Ambulance Offload Delay and the Offload Zone:
An Empirical Analysis of the Effectiveness of an Offload Time Reduction Effort

by

Molly Elliott

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DEDICATION

I dedicate this work to everyone in the healthcare industry who chose such a demanding and stressful career because they believed in making the world a better place. Their selfless commitment inspired me to push through the challenges of academia to complete my own contribution to the field.

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ABSTRACT

When ambulances arrive at a crowded emergency department (ED), paramedics must wait with the patient until ED space opens, causing offload delay and reducing the number of ambulances available to the community. An Offload Zone (OZ) is a monitored waiting space for ambulance patients, designed to reduce offload delay and allow ambulance crews to return to service more quickly. The implementation of OZ-style concepts has been trialled around the world, but it is not clear why these efforts often have mixed results. In this analysis, data reflecting patients' journeys through the ED are analyzed to show how the OZ affects the ED as a system and patients as individuals. Data from two hospitals in Halifax, Canada are contrasted to highlight differences in their OZ implementations and results. This study finds that these hospitals reduced offload delay to a certain extent, and identifies systemic factors that can lead to OZ issues.

LIST OF ABBREVIATIONS USED

AOD	Ambulance Offload Delay
CAD	Computer Assisted Dispatch
CTAS	Canadian Triage and Acuity Scale
DGH	Dartmouth General Hospital
ED	Emergency Department
EDIS	ED Information System
EHS	Emergency Health Services
EMS	Emergency Medical Services
ePCR	Electronic Patient Care Record
LWBS	Leave Without Being Seen
MD	Medical Doctor
MIN	Master Incident Number
OZ	Offload Zone
QEII	QEII Health Sciences Centre
RN	Registered Nurse

GLOSSARY

Boarding: A situation where admitted patients remain in the ED because there are no appropriate inpatient bed spaces available.

Canadian Triage and Acuity Scale: A standardized sale for measuring the seriousness of an emergency patient's condition, where 1 is the most severe and 5 is the least severe.

Crowding: A situation where the demand for emergency services exceeds available resources for patient care.

Clinical impression: The general category of illness/injury with which a patient presents.

ED length of stay: The time interval between a patient's arrival to and departure from the ED.

Emergency Health Services: The name of the paramedic service provider for Nova Scotia.

Emergency Medical Services: A generic term for paramedic services.

Offload: The transfer of care of an emergency patient from the paramedics to the ED staff.

Offload delay: The period of time taken for a patient's offload beyond the targeted benchmark for offload time.

Offload time: The time interval between a patient's arrival to the ED and their offloading from the ambulance.

Patient-level comparison: A term used in this paper to refer to the comparison between patients who pass through the OZ and those who do not. This type of comparison uses only data from periods when the OZ is open.

Time to ED bed: The time interval between a patient's arrival to the ED and their reaching an ED bed. For this measure, an OZ bed does not qualify as an ED bed.

Time to MD: The time interval between a patient's arrival to the ED and their first contact with a physician.

Unit-level comparison: A term used in this paper to refer to the comparison between time periods when the OZ is open and when it is closed.

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CHAPTER 1 INTRODUCTION

Ambulance offload delay (AOD) occurs when patients arriving at a hospital are not transferred to the emergency department (ED) in a timely manner, forcing the ambulance to stay and monitor the patient until they can be admitted.

AOD has become increasingly prevalent in urban centres across Canada. A 2023 report by the Office of the Auditor General of Nova Scotia states that province-wide average ambulance response times increased from 14 minutes in 2021 to 25 minutes in 2022. They cite offload delay as one of the main causes, noting that in 2022 paramedics spent on average a quarter of their working hours waiting to offload patients.

In Canada's larger urban areas, this problem is not new, for example in Toronto where the average offload delay was reported to be between 3 and 8 hours in 2007 (Almehdawe, 2012). Recently the phenomenon has become more widespread, with reports of increased offload time in British Columbia due to shortage of ED beds and in Saskatchewan due to pressures from the COVID-19 pandemic (Bain et al., 2022).

Statistics from across the USA reveal that the national average for waiting time before paramedics are able to hand off their patients grew from 20 minutes in 2006 to 45 minutes in 2014, representing a loss of nearly 5 million hours of Emergency Medical Services (EMS) productivity. In California, it was found that hospitals serving a larger population are more likely to report AOD as a significant problem (California Hospital Association, 2014).

The problem exists outside North America as well. An Australian study (Cone et al., 2012) found that 17.5% of ambulance patients experienced AOD, with patients in large cities or in transport to large hospitals, or those over 65 years old, being more likely to experience delays.

AOD has a range of potential consequences on the medical system, both clinical and systemic (Schwartz, 2015). For EMS, it can lead to decreased ambulance coverage and longer response time for other calls, as well as additional time required by administrators and supervisors to reorganize resources. Many EMS systems have a contractual performance standard for response time, so AOD can incur costs through fines and penalties or through extra measures such as hiring more staff to keep response times at required levels (California Hospital Association, 2014; Cooney et al., 2011).

A review of studies concluded that delays can compromise access to care, quality of care, and patient outcomes, especially for vulnerable populations such as racial and ethnic minorities (McHugh, 2013). More specifically, negative patient outcomes may include delay to treatment, poorer pain control, and increased morbidity and mortality (Cooney et al., 2011). The wide-reaching effects of AOD have led to it being regarded as an important marker of ED performance and quality (Cooney et al., 2013).

Perhaps the most important consequence of AOD has been the increasingly common phenomenon where a region's entire fleet of paramedic crews becomes occupied, either with active responses or due to being tied up in AOD, and subsequent emergency calls cannot be quickly responded to. Such events are on the rise in many places where AOD is a problem, for example in Ottawa, Canada, where the incidence of "level zero" events doubled from 2021 to 2022, and the city averaged 203 minutes per day in 2022 with no crews available (Porter, 2023). It can be difficult to empirically measure the outcomes of such events, since patients are often waiting at home outside of the clinical setting, but there are many news reports covering some of the worst consequences of delayed emergency responses. In Nova Scotia, there have been reports of a death while awaiting an ambulance at the patient's home (Gorman, 2021) and at a rural hospital awaiting an ambulance transfer to a larger hospital (Gorman, 2019). In Montreal, a woman died after waiting 7 hours for an ambulance (Haines, 2022). Jolly (2023) profiles four cases across the UK occurring in a span of five weeks where patients died at home or in hospital following waits of 1.5 to 16 hours for ambulances, also noting that the Royal College of Emergency Medicine estimates between 300 and 500 people per week across the UK are dying as a result of delays and issues in emergency care. An independent investigation in the city of Victoria, Australia found at least 33 cases in 18 months where patients' deaths were linked to delayed ambulance responses (Brown, 2022).

To reduce AOD, a dedicated and monitored "waiting room for ambulance patients" has been trialled to act as a buffer between EMS and the ED. Although the implementation is somewhat different in different regions, the goal for the buffers is the same: to have patients wait with ED medical personnel instead of with the ambulance crew, allowing the ambulance crew to return to service sooner. The Ministry of Health and Long-Term Care in Ontario, Canada hired dedicated offload nurses to monitor low-acuity ambulance patients while they wait for an ED bed (Newell et al., 2013). An offload nurse was used on a trial basis in Australia in 2012 (Greaves et al., 2017). In Halifax, Canada, the Capital District Health Authority (previously an independent healthcare district, but since assimilated into the Nova Scotia Health Authority) and the local paramedic provider trialled a waiting area known as the "offload zone" (OZ) in the municipality's two largest EDs. Detailed patient flow information for Halifax's OZ concept is available from Carter et al. (2015).

The effectiveness of OZs and offload nurses at reducing AOD remains an open question. A trial reported by Greaves et al. (2017) in Australia found it to have only marginally reduced AOD. Carter et al. (2015) found that the OZ in Halifax is often at capacity, hindering its effectiveness. They reported that "one unexpected finding of the process map was that the real-life functioning of the OZ deviated significantly from the original protocol." Similarly, Laan et al. (2016) reported that when EDs lack incentive to admit patients from the OZ, AOD will not be improved. In contrast, Clarey et al. (2014) examined ambulance turnaround with discrete event simulation which demonstrated a clear reduction in AOD when dedicated nursing levels are increased. However, the authors also reported that this would require unacceptably low staff utilization in practice.

The goal of this study is to provide an empirical analysis that assesses the effectiveness of a real-world trial of the OZ, and contribute to the body of work seeking to understand what factors cause issues with the OZ in practice. This thesis examines the OZ as used by two EDs—Dartmouth General Hospital (DGH) and the QEII Health Sciences Centre (QEII)—in the urban region of Halifax, NS. Together they serve the municipality's population, which was just under 400,000 at the time of this study. QEII is a larger facility and is closer to the downtown core, and so serves more emergency patients. In 2013, QEII fielded around 12,000 ambulance arrivals and 58,000 walk-in ED patients, while DGH fielded around 6,000 ambulance arrivals (walk-in data were unavailable). A third ED exists in Halifax at the IWK Health Centre, for children 16 years or younger, which was not part of the study. These two hospitals have the two highest figures for average offload delay in the province, according to the most recent statistics (Office of the Auditor General of Nova Scotia, 2023): 195 minutes at QEII and 170 minutes at DGH.

