are typically lower on weekends than during weekdays.

Another example from Study I is the 24-hour pattern for bed occupancy resulting from the ED's inflow patterns, the time it takes to perform the diagnostic work in the ED, and the fact that ward discharge rounds mainly occur during office hours. This natural cycle has a peak in the morning just before the first discharges are completed and then declines during the day until 4 pm when ED arrivals are gradually admitted until the next day. In Study I, we choose to define the exposure as the average bed occupancy during the 24 hours before the arrival hour to remove the effect of this considerable but expected diurnal variation and adjust for weekday/weekend. Sensitivity analysis was also performed with a definition of the exposure that used the bed occupancy at the time of arrival and then adjusted by arrival hour in the statistical model.

Our primary crowding measure in studies II and IV was based on the ED census. It was inspired by the measure used by Mataloni et al. Both measures are similar in that they compare the current ED census to the historical distribution of that specific ED and shift. This construction means that both measures take the natural variation of ED census between shifts into account. Still, our measure also differentiates between weekdays and weekends since the ED census usually is lower on weekends. Another improvement that we introduced was that Mataloni et al. uses the ED census at arrival. In contrast, we use the average hourly ED census and predicted ED census during the duration of the ED visit of the exposed patient. The definition makes our measure slightly more complex to understand but gives a more accurate time-match between when the exposed patient was present in the ED and when the ED was crowded.

In Study II we also used a secondary measure of crowding for sensitivity analysis. It is based on ED LOS and builds on the measure introduced by Guttmann et al. The innovation in Guttman's calculation is that it uses the ED LOS for the other patients arriving at the same shift, not including the exposed patient. The link between the exposed patient and the crowding measure can then be broken, and the first requirement is fulfilled. Based on this, We developed the definition further to improve comparability between different types of EDs, and account for natural variations in ED LOS due to case-mix. The downside is that it is relatively complex to understand.

6.1.5 Categorization of crowding

We hypothesize that the association between crowding and mortality is not linear and that the risk of increased mortality is only present at the highest levels of crowding. The most common threshold used in previous studies is to define crowding as the top quartile of exposure.[15, 18, 112-114]

In Study I, we found increasing point estimates only in the top 1% of visits, so we also wanted to include a category for very high crowding levels. The problem with defining an extreme category is that it requires so many observations to get enough power. Our assumption was that the 95% threshold used by Mataloni et al[114] would strike the right balance between capturing very high levels of crowding while still including enough observations. In the study by Guttmann et al[12] we identified a potential concern that the reference category represented an ideal and not a normal situation in the ED. The reference category included only less than 5% of the patients that arrived during a shift where the mean ED LOS was less than 1 hour. The calculation of mean ED LOS did not include the exposed patient in this study. However, we see a risk that these ideal work-shifts could only achieve such performance if there were no or very few complex or high severity patients in that work-shift. Besides, the relative risk ratios become inflated and difficult to interpret. We choose to define the reference category as the three lowest quartiles of the exposure to represent normal working conditions in the ED.

6.1.6 Adjusting for the severity of illness, and other patient characteristics

Even if it is possible to reduce a lot of the confounding-by-severity through a careful definition of the exposure and by adjusting for time, there may still be confounding due to the severity of the exposed patient's disease and other patient characteristics. For Study I, we included many detailed patient characteristics but did not see any impact of the socioeconomic variables, so they were removed for Study II. In this study, the conclusion was that the model did not perform better when including the historical information on comorbidities and prior hospital admissions. This conclusion opened an opportunity to perform Study IV, leveraging the SVAR national register that did not include this historical information (Table 17). The finding that the patient's medical history does not impact the model makes sense. Even if the patient background and history are associated with the mortality outcomes, it is not necessarily associated with the crowding exposure. Patients seek care independent of when the ED is crowded since they are generally not aware of the ED situation when seeking care, and the decision is more based on an urgent need for care.

Our cohort studies' included detailed patient information like EMS arrival, triage priority, and chief complaint. Furthermore, we also had information on other more long-term indicators of the severity of illness. This means that we could better control for confounding than the studies we judged had the highest quality, as shown in Table 17.