The other healthcare provider involved in the offload zone concept is Emergency Health Service (EHS). EHS is Nova Scotia's ground paramedic service, serving a catchment area of 55,000 square kilometres and a population of nearly 1,000,000 at the time of this study. The province contains a mix of urban, suburban and rural regions. The annual 9-1-1 emergency call volume was approximately 132,000 in 2012. A staffing mix of primary, intermediate, and advanced care paramedics work in the ground ambulance system in a single agency.

The analysis is designed to examine the treatment processes and time benchmarks for patients arriving to the ED by ambulance, to determine how the OZ is used and what its effects are. The concurrent comparison is completed using statistical analyses and one year of historical data from two hospitals. The OZ would most often be open during the daytime, however, there were times that it could not be opened as scheduled due to staffing reasons, forming a natural comparison. The first major comparison group is between periods when the OZ is open versus periods when it is closed, to reveal the OZ's systemic effects. The second major comparison group is between patients in the OZ versus those outside of it, to reveal the OZ's individual patient effects. Further comparisons stratified by systemic and demographic variables are explored.

In this thesis, Chapter 2 reviews further literature related to AOD and efforts to reduce it. Chapter 3 introduces the data and the methods used in this research. Chapter 4 presents numeric results and discusses their interpretation. Chapter 5 provides further discussion and conclusions.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This literature review's purpose is to describe the phenomenon of offload delay, overview some relevant research studies on the subject, and highlight the need for further research on the Offload Zone. Ambulance offload delay itself is examined, in terms of its causes, effects, and possible solutions, to provide context. Because the process mapping and statistical analyses of this thesis are intended to contribute to the future development of operations research studies and tools, the application of operations research on offload delay is also reviewed, with a focus on queuing theory and simulation. One queuing model and one simulation model are found to be of particular interest with respect to the Offload Zone's functioning.

AOD is an emergency health phenomenon where ambulance patients arriving at the hospital are not able to be offloaded and transferred to the ED within the designated time, typically due to hospital congestion, forcing the ambulance to wait and monitor the patient until they can be accepted. One proposed solution to this problem is the use of an OZ, an area where a number of offloaded patients can be supervised by dedicated staff while they await admission. Since the OZ's initial trial in Halifax, Nova Scotia, a few studies have assessed its functionality. This literature review provides context for the AOD problem and review relevant research on the topic, to reveal the need for an empirical analysis of data from the OZ's trial period.

In subsection 2.2, AOD itself is examined. Its causes and some previously attempted or suggested solutions are outlined to provide context for the discussion of research. Particular attention is paid to ED crowding as a cause and ambulance diversion as a solution, due to their complex relationship with AOD. Previous solutions using patient consolidation tactics which set the stage for the OZ's conception are described. The two completed studies on Halifax's OZ are described, indicating the need for further research on the program. A program similar to the OZ that was trialled in Australia is also highlighted.

In subsection 2.3, the application of industrial engineering tools to the AOD problem is reviewed. After brief discussion of applications in healthcare as a whole, focus narrows to AOD, crowding, and diversion. Detailed discussion is provided for two studies that were found to be of particular interest for this review.

Finally, subsection 2.4 summarizes the main body of the review, concluding that empirical analysis of Halifax's OZ is needed to better understand its impact, that the results would constitute a benefit to Halifax's EDs and other emergency health systems, and that the study will contribute to future work in OR applications on the subject of AOD reduction.

2.2 Ambulance Offload Delay

AOD is generally defined as time that passes between the targeted time limit for patient offload and the actual time that their transfer of care (TOC) occurred. According to Schwartz (2015), the point of TOC of a patient from EMS to the ED staff was initially not defined, as it happened intuitively and almost always within minutes of arrival at the hospital. It was often marked by either the patient's removal from the ambulance stretcher and a verbal report by the paramedic, or the beginning of the ED staff's procedures on the patient. A formal definition of the point of TOC was not considered until AOD began to emerge as a problem (Schwartz, 2015). Even now that international attention is being given to AOD (Cooney et al., 2013), attempts at defining TOC have been met with resistance from both sides. The definition is often flexible, which can lead to conflicting interpretations and disagreements over who is responsible for a patient at a given time (Schwartz, 2015).

The standard for offload time can vary by hospital, but is generally set at 30 minutes in Canada (Cooney et al., 2013). Exceeding this threshold implies that ambulance offload delay has occurred.

Before discussing the current state of OR work on AOD, it will be beneficial to provide context by examining the causes behind it and the solutions that have already been tried or suggested, including several programs similar to the OZ.

2.2.1 Causes

AOD is not an isolated issue, but a symptom of a larger problem, involving multiple interconnected phenomena including ED crowding, ambulance diversion, ED boarding (a term referring to admitted patients remaining in the ED because there are no appropriate inpatient bed spaces available), and obstructions in hospital throughput (California Hospital Association, 2014; Cooney et al., 2011).

AOD has been called an "inevitable consequence" of crowding (Schwartz, 2015), and ability to offload is regarded as the best proxy measure for crowding (Beniuk et al., 2011). The two problems are tied together in a complicated way: ED crowding as measured by the National ED Overcrowding Scale has been found to be predictive of AOD (Cooney et al., 2013), while AOD has been found to be a strong predictor of an ED length of stay longer than 4 hours (Crilly et al., 2015), which in turn contributes to crowding (Geelhoed & de Klerk, 2012).

This literature review's focus is on AOD, but given its complex relationship with crowding, it will not be possible to offer a robust analysis of the former without devoting attention to the latter.

ED crowding is "a situation in which demand for service exceeds the ability to provide care within a reasonable time, causing physicians and nurses to be unable to provide quality care" (Canadian Association of Emergency Physicians, n.d.). While crowding causes more delay for low- than high-acuity patients, it is particularly dangerous for critically ill patients, as EDs are designed and equipped for rapid stabilization, not prolonged critical care (Cowan & Trzeciak, 2005). In events where patients are cared for in unconventional places like hallways or waiting rooms, there are usually inadequate facilities to provide high-quality care. Crowding can also lead to stress on caregivers and increased potential for medical error (Canadian Association of Emergency Physicians, n.d.). Some research has found that it leads to delays in treatment for patients with cardiac problems, pain, pneumonia, and other conditions, and AOD may contribute additionally to these outcomes (Schwartz, 2015).

In the 1990s, both decision makers and the public placed the blame for ED crowding and delays on a large volume of low-acuity patients (Schwartz, 2015). While much of the public still believe this to be the case (Canadian Association of Emergency Physicians, n.d.), it has in fact been found that low-acuity patients require few resources, and ED crowding is primarily due to patients who need to be admitted to the hospital but are not able to be moved due to a lack of inpatient beds (Cooney et al., 2011; Cowan & Trzeciak, 2005; Higginson, 2012; Ovens, 2011). In this event, often referred to as "ED boarding," patients may be stuck in the ED for upwards of 24 hours (Cowan & Trzeciak, 2015). The AOD problem arises when the ED is at full occupancy, and staff are unable to free beds to accept new patients. Many ambulance patients do not have severe conditions, which limits incentive to speed up the clearing of occupied beds (California Hospital Association, 2014). This extensive group of problems and chain of causality is present in Canada, the US, and internationally (Schwartz, 2015).

Of course, ED boarding is not the only cause of crowding. A recent multi-stakeholder discussion held by Canada's Drug and Health Technology Agency (CADTH) (2023) identified a number of factors related to ED crowding in the Canadian health system. They identified direct causal factors, which are categorized as being related to input, throughput, or output of patients, as well as additional contextual factors, which may be applicable at the ED level, the hospital level, or the sociocultural level. Causal factors related to throughput include barriers to operational efficiency, staffing considerations, and various types of delays. As CADTH notes, most studies that describe or assess interventions in ED crowding focus on these throughput factors, which tend to be the easiest to impact via policies and procedures within the ED itself. Input factors, such as limited primary care resources in the community, output factors, such as lack of space in inpatient wards, and contextual factors, such as population growth and shift, must be addressed outside the ED or by multiple stakeholders. As a result, the interventions relevant to these factors may be more difficult to put in place or to assess for effectiveness.

Additional factors found to influence ED crowding in settings across the world include: increasing acuity and complexity of medical issues, increasing psychiatric holds due to lack of mental health resources, lack of home-care and long-term care resources, lack of access to specialist care providers, lack of space and equipment, increased documentation requirements, and difficulty in arranging post-ED placement and follow-up care (California Hospital Association, 2014; Canadian Association of Emergency Physicians, n.d.; Schwartz, 2015). Inpatient throughput itself is connected to many other factors as well, including inpatient capacity, nurse-to-patient ratios, hospital regulations limiting areas of care, and ability to rapidly turn over hospital beds (California Hospital Association, 2014).

2.2.2 Practical Solutions to Crowding and AOD

As the AOD phenomenon exists at the intersection of ED and EMS services, both groups need to be involved in determining an effective solution. It is important to note that EDs and EMS providers have individual agendas and incentives that may conflict when it comes to AOD—namely, the ED's lack of space to accept patients versus EMS's need to return to the community (Schwartz, 2015). Henderson (2011) has suggested changing both groups' performance measures and the way they are written into contracts, for more compatible incentives and better cooperation. The California Hospital Association (2014) reports that collaboration between hospitals and EMS is a common factor in achieving low AOD.

If the only way to fully address AOD is with a multidisciplinary, system-wide approach, developed with the involvement of all stakeholders (Cowan & Trzeciak, 2005; Schwartz, 2015), then it follows that a unilateral approach will not be sufficient to eliminate all aspects of the problem. The addition of resources to the ED or EMS may seem like an obvious and tempting tactic, but Henderson (2011) notes that such approaches do not address the downstream issue of inpatient throughput, and will offer only temporary relief. Likewise, any effort to decrease AOD without improving ED throughput will not address crowding (Cooney et al., 2011), and nor will strategizing EMS dispatching, despite its ability to improve ambulance coverage (Henderson, 2011). On the other hand, Crilly et al. (2015) concede that targeted improvements to ED processes may be useful to pursue until a broader systemic approach is developed. Cowan and Trzeciak (2005) agree, suggesting that since ED boarding may take a long time to solve, EDs should meanwhile try to adapt to perform as best they can in their crowded conditions.

One avenue to combat crowding and AOD has been to reduce ED demand. Such efforts have included adding walk-in clinics and urgent care centres to communities to shift demand elsewhere (Schwartz, 2015). A review of studies on community paramedicine for elderly patients (van Vuuren et al., 2021) found evidence that their operation could reduce stress on other parts of the healthcare system, including emergency calls and ED visits. Another review of studies on "telephone triage" (Eastwood et al., 2015) found that while most of the studies focused on validating safety, some showed evidence that telephone triage succeeds in diverting non-emergent patients away from EDs. The authors point to the need for research as to whether this actually translates to reduced ambulance demand. Ambulance diversion—the practice of refusing to accept ambulances and requiring them to divert their course to a different hospital—was first developed as a response to crowding (Lagoe & Jastremski, 1990), but over decades of practice and analysis has come to be seen as a controversial and ethically ambiguous approach (Adkins & Werman, 2015). Due to its relationship with AOD and crowding, diversion will be discussed in more detail in the next subsection.

Some ED-focused AOD reduction measures that have shown promise include overcapacity protocols, streamlining of the ED intake process, and continuous quality improvement (California Hospital Association, 2014; McRae et al., 2012). Some clinical and economic analyses (Baugh et al., 2011; Schreyer & Martin, 2017) have found that a holding unit for low-needs patients (i.e., a buffer between the ED and the inpatient unit) can be an effective approach, and their implementation in EDs has been increasingly common (Mace et al., 2003). A few hospitals have found success in borrowing from manufacturing industries, adapting Lean management tools for use in the ED. Ng et al. (2010) describe using the Toyota Production System to reduce ED wait time without adding beds or funding. Chan et al. (2014) found that a Lean design including priority admission triage, communication enhancements, and the use of a new blood test was able to improve wait times for triage, consultation, and admission. Several hospitals in Toronto, Ontario found that AOD was "largely solved" after implementing some best practice and Lean management measures recommended by an expert panel, including targeted staff increases, process improvements, and culture changes (Ovens, 2011).

Beyond what has been previously assessed in studies such as the above, some other solutions have been proposed and either have not been tried or have not been formally assessed for effectiveness. Some suggestions include expedited discharge of inpatients, and planning ahead for the needs of patients who are awaiting admission (Cowan & Trzeciak, 2005). Higginson (2012) remarks that while many solutions have been proposed, most have weak evidence behind them, indicating a need for more analytic assessment on the subject.

Ambulance diversion was first reported on by Lagoe and Jastremski in New York City in 1990. They discussed the then-emerging crowding issue (at that time blamed on large numbers of non-emergent patients), and how diversion was conceived to address it by sending low-acuity patients to the less busy EDs in an area even if they were farther away from the patient's pickup point. The practice was widely favoured, and became increasingly common. In some places, it became the go-to strategy for relieving crowding. In 2003, 45% of American EDs had used diversion in the previous year (Handel et al., 2011).

While diversion is indeed effective in short-term relief of crowding (Cooney et al., 2011; Handel et al., 2011), it results in a longer transport time for those who are diverted, and the body of research on the phenomenon has revealed some negative consequences, such as lower quality of care, delays for some types of critically ill patients, and increased death rates from heart attacks (Canadian Association of Emergency Physicians, n.d.; Handel et al., 2011; Henderson, 2011). In light of the true cause of ED crowding—not low-acuity patients, but inpatient blockage—diversion began to see less support as a viable solution (Cooney et al., 2011). In Canada, the end of diversion can be traced to 2001, when new policies were put in place in Ontario following a Toronto asthma patient's death in 2000 after being diverted from the nearest hospital to his home ("Changes to ER procedures", 2001). At the international scale, 2003 was the turning point at which many EDs began trying to reduce the use of diversion, although it has remained in use across the USA, and was still considered a major concern as recently as 2011 (Handel et al., 2011).

However, the criticism of diversion has not been universal—Adkins and Werman (2015) argue that it is a "necessary evil," as the safety considerations of the many patients in crowded EDs outweigh the risks to the few who are diverted. Carmen and Van

Nieuwenhuyse (2014) acknowledge that because crowding and diversion are causally linked and frequently co-occurring, it is difficult to disentangle their respective effects and show conclusive evidence that diversion actually contributes to clinical risks. Some have pointed out the inverse relationship between diversion and AOD: all else being equal, reducing diversion will lead to an increase in AOD (Cooney et al., 2011; Schwartz, 2015). While both types of delay can lead to negative clinical and systemic outcomes, the general opinion of hospital policymakers seems to be that it is better to minimize AOD even at the expense of allowing diversion, because AOD tends to be longer than the additional transport time caused by diversion (Carmen & Van Nieuwenhuyse, 2014; Cooney et al., 2011; Cooney et al., 2013; Henderson, 2011). A recent literature review on AOD-related papers (Li et al., 2019) found that of 89 articles that propose a solution to AOD, 58 suggest diversion as a tactic.

A more recent approach to reducing AOD has been the consolidation of patients under fewer health care providers. Sometimes this occurs on the EMS side, where one waiting paramedic crew will take over a second crew's patient to allow the latter paramedics to leave the hospital and return to service; at other times, it is on the ED side, where designated staff will monitor offloaded patients (Schwartz, 2015). In 2010, the EMS provider in Calgary, Alberta was considering the EMS-side setup, after having tried an ED-side approach some years previously without success ("AHS tackles ER 'offload delays'", 2010).

For the ED-side approach, the typical model is for a nurse and/or paramedic to be placed in the hospital to act as a buffer between the ambulance and the ED. They are tasked with receiving patients from ambulances, which allows the paramedic crew to depart immediately, and monitoring the patients until the ED has room to admit them. The staff may be asked to help with general ED tasks when not busy with offloading duties (Henderson, 2011). In Australia, such a setup was assessed, and it was found that the addition of an offload nurse marginally improved wait time to see a physician (Greaves et al., 2017). Critical to any analysis of this design is whether or not physicians can begin care on patients in the offload monitoring area.

Perhaps the most extensive example of this method is in the province of Ontario, Canada. In 2008, the Ministry of Health and Long-Term Care began the Offload Nurse Program, selecting a number of hospitals across 14 municipalities to receive funding for a dedicated offload nurse (Office of the Auditor General of Ontario, 2012). By 2016, the program had expanded to fund 49 hospitals in 20 municipalities (Ministry of Health and Long-Term Care, 2016). Details like working hours, maximum supervisory capacity, and specific duties were left up to individual regions (Isaacson, 2008; McCallion, 2011; Middlesex County Council, 2015). Some regions, such as Niagara, implemented the offload nurse alongside a range of other new ED measures (McCallion, 2011).

At this time of this literature review, no formal studies of the program had been completed, but various government bodies and media outlets have reported on it, seeming to indicate that its success has varied by location. Most participants saw initial improvements; for example, Hastings and Toronto both observed a 15% reduction in AOD after the first year (City of Toronto, 2009; Hendry, 2012). For some regions, that initial trend continued, like in Ottawa, where there was a 29% reduction from 2009 to 2013 (Ottawa Paramedic Service, 2014). For others, the trend reversed—in Niagara, AOD fell 77% from 2010 to 2014 and then rose 516% from 2014 to 2017 (Forsyth, 2017), and in Waterloo, it dropped by 54% from 2012 to 2013 and rose 99% from 2013 to 2015 (Desmond & Weidner, 2016). In a few unfortunate regions, the program never seemed to work—despite participating since the program's inception, Halton found its AOD steadily increasing to double its pre-program rate by 2014 (Halton Region, n.d.).