Table 17. Patient characteristics included in statistical model of selected studies

Patient characteristics	Study I	Study II	Study IV	Guttmann[12]	McCusker[14]	Sun[15]
Age	Yes	Yes	Yes	Yes	Yes	Yes
Sex	Yes	Yes	Yes	Yes	Yes	Yes
Arrival by EMS	Yes	Yes	Yes			
Triage priority	Yes	Yes	Yes	Yes		
Chief complaint	Yes	Yes	Yes	Yes	No, but final ED diagnosis	
Comorbidities	Yes	Yes			Yes	Yes
Prior hospital admissions	Yes	Yes		Prior ED visits	Health service usage incl mental health and long-term care	
Socioeconomic factors	Education and marital status			Income and community type	Socioeconomic factor and community type	White or non-white

6.1.7 Managing seasonality effects and differences between EDs

The Danish study on bed occupancy[35] adjusted for 3-year periods and calendar month. This is the most common method to handle seasonality, and similar approaches to introduce a covariate for month or season is used in high quality articles of crowding.[12-15] This takes care of the bulk of seasonal variation but there are potential solutions to improve this further.For example, the influenza season typically leads to increased hospital resource utilization and higher mortality and do not always occur during the same months every year. At the beginning of Study I, we identified the potential effect of the flu-season. We started to gather information on the historical number of laboratory-confirmed cases to create a dummy variable that we could include in the statistical model. However, when analyzing the historical bed occupancy, we found recurring patterns with lower bed occupancy but higher average mortality proportion during Christmas that were large enough to impact the result. We also identified repeated trends in bed occupancy during the summer holidays, so we realized that there could be other unknown seasonality effects.

After discussions with our statistician, we decided on the survival analysis method used in studies I, II, and IV. The Cox proportional hazards model stratified by hospital can handle both known and unknown seasonality effects since we have chosen the calendar date as the underlying time dimension. Using the calendar date, we can ensure that "risk sets had comparable exposure information, that is, within a risk set, exposures were drawn from the same calendar period." [121] Additionally, the stratification allows for independent baseline hazards between hospitals but assumes that the HR is the same for all hospitals. The advantage is that the model controls for both known and unknown seasonality effects and acknowledges that hospitals may have different conditions (i.e., competence, processes, and case-mix) and different baseline risk.

The downside is that there is a potential dilution of the true association. However, we agreed it was a fair price to pay to have risk sets that included patients from the same calendar period and allowed the baseline risk to differ between hospitals.

6.2 LIMITATIONS

A significant limitation in all the four studies in this thesis is the choice of retrospective study designs that limit our ability to infer causality. Given the retrospective study designs, the primary challenge is designing the studies to avoid confounding. For the analyses of demand and capacity imbalance and mortality, the most important type is confounding-by-severity, where the exposure is associated with the severity of the patient's illness. We have been cautious about defining the proxy-measures for crowding and hospital bed occupancy (exposures) so that this effect is as limited as possible. Furthermore, we have adjusted for factors known to be potential confounders, but there may still be residual confounding.

Ideally, we could have performed intervention studies to investigate differences in mortality. However, from a time and resource perspective, it was not possible. Interventions would require large operational changes in the ED and hospitals and require additional resources that would be very difficult to secure. The COVID-19 situation during the spring of 2020 presented an opportunity to study how rapid operational changes impacted the ED and the hospital in Study III. The study design was again retrospective. In this case, we were in a very stressed situation where our focus had to be on staffing and delivering quality care instead of designing and performing a prospective study.

The difficulty in performing large scale interventions seems universal. We could only find one large intervention study where the hospital bed occupancy was lowered, and crowding and mortality changes were evaluated.[122] However, the study had limitations as it used a before-after design and did not fully adjust for potential case-mix differences.[37] The learnings and conclusions of this thesis may lead to increased awareness and interest and may open opportunities for more demanding intervention studies.

All the studies are based on existing data from EHR-systems, which results in some limitations. Manual registrations could be incorrect, or the registration could be delayed, which could impact timestamps. Since we have included multiple hospitals, there could be differences in how data is defined in the different EHR-systems. For Study I-II in Stockholm, all hospitals are using TakeCare except one that uses Cambio Cosmic. Study III is a single-center study, and Study IV uses the national register SVAR that has tried to standardize data definitions. However, there is still a risk of bias due to incorrect data or differences in definitions across included hospitals.

As stated earlier, the study of demand and capacity imbalances and mortality requires large amounts of data to get enough power. Even with the large amounts of data that we had access to, there is a risk of false-negative results. We tried to avoid this by performing a power analysis and designing the study accordingly. A large number of observations may also increase the risk of false-positive results that could come from "fishing" after associations. We have tried to avoid this by defining our research questions prospectively and have limited the number of further subgroup analysis not required for answering the main research question. The p-value for statistical significance was also set to 0.05 a priori.

The large amounts of data require strong data management, and mistakes when writing the program code are possible. We reduced the risk through continuous logical testing of the data to check that known associations were preserved. For example, the variables age, and triage priority, should both be associated with mortality. These are elementary examples, but we have performed many similar tests continuously to ensure the data's integrity. There is also a risk of coding errors in the statistical analysis. To avoid this, we performed code reviews where a separate investigator analyzed critical parts of the program code.