In Nova Scotia, the regional health authority took inspiration from these previous attempts to trial a similar program at two hospitals in Halifax starting in 2012. In this version, the OZ is staffed by a dedicated nurse and paramedic, who can together manage up to 6 patients at once (Laan et al., 2016). The OZ was intended originally only for supervision and any necessary emergency interventions, not for assessment or treatment (Carter et al., 2015). Since the trial's conclusion, its effectiveness has only been reported on anecdotally by staff members, but its functionality has been examined in a few studies.

Carter et al. (2015) developed a process map describing the real functioning of the OZ and used it to conduct a hazard analysis. They identified the most important potential failures and recommended actions that may prevent them. The biggest clinical risk was improper care due to lack of equipment. The biggest systemic risk was patients receiving treatment within the OZ, which could delay their entry to the ED, in turn filling the OZ and once again causing AOD. Their results showed that the actual functioning of the OZ differed significantly from the original protocol.

Laan et al. (2016) delved into the systemic issue numerically, with a queuing model designed to find the optimal patient selection criteria for reducing AOD. Their findings showed that in the case of Halifax's OZ, ED beds should be given to OZ patients at least 35% of the time in order for the OZ to have a positive impact on AOD, with diminishing returns above 60%. The results are sensitive to the OZ's capacity and clinical load, in that increased OZ capacity or diminished clinical load will reduce the pressure to pick from the OZ. While these results provide an indication of how the OZ concept needs to be tweaked, an abstract policy of selecting OZ patients a certain percentage of the time may be difficult for ED staff to monitor and enforce.

Acknowledgments of Canada's various forays into this type of program typically come with the criticism that their effectiveness lacks formal evaluation, or have yet to be implemented in a systemic way. (Crilly et al., 2015; Schwartz, 2015). Schwartz does, however, applaud Carter et al.'s (2015) hazard analysis, finding it to be in line with his call for an integrative cross-system approach. However, as the OZ's trial has not yet been empirically assessed for effectiveness, there is still a need for further analysis.

The study most comparable to this thesis (Crilly et al., 2019) performed a retroactive statistical analysis on an Australian offload program trialled in 2012. The main differences between this program and Halifax's program are highlighted in the table below (Table 1). The statistical analysis found modest but significant improvements in offload compliance, time to be seen, and length of stay, noting that less urgent patients had the best improvements.

Table 1 Points of contrast between Halifax and Australia offload program trials

Trial details	Halifax Offload Zone	Australia Offload Nurse
Trial period	1 year	39 days
Operation schedule	Variously open and closed	Open 24/7
Staffing	Nurse and paramedic	Nurse
Treatment intended	Patients intended to be monitored only	Patients intended to begin treatment

2.3 Industrial Engineering Work on AOD

The history of industrial engineering in health systems goes back to the 1950s and 1960s (Ross & Bidanda, 2014). Initial analytic models were quantitative and deterministic, focusing on resource optimization (Romero-Conrado et al., 2017). Decision-making tools were popular, both in hospital (e.g., planning bed numbers, managing medicine inventory) and EMS applications (e.g., choosing base sites, scheduling staff) (Henderson, 2011; Romero-Conrado et al., 2017). By the 1980s, however, it became clear that healthcare was associated with many complex social variables, some of which are not identifiable or measurable, leading to flawed results in quantitative decision-making tools. Thereafter, the more flexible category of decision support systems—tools to help administrators and clinicians make decisions, rather than computer models that make decisions themselves—gained favour, and has become an increasingly significant area of industrial engineering in healthcare (Romero-Conrado et al., 2017)). Another driving force in the evolution of healthcare applications has been the consideration of patient safety, in particular finding a balance of minimizing resource usage while still providing a sufficient quality of care (Romero-Conrado et al., 2017).

The power of industrial engineering techniques has steadily increased alongside improvements in hardware and software technology (Romero-Conrado et al., 2017) and the quantity and quality of available data (Henderson, 2011). Healthcare has always generated a lot of information due to recordkeeping requirements, and its increasing digitization makes it easier for researchers to access it. Data are also being collected from novel sources, such as fitness devices or genetic sequencing, and in finer granularity, thanks to growing data storage capacities, both of which factors will allow personalization of analysis. Some areas with the most potential for improvement through big data analytics include clinical decision support, patient monitoring, predictive analytics, and personalized treatment and medicine, all of which have potential for application in the ED (Raghupathi & Raghupathi, 2014).

More recently, researchers have drawn from across the spectrum of industrial engineering and operations research methods for developing planning and decision support tools related to AOD. Various approaches have been used for making decisions related to ambulance diversion, including Markov decision process (Li et al., 2021) and mixed integer programming (Acuna et al., 2020). Other tools are for prediction and planning, such as a hybrid decision tree algorithm to predict the severity of AOD within the next 1–5 hours (Li et al., 2022) and a machine learning model to predict an individual patient's offload time (Walker et al., 2021).

As noted by Almehdawe et al. (2013), most research on AOD is clinical, covering the importance and implications of the problem. Li et al.'s review (2019) calls for more research in several specific avenues, including system-wide mitigation efforts, addressing root causes of access block, and evaluations of prior mitigation efforts. Despite the wide acknowledgment that inpatient blockage is the primary cause of crowding and AOD, a review of operational research studies on ED flow (Carmen & Van Nieuwenhuyse, 2014) notes that patient discharge is the least studied area for ED improvement, likely because it is not fully within the control of ED staff. This observation hearkens back to the previously cited calls for integrative, multidisciplinary perspectives on the problem. In the course of this review, very few analytic studies that specifically deal with AOD were found, and only two models that resemble the functionality of Halifax's OZ were identified.

There is an established area of study in simulation regarding the use of buffer zones between the ED and the inpatient unit to place patients who no longer need emergency treatment but cannot yet be removed from the ED (Haghighinejad et al., 2016; Hannan, 1975). This is similar to the OZ concept, but in a different place in the system. A study of note is Kolb et al.'s (2008) comparison of various configurations for such a buffer. The buffer types tested are a holding area for patients awaiting inpatient admission, an observation unit for patients expected to need monitoring for less than 24 hours, a discharge lounge for patients waiting for transportation, and some combinations of those three ideas. Their results showed that each type of buffer can improve the system, but that combination buffers were much better than any of the three pure concepts applied on their own. In the context of Halifax's ambulance transfer processes, the patient flows that could be considered buffers include the OZ, the redirection of low-severity patients to wait in the walk-in area, and the ED unit reserved for straightforward and quick-to-resolve issues.

Of all industrial engineering applications identified, queuing theory accounts for the majority of work on AOD. It can be applied widely across the crowding/AOD continuum of issues, for example, in ambulance transfer policies (Hua & Xing, 2021), and in resource reallocation (Liu et al., 2022). Majedi (2008) claims to be the first to have modelled the ED and EHS together to investigate AOD rather than focusing on one or the other. The conceptual model is functionally similar to Halifax's OZ, in that an ambulance in a state of offload delay can begin treating a patient at a rate slower than that of the ED. One of the assumptions made in the study is that if all ambulances are occupied then it is assumed that any emergency calls received are queued until an ambulance becomes free, while in reality such cases are typically handled immediately by a neighbouring EMS provider (Almehdawe et al., 2013). Majedi's model is used for analyzing the nature and sensitivities of AOD. Using assumed parameter values, the inputs for ED capacity, ED treatment time, and number of ambulances are varied. They find that either adding ED beds or reducing ED treatment time results in similar levels of system improvement and AOD reduction. In this model, adding ambulances actually worsens offload delay, because without changing the ED, added ambulances simply move more of the total population of queued patients from the waiting-to-be-picked-up queue to the waiting-in-an-ambulance queue. Although this quirk may simply be a result of the assumption that patients queue for ambulance pickup, the author interprets it to mean that the ED is the bottleneck of the system and that allocation of resources in the ED will go further there than if added to the paramedic service.

The AOD problem can be framed in terms of queuing and simulation as an imbalance in λ (the arrival rate of patients) and μ (the service rate of the ED). In a mathematical model, when $\lambda < \mu$, there will be queues at certain times as a result of fluctuations in arrival and processing rates, but eventually every patient will be processed. When $\lambda \geq \mu$, the queue of patients waiting to be served will inevitably grow unbounded. In the ED setting, λ is a reflection of the combined amount of walk-in and ambulance arrival rates, while μ is primarily related to factors such as the type of conditions that patients present with, the ED staff levels, and the speed at which testing and ancillary services can be returned. ED boarding, while not related to the ED's μ, is blocking that occurs as a result of the μ in downstream parts of the healthcare system.

2.4 Summary and Thesis Positioning

AOD is a serious problem in emergency healthcare, with many clinical and systemic risks. It is increasingly prevalent in Canada and internationally, and will continue to worsen if it remains unchecked. It is part of a complex network of problems rooted in ED crowding and a lack of inpatient resources. This broad problem will ultimately require a multidisciplinary, system-wide solution, but in the meantime specific interventions are useful in mitigating its effects. A variety of targeted solutions have been trialled over the decades, but none have been able to resolve the issue. One of the more recent trends in solution attempts has been patient consolidation tactics, namely the OZ concept. This style of approach is promising, but almost none of its various implementations have been formally assessed for effectiveness, which is why the analyses in this thesis will be an important contribution to the body of research.

Operations research has been widely applied in healthcare, and different tools find different levels of applicability depending on the area. In the realm of AOD and ED crowding, descriptive studies are the most common. At present, the few operations research studies focusing on AOD model it with queuing theory. Some studies use a configuration resembling Halifax's OZ but have limited applicability to its issues. The data and analyses presented in this thesis will be useful for future analytical work to improve Halifax's OZ and other programs like it, such as simulation or queuing studies to determine effective patient allocation policies or functional tweaks to the OZ.

CHAPTER 3 DATA AND METHODS

3.1 Introduction

In this chapter, the data systems, data extraction, data preparation, and study analysis methods to assess the effectiveness of a real-world trial of the OZ are presented.

The EHS and hospital data collection systems are briefly described, along with the specific data that were requested for his study. The data preparation is discussed in terms of linking the disparate datasets provided by the two medical organizations, verifying that linking matches had been made correctly, and screening for erroneous information.

For analysis the data are broken down into two main types of OZ-related comparison groupings, with a number of demographic and situational variable stratifications, all of which are laid out here. The statistical tests used in the analysis are a two-sample t-test, a chi-square test of independence, a two-proportion z-test, and a one-proportion z-test. These tests are explained in terms of their calculation methods and what they are seeking to determine from the data.

3.2 Data

Nova Scotia's EHS ground paramedic service covers a catchment area of 55,000 square kilometres. The province contains a mix of urban, suburban and rural regions. At the time the data were collected, the province's population was just under 1,000,000 and the annual emergency 9-1-1 call volume was approximately 132,000. A staffing mix of primary, intermediate, and advanced care paramedics work in the ground ambulance system as a single agency. The data for this study were collected for ambulance trips to two EDs, DGH and QEII, which are the two full-service EDs in the urban region of Halifax, NS.

Dates cannot easily be classified as "OZ-open" or "OZ-closed." The opening periods are of variable start and end times, subject to staff availability as opposed to scheduled or purposeful closure. During the entire trial period, only 26 days at DGH and two days at QEII did not have any OZ-open periods, however, the openings are sometimes as short as one hour. In terms of whether the OZ was in operation upon a patient's arrival, 50.8% of patients arrive during OZ-open periods at QEII, and 56.3% at DGH.

Demographics are reported descriptively, including sex, age, severity of condition as measured by the Canadian Triage and Acuity Scale (CTAS), and the general category of illness/injury with which they presented ("clinical impression"). Each record specifies whether or not the OZ was open at the time that the patient arrived, as well as whether the patient entered the OZ. The time patients wait to be offloaded, wait for an ED bed, wait to be seen by the ED physicians, and total ED length of stay are reported for each patient.

3.2.1 Data Systems and Linkage

For all 9-1-1 calls in the province to which an ambulance is dispatched, data are collected by EHS paramedic charting via a tablet-based electronic patient care record (ePCR), and with time stamps sent by radio to the EHS dispatcher and recorded into the computer assisted dispatch (CAD) system. Data such as time stamps, interventions, chief complaint, triage level, demographics, vital signs, etc., are electronically queriable on all calls. The EHS ePCR and CAD databases maintain atomic clock synchronization. Information is uploaded to the EHS clinical data warehouse daily. Data from all EDs are recorded electronically in the ED, into the ED Information System (EDIS).

Twelve months of data (from January 2, 2013 to January 1, 2014) beginning approximately eight months after the OZ became operational were extracted. A full year was wanted to avoid seasonal fluctuations in volume or operations. Case finding began with collecting the master incident number (MIN) for all ambulances that transported an emergency patient to either the QEII or DGH. The EHS ePCR and CAD were then queried for these MINs. These raw data were provided in two separate spreadsheets: dataset #1 and dataset #2, split for privacy purposes. Dataset #1 contained medical information related to the call, and dataset #2 contained the necessary elements of the patients' personal information needed to match records to the EDIS data.

Table 2 Datasets extracted from EHS and ED information systems and the fields they contained

Dataset #1: EHS medical information	Dataset #2: EHS personal identifier information	Dataset #3: EDIS records
MIN	MIN	ID
Age	First name *	First name *
Date of birth	Last name *	Last name *
Sex	Date of birth *	Date of birth *
CTAS	Date of service *	Date of service *
Incident time	Health card number *	Health card number *
Arrive hospital time		Hospital site
OZ in operation		Site arrival time
Patient placed in OZ		ED arrival time
Time into OZ		Patient registration time
Time into ED bed		Patient triage time
Ambulance available time		CTAS
Time disposition assigned		Clinical impression
		Time to ED bed
		Time to RN
		Time seen by MD
		Time disposition assigned
		Time departed ED

Dataset #2 was brought to the hospital's Emergency Medicine IT manager, and was used to query EDIS and create dataset #3. Because EHS and the EDs do not share a common incident identification key for their respective data systems, deterministic linkages were used to pair records pertaining to the same incident. To form a link, matches needed to be found for at least three of the following personal identifiers: first name, last name, date of birth, date of service, and health card number. Table 2 summarizes the three datasets and marks link-forming fields with a * symbol. The SOUNDEX function in analytics software SAS was used to match names that may have been otherwise unmatchable due to typos or spelling errors. Names matched with the SOUNDEX function were manually reviewed after the function was run. Records from dataset #2 that did not find a match were reviewed for errors such as mistaken entry of a health card number, reversal of month and day in dates, or other issues with names such as reversal of first and last name.

3.2.2 Data Preparation and Verification

There were 18,640 EHS records extracted in datasets #1 and #2. Datasets #2 and #3 were matched with a 98.7% success rate. The combination of dataset #2 and #3 resulted in dataset #4, which was the starting point for this thesis's work, and which needed to be verified and cleaned before analysis.

Duplicate MINs were identified within dataset #4. The 135 duplicates detected were examined manually. Of these, 122 were found to be erroneously created records which combined information from other valid entries existing in the dataset, and were deleted. The remaining duplicates were instances of the same MIN being used for patients who took multiple ambulance trips in one day. These had likely been separate incidents with separate MINs but were assembled incorrectly due to the overlapping date and patient information. For each pair, it appeared that one contained correct information and the other contained a mix of information and timestamps that did not make sense, and so the latter of each pair was deleted.

During extraction of dataset #3, an identifier called EDIS Unique ID had been created which considers each set of EDIS timestamps and gives duplicate IDs to entries that share identical timestamps. Duplicate EDIS Unique ID fields were identified within dataset #4. The 34 duplicate pairs detected were examined manually. They appeared to have resulted from an error where one entry is populated with information from a different entry instead, causing two entries with different MINs but identical EDIS timestamps. By comparing EHS and EDIS arrival timestamps, each pair's correct entry was identified, and the erroneous entry deleted.

For some records, matches were made based on name trims or phonetic (SOUNDEX) versions of the patient's names. The 231 such records were examined manually for accuracy. Two records were deleted which appeared to have been created from different patients who coincidentally have the same first and last name.

Discrepancies between EHS and EDIS data about which hospital a patient was taken to were investigated. A supplementary data file which logs transfer-of-care information was consulted to confirm where each patient had actually been transported. This file was able to solve 28 of the discrepancies, but 24 remained conflictive. It appears to be an issue that occurs sometimes when multiple patients are transported in the same ambulance. With no way to resolve the discrepancy, these 24 records were deleted.

Discrepancies between EHS and EDIS data about patients' birthdates were investigated. The majority appeared to be small typos or reversals of month and day, which provides reassurance that the matchups were correct. Focus was narrowed to consider only differences between birth years, which is important for computing accurate age statistics. There were 160 such discrepancies, and with no way to tell which was the correct one, the birthdates from the EDIS transfer-of-care log were arbitrarily chosen to be used. Therefore, an error rate of around 0.0044% can be expected in patient age data.

The differences between EHS and EDIS timestamps for patients' arrival were examined. Only 6.5% of all records had the same timestamp in both database systems, however this is expected, as paramedics and hospital staff do not synchronize their inputs for this datapoint, and it is reasonable to expect a difference in what time they observe the arrival of a patient. The median amount of difference is 4 minutes, and the mean difference is 8.88 minutes with a standard deviation of 47.87. At least 95% of the records have EHS and EDIS arrival timestamps that are within 23 minutes of each other. In the case of EHS, errors in timestamp information may occur due to typos, or reporting information belatedly and misremembering the time. In the case of EDIS, an automatic timestamping system is used, so typos are not expected, but errors can occur when a patient's record is updated belatedly. To see whether large differences in reported arrival time are correlated with OZ activity, two-proportion z-tests were performed for comparison. Cases where the EHS arrival time was >23 minutes earlier than the EDIS time occurred 0.99% of the time when the OZ was closed and 1.46% of the time when it was open (significantly different proportions with $p = 0.004$). They occurred for patients outside the OZ 1.60% of the time and patients inside the OZ 1.33% of the time (no significant difference). For cases where the EDIS arrival time was >23 minutes earlier, these figures were 3.29%/3.56% and 3.47%/3.64% respectively (neither being significantly different). An earlier EHS arrival time can generally be assumed to mean that the EDIS time was logged belatedly. The difference in proportion for earlier EHS arrival times may be due to the OZ's operation giving ED staff more work to keep up with at once, and making them more likely to delay the processing of a new ambulance arrival. For the purposes of this thesis's analysis, it was decided to use whichever arrival timestamp was closest to each patient's triage timestamp. This is because triage is intended to happen as soon as possible after a patient's arrival, therefore the arrival time closest to it is less likely to be erroneous.