In three of the four studies, we focus on the associations between hospital bed occupancy and crowding with mortality. Even if we do not find an association with increased mortality, there may still be many other adverse outcomes that impact patients and the staff. Even if mortality is a rare outcome following ED care, we choose to focus on mortality, which is well-defined and meaningful.

Our choice to define crowding as a relative scale and not a state is a limitation in our findings' practical value. Ideally, we would have identified an absolute threshold where crowding was associated with higher mortality, valid across EDs and over time. Further research evaluating several different definitions of crowding similar to the recent work by Jones and van der Werf[13] would be valuable.

6.3 FINDINGS

In the following sections, the four studies' most important findings will be discussed for each specific aim in the thesis.

6.3.1 Thesis aim #1 – bed occupancy and mortality

Study I included ED visits in Stockholm county during 2012-2016 and did not find evidence of a direct association between hospital bed occupancy and mortality following an ED visit. There was an elevated but non-significant HR estimate with 95% CI of 1.10 (0.96–1.27) in the highest category of bed occupancy >104%. However, the analysis lacked power, and the confidence intervals were wide as there were too few deaths in this category.

These results were not in line with two prior studies. A Danish study[35] identified a significant association between average ward bed occupancy for individual medical wards during the first 24 hours after admission and 30-day mortality in a large cohort of 2.7 million hospital admissions. The Danish emergency care system was different from in Sweden and many other countries with large EDs. Patients were admitted directly from primary care and urgent care centers to the medical wards, so results are not entirely comparable. Boden et al.[21] performed a before-and-after study, where a UK District General Hospital lowered the medical bed occupancy through several interventions and identified significant reductions in mortality and improved adherence to the 4h-target in the ED. It is the only study of a deliberate intervention of the bed occupancy level, but the study design could not fully adjust for case-mix differences.[37]

Since Study I was performed, the hospital bed occupancy[39] in Stockholm has increased from 94% in the study period 2012-2016 to 103% in 2018 and 104% in 2019. The results may have been different with more recent data.

Altogether, a relative difference in hospital bed occupancy may not be directly associated with increased mortality. The indirect effects of a high hospital bed occupancy will be discussed further in section 6.3.3

6.3.2 Thesis aim #2 – bed occupancy and crowding

In Study I, we evaluated ED LOS in six of the seven EDs in Stockholm county 2012-2016 for different hospital bed occupancy levels. All hospitals showed increasing ED LOS with higher hospital bed occupancy. Each 10% increase in bed occupancy was associated with a 16-minute increase in ED LOS for all patients. In contrast, the estimate for admitted patients was 28 minutes, indicating increased crowding levels with higher hospital bed occupancy.

In Study III, the mean ED LOS in different phases in the development of the first wave of COVID-19 was analyzed. Despite having very few observations, there was still a statistically significant association between the bed occupancy in the emergency wards and ED LOS with an estimated correlation of 0.94 (0.55 – 0.99) with a p-value of 0.005

The apparent association between hospital bed occupancy and ED LOS was expected and in line with the previous research[123]. There seems to be clear evidence of the importance of the output dimension of crowding,[79] and the impact on the patient flow when operating above optimal levels of the hospital bed capacity.[124]

In summary, a higher hospital bed occupancy is associated with increased crowding.

6.3.3 Thesis aim #3 – crowding and mortality

In Study II, we investigated the association between crowding and mortality in all seven EDs in Stockholm county 2012-2016. We identified an 8% increased risk of mortality in the high category of crowding, including the top 5% of patients that were most exposed to crowding. The association is in line with previous findings in similar multicenter studies.[12, 14, 15]

However, in Study IV, the results were different. In the overall analysis, including visits from 14 EDs during 2015-2019, the association was only statistically significant for 7-day mortality, but not for the outcome 30-day mortality. The mixed results were likely due to a difference between the counties. Subgroup analysis showed apparent results in Stockholm with a 6% higher risk, HR (95% CI) of 1.06 (1.01-1.12) in the moderate category of crowding and 11% higher risk, HR (95% CI) of 1.11 (1.01-1.22) in the high category of crowding for admitted patients. In Skåne, the results were mixed, and in Östergötland, there were no signs of an association between crowding and mortality.

It seems that the associations between crowding and mortality vary by hospital, and it is not universal. The lack of association can also be seen in two single-center studies from Belgium[18] and the Netherlands.[115] The absence of an association in some EDs is very promising, indicating that the association between crowding and mortality may potentially be avoidable.

Noteworthy is that Stockholm also had the highest hospital bed occupancy with an average of 101% during the study period in Study IV (2015-2019). The bed occupancy can be compared to Skåne that had 92% and mixed results on the association between crowding and mortality, and Östergötland, with the lowest bed occupancy of 81% that did not have any association.