Various data categories could be used to reflect the time a patient is offloaded from the ambulance. They include the offload timestamp recorded in EHS's CAD, the offload timestamp recorded in EHS's ePCR, the offload timestamp recorded in the hospital's OZ database, and the time the ambulance has marked itself available for a new call. Each of these fields had a large rate of missing data: 65.3%, 95.8%, 76.9%, and 34.4% respectively. (Note that the rate of missing data for the OZ database is counting all patients, even those who do not enter the OZ; the rate drops from 76.9% to 23.4% when considering only patients who entered the OZ.) There are 14.8% of records that have none of these timestamps. These sources of data were ranked in terms of desirability. EHS's CAD timestamp, which is a quick communication via radio to the dispatcher, is the easiest to complete and the most likely to be performed promptly after the patient is moved. EHS's ePCR timestamp is also likely to be completed before the paramedics begin preparing their ambulance for departure. EHS's availability timestamp is less desirable, since it typically takes the paramedics some time after offloading a patient to clean and reorganize before they are available for another call. Finally, the OZ database is the least desirable, since it differs from the other sources in terms of the types of entry error it is susceptible to, and relying on it as little as possible should make the dataset more consistent. For analysis, each patient record in the dataset uses the highest-desirability source that is available.

Some measures were taken to make the clinical impression field more easily analyzed. This field is an extensive dropdown list of options that can be selected to describe the nature of the patient's complaint. A number of records had more than one clinical impression attached to the same incident. For the most part, these were similar items, e.g. "chest pain" with "heart attack," and so a single description was chosen to best represent the condition.

However, 73 records had seemingly conflicting or unrelated items, e.g. “traumatic injury” with “allergic reaction.” These records were given the label “Complex.”

After this adjustment, there were 86 possible designations for a patient’s clinical impression. This is too many to meaningfully represent in analysis, particularly because about half of them have small sample sizes (fewer than 30 patients). Therefore, clinical impressions were grouped into categories based on similarity of the condition or of the body system affected. This resulted in 25 categories, of which the five smallest categories involve a sample size smaller than 30 at one or both sites. The category groupings were verified and critiqued by an emergency physician. For example, she recommended giving “multi-system trauma” its own category rather than including it in the general “trauma” category, since it is usually much more complicated to treat than an injury to a single area of the body. See Table 3 for the full list of clinical impressions and the category each one was placed into, noting that “NYD” stands for “Not Yet Diagnosed.”

About 4.5% of the dataset is missing a clinical impression (categorized as “NULL”). The clinical impression field is typically mandatory for the ambulance staff to fill out, except for in a handful of cases, namely various types of patient transfers. Since an inpatient transfer would not be directed to the ED, it may be the case that these NULLs are due to outpatient transfers from a crowded ED to a less crowded one. If so, it can be assumed that NULL clinical impressions comprise various low-acuity conditions.

The remainder of the data to be used in analysis are sourced from EDIS only. Key information categories were examined for rates of missing entries. Of all data points to be used in the analysis, two were found to have missing entries. Timestamp to reach an ED bed is missing 7.3% of entries, potentially due to patients leaving without being seen, patients being treated in the OZ or hallway, or staff forgetting to mark the time. Timestamp to see a physician is missing 2.9% of entries, potentially due to patients leaving without being seen, patients having a complaint that does not warrant a doctor’s assessment, or staff forgetting to mark the time. Patients who leave without being seen are not marked in the data, but assuming that someone who leaves without being seen will have a series of missing timestamps, it can be estimated that between 1.9% and 2.7% of patients leave without being seen. While calculating intervals between timestamps, care was taken to ensure that no intervals were mistakenly generated using a missing timestamp.

After cleaning the data as described, 18,183 records remained, for an overall deletion rate of 2.45%. Due to the columns that had missing entries, as discussed above, some calculations will have a sample size smaller than 18,183. Columns containing patients' identifying information were no longer needed after preparation of the dataset, and were deleted for privacy prior to beginning the analysis.

Table 3 Clinical impression categories with patient sample sizes in parentheses as (Hospital A/Hospital B), and the clinical impressions included in each broader category

Clinical Impression Category (Incidences)	**Clinical Impressions Included**
Trauma (1967/987)	Abdominal Injury; Arm Injury; Back Injury; Chest Injury; Eye/Ear/Nose/Throat Injury; Elbow Injury; Electrocution; Facial Injury; Foot Injury; Hand Injury; Head Injury; Hip Injury; Knee Injury; Leg Injury; Neck Injury; Pelvic Injury; Shoulder Injury
Gastrointestinal/ Genitourinary (1720/1090)	Abdominal/Flank Pain; Diarrhea; GI Bleed; Hematuria; Nausea/Vomiting; GI/GU (NYD); Renal Colic; UTI Complaint
Neurological (1423/656)	Altered Mental Status; Cerebrovascular Accident/Transient Ischemic Attack; Dizziness/Vertigo; Gait Disturbance/Ataxia; Migraine/Headache; Neurological (NYD); Seizure
Cardiovascular (1330/641)	Abdominal Aortic Aneurysm; Angina; Arrhythmia; Bradycardia; Chest Pain (NYD); Congestive Heart Failure; Deep Vein Thrombosis; Hypertension; Hypotension; Palpitations; ST-Elevation Myocardial Infarction; Tachycardia; Shock – Hypovolemic
Respiratory (950/515)	Airway Obstruction; Respiratory Arrest; Aspiration; Asthma; Chronic Obstructive Pulmonary Disease; Pulmonary Embolism; Pneumonia; Pulmonary Edema; Shortness of Breath (NYD); Spontaneous Pneumothorax
General Malaise (904/523)	Failure to Thrive; General Malaise; Palliative; Weakness/Fatigue
Psychological (797/398)	Abnormal Behaviour; Anxiety; Mental Health Crisis; Psychological (NYD); Suicide; Violent Behaviour

Clinical Impression Category (Incidences)	Clinical Impressions Included
NULL (507/304)	NULL
Wellness Check (414/211)	Medication Check; No Apparent Injury/Illness; Wellness Check
Fainting (328/150)	Syncope/Pre-Syncope
Toxicology (318/156)	Chemical Exposure; Overdose/Poisoning; Toxic Inhalation
Substance Misuse (207/81)	Substance Misuse/Intoxication
Chest Pain (Non-CV) (150/123)	Chest Pain (Non-Cardiovascular)
Eye, Ear, Nose, Throat (128/69)	Broken/Avulsed Tooth; Difficulty Swallowing; Ear Pain; Epistaxis; Esophageal Obstruction; Eye Injury; Eye Pain; Foreign Body; EENT (NYD); Sinus Complaint; Vision Disturbance
Sepsis (107/59)	Sepsis; Shock – Septic
Glycemic (98/85)	Hyperglycemic; Hypoglycemic
Skin (87/53)	Burn; Cellulitis; Pressure Sore; Rash (NYD)
Pain (76/55)	Pain (NYD)
Allergic Reaction (66/50)	Allergic Reaction
Multi-System Trauma (65/29)	Trauma – Multi-System Injury
Ob/Gyn (56/27)	Childbirth; Ob/Gyn (NYD); Pregnancy Issues; Per Vaginum Bleed; Sexual Assault; Stillbirth; Threatened Abortion
Complex (53/20)	Complex
Cardiac Arrest (42/35)	No Return of Spontaneous Circulation; Obvious Death; Return of Spontaneous Circulation; Traumatic
Medical Device Complication (24/27)	General Medical Device Complication
Environmental (12/10)	Bite/Sting; Hyperthermia; Hypothermia

3.2.3 Data Independence

During the study period, there were many times when the OZ was open and many when it was not. The primary reason cited for the OZ being closed was staffing shortages, a random and exogenous factor independent of the demand in the ED. This independence was investigated and is summarized in Figure 1, where the hospital identifiers are removed. Subfigures a) through c) pertain to Hospital A and subfigures d) through f) to Hospital B. Subfigures a) and d) plot the number of hours the OZ is open as a function of daily ambulance arrivals. Independence is assumed because the 95% confidence intervals overlap and because there is no discernible trend present. In subfigure d) an apparent upward trend is present but when considering only the majority of the data (which falls between 12 and 24 arrivals per day) this trend is negligible. These results show that the OZ has roughly the same chance of being open on any given day regardless of the level of daily ambulance arrivals. Subfigures b) and e) display the probability that the OZ is open as a function of the hourly ambulance arrivals. According to these charts, OZ-open periods are typically busier than OZ-closed periods, at both hospitals. Note that subfigure b) excluded hourly arrivals of 8 due to a low sample size of 2. Finally, subfigures c) and f) plot the number of hours open as a function of day of the week and likewise the 95% confidence intervals overlap and there is no discernible trend. These figures show that cyclical patterns, such as weekly staffing schedules or the daily arrival patterns of patients as influenced by the typical work week, do not influence whether the OZ opens.

The trends observed in subfigures b) and e) are a result of the OZ generally having its open periods during the daytime, which is both when more staff tend to be available for scheduling and when there is higher demand on the ED. It is of course sensible for the hospital not to keep the OZ open during periods known to have lower demand, but for the purposes of this study, it means that results of unit-level comparisons may be skewed. However, this bias is self-limiting, because hospitals will generally do their best to schedule staff levels corresponding to demand levels, and thus the difference between daytime and nighttime delays will not be excessive. As well, for comparisons where the OZ reduces offload time, this bias actually makes the results more convincing than if it were an unbiased dataset. It would be expected for busier daytime periods to generally have more AOD than less busy nighttime periods, so if the comparison shows a reduction when the OZ opens, then the actual net reduction is probably even more substantial than what is estimated by the test. To clarify the results, these unit-level tests can be cross-referenced with their corresponding patient-level tests, which are not subject to the same data skewing effect since they use data only from OZ-open periods. Considering all of this, the dataset can still be used in spite of this dependency.

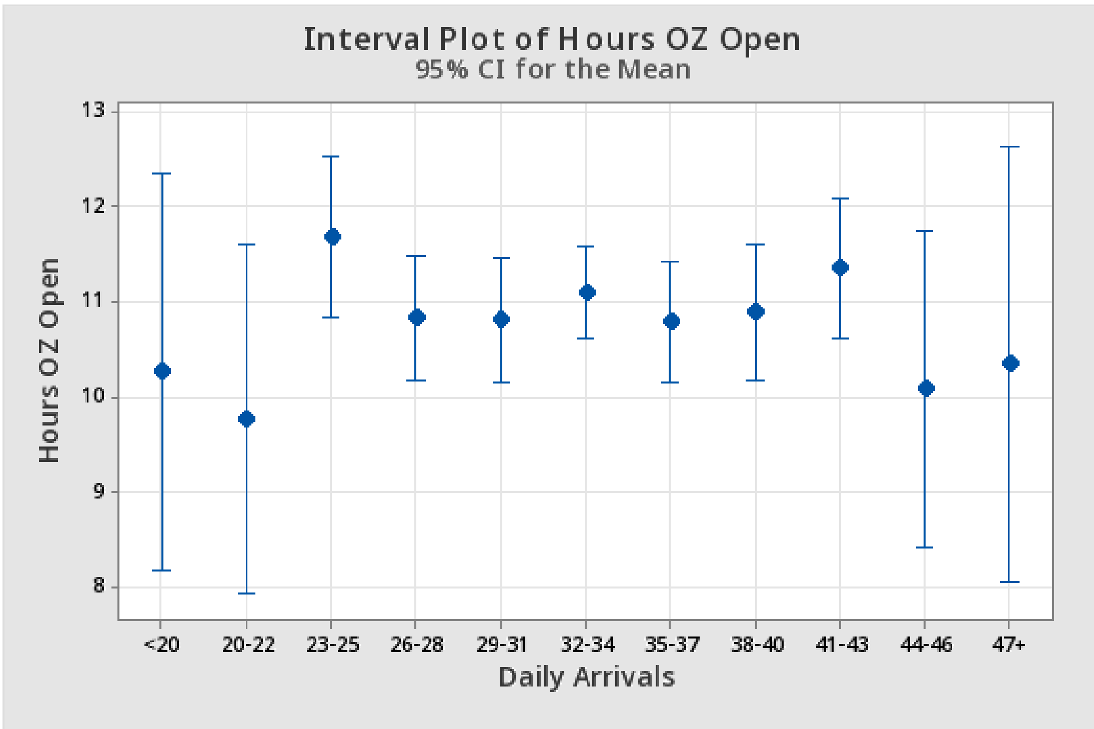

Figure a) Hours OZ is open as a function of daily ambulance arrivals at Hospital A

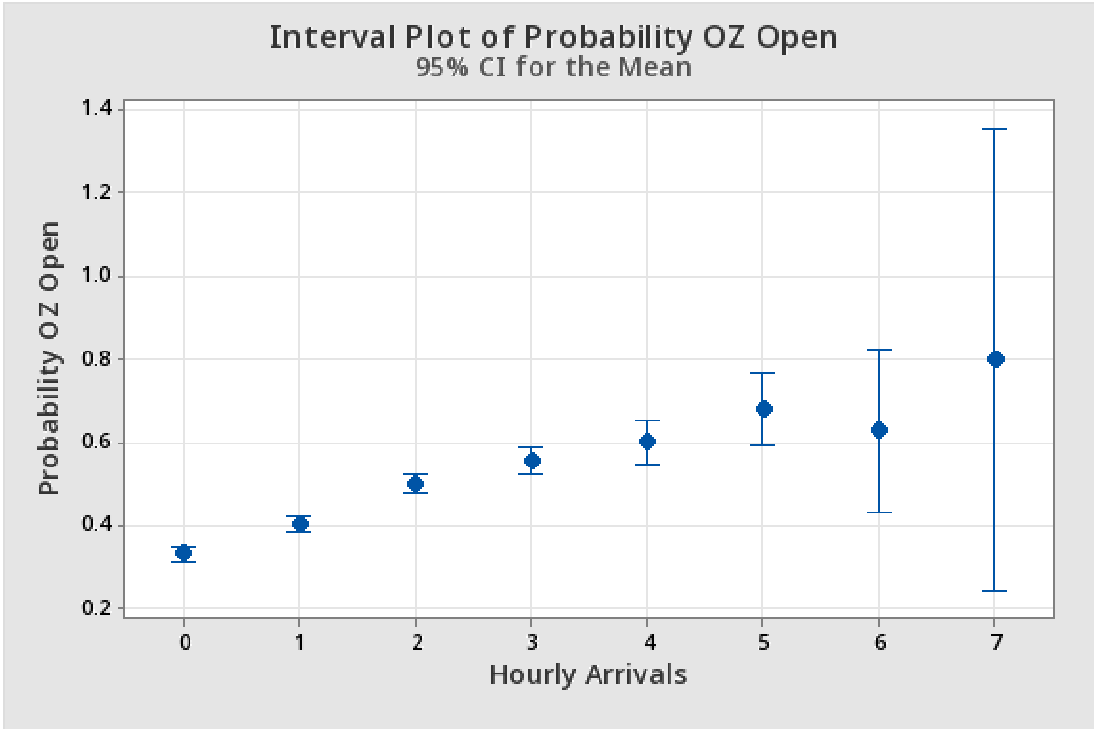

Figure b) Probability OZ is open as a function of hourly ambulance arrivals at Hospital A