Furthermore, Stockholm results in Study IV can also be compared to Study II that used the same methodology and included visits from 2012-2016. In the earlier period, the bed occupancy was 94%, and the increased risk of mortality within 30 days was 8% in the high category of crowding, including all patients. In the later period with higher bed occupancy of 101%, the increased risk was 6% already in the moderate category of crowding and 8% in the high category.

I cannot draw any firm conclusions from these few observations. Still, it seems plausible that there is an interaction where a high hospital bed occupancy reinforces the association between crowding and mortality. The lower bed occupancy in Skåne and Östergötland may function as protection, limiting the most dangerous consequences of crowding. The mechanism could be that there is a higher likelihood that you have access to inpatient beds and can avoid boarding very sick patients in an overloaded ED in these counties.

Recent research from France and New Zeeland also indicates that boarding is associated with higher mortality risk. Boulain et al. [81] used propensity-score matching to manage confounding-by-severity and showed that patients experiencing a boarding time longer than four hours were at increased risk of in-hospital death. Jones et al.[13] studied a large cohort including ED visits from over 2 million individuals in New Zeeland and assessed different crowding and boarding definitions to evaluate the association with 7-day mortality. They found that the proportion of patients with an admission decision and extended ED LOS over eight hours at the at the time of arrival of the exposed patient had the strongest association with increased mortality among the different crowding measures. Together, these two studies also point towards the importance of the output dimension and that the access to inpatient beds may be critical in the association between crowding and mortality.

The association between crowding and mortality varies by hospital, and there are statistically significant associations in some, but not all. Since the association is not universal, it may potentially be avoidable. Access to inpatient beds is vital for ED patients in need of inpatient care. There are signs that a high hospital bed occupancy may modify and reinforce the association between crowding and mortality. This potential interaction is an important area for future research.

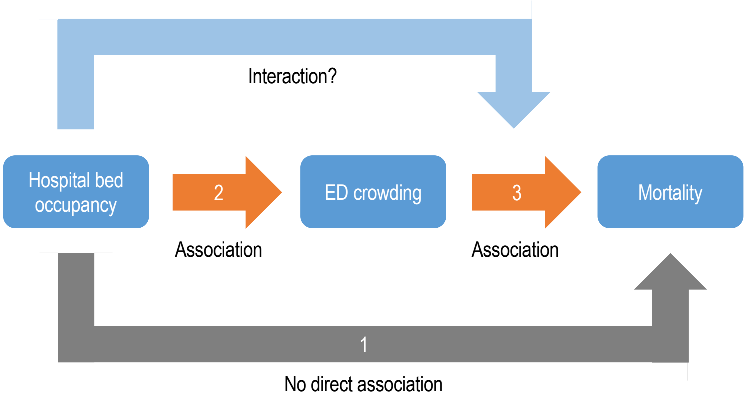
7 CONCLUSIONS

We performed three large retrospective cohort studies, including over two million ED-visits in each, together with a descriptive study of the developments during the first wave of COVID-19 at a university hospital. My conclusion of our findings is that:

1. a relative increase in the hospital bed occupancy is not necessarily associated with increased mortality among patients seeking care at the ED.
2. a relative increase in hospital bed occupancy is associated with additional workload and increased crowding in the ED.
3. the association between crowding and mortality varies by hospital, and there are statistically significant associations in some, but not all. Since the association is not universal, it may potentially be avoidable.

An additional finding is that there are signs that a high hospital bed occupancy may modify and reinforce the association between crowding and mortality. If this would be the case, patients exposed to a combination of boarding and crowding may be at risk of poor outcomes. Investigating outcomes and mechanisms for this patient group should be a priority in future research.

Figure 9, Conclusions



8 POINTS OF PERSPECTIVE

Research of organizational and process-related exposures and clinical outcomes using established epidemiological methodologies is an important research area with great potential to improve current practices in healthcare delivery. One key enabler is access to a considerable amount of high-quality data from multiple hospitals. The SVAR register used in Study IV is promising and contains the essential data required for EDs in Sweden. However, the national coverage is still too weak. A mandatory national quality register for emergency care would enable researchers and authorities to improve the quality of research and develop better methods to follow up the delivery of emergency care to drive improvements in quality and patient safety.

The recent research by Boulain et al. [81] and Jones et al.[13] show that boarding is an important area for future studies. In this thesis, I argue that there are signs of a potential interaction between hospital bed occupancy and the association between crowding and mortality. Based on this, I believe that it should be a priority to investigate the outcomes and clinical mechanisms for patients with an admission decision, that are exposed to boarding during work-shifts when the ED is simultaneously operating at high levels of crowding.

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