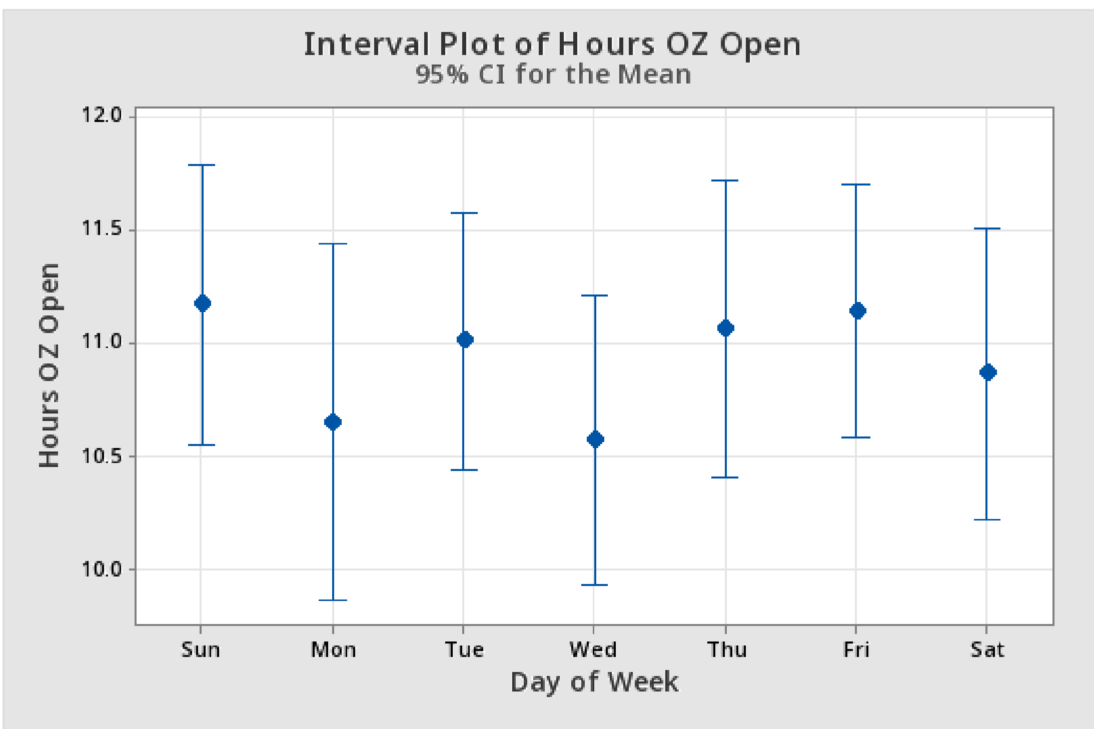

Figure c) Hours OZ is open as a function of day of the week at Hospital A

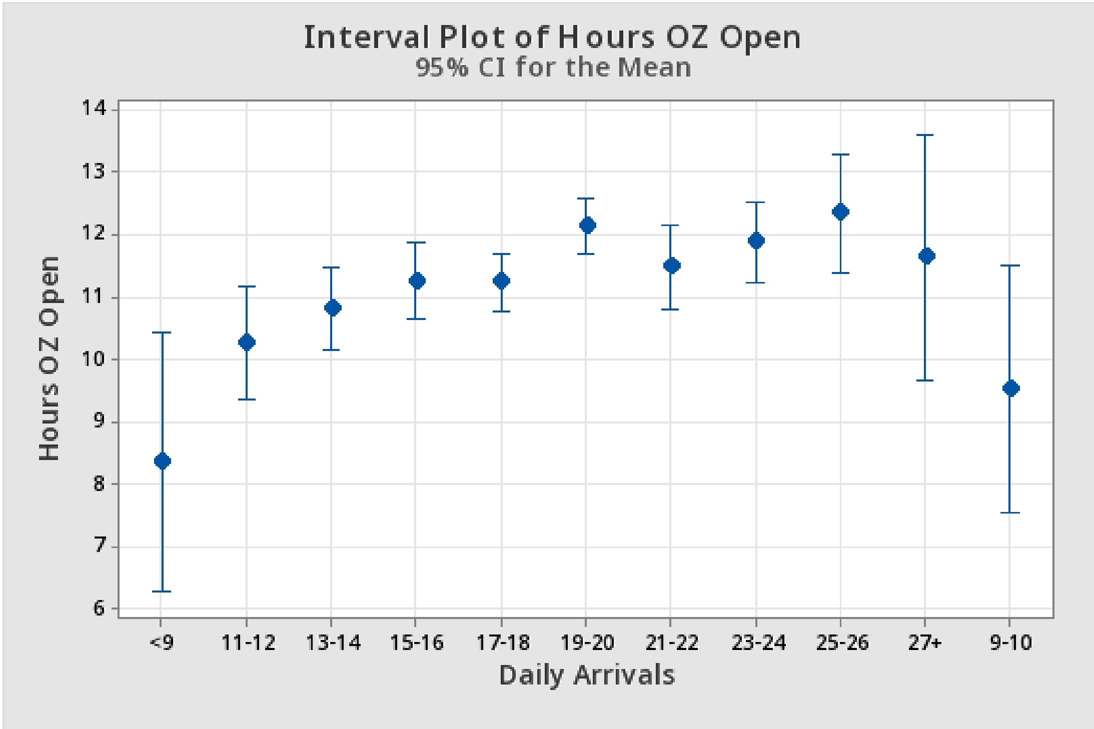

Figure d) Hours OZ is open as a function of daily ambulance arrivals at Hospital B

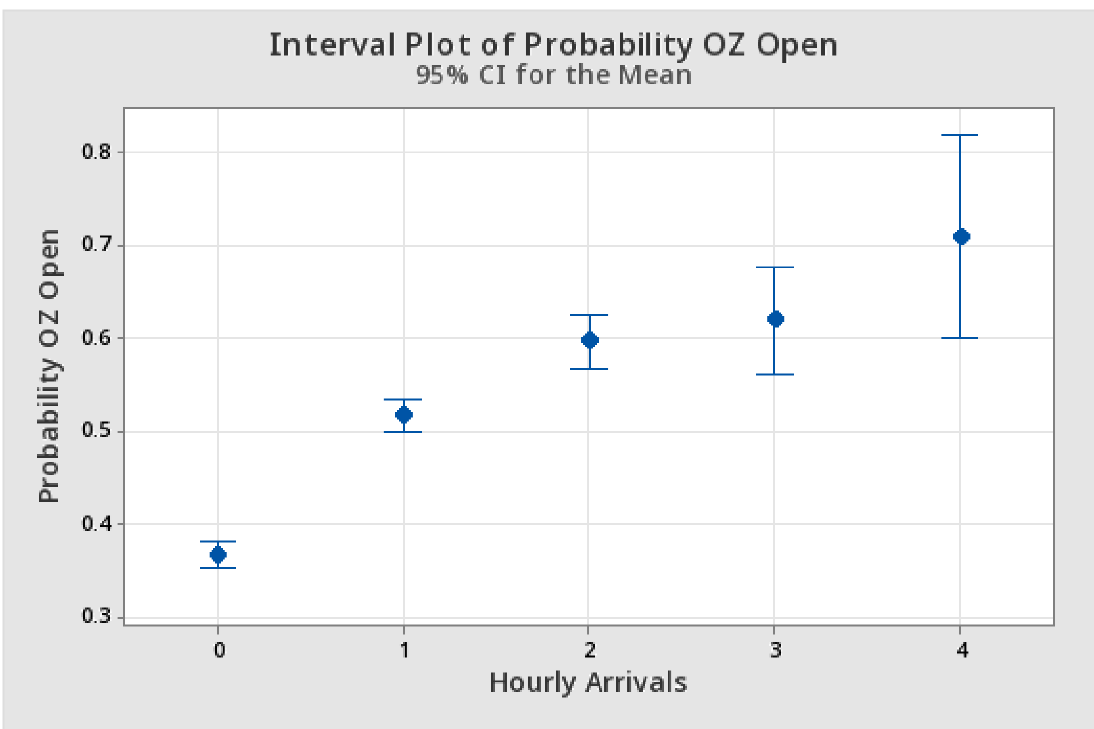

Figure e) Probability OZ is open as a function of hourly ambulance arrivals at Hospital B

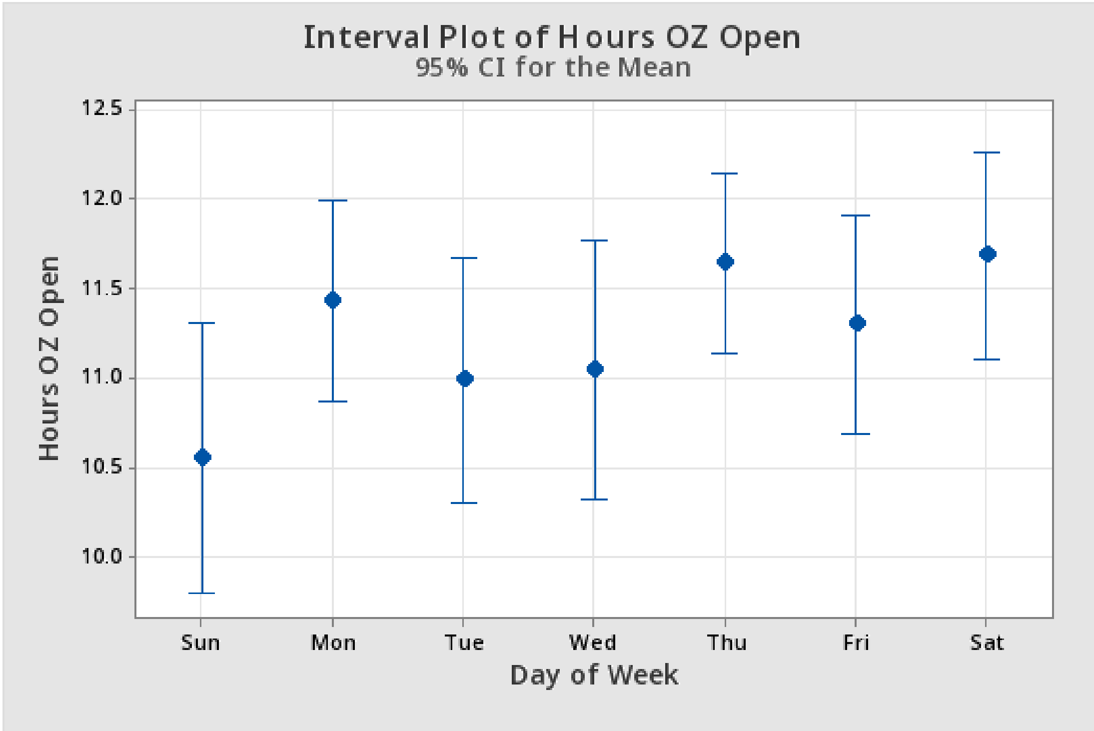

Figure f) Hours OZ is open as a function of day of the week at Hospital B

Figure 1 Demonstration of data independence: Subfigures presented on the previous three pages display means and 95% confidence intervals, and overlapping confidence intervals imply data independence

3.3 Methods

In this subsection, the data are laid out in terms of the main OZ-related comparison groups that are used to assess its functionality. These comparison groupings apply to all of the data arrangements and statistical tests done throughout the analysis. The first part of the analysis examines the sequence of steps that patients take on their path through the ED, and the second part looks at key time benchmarks in the patients' ED journeys. Some situational and demographic variables are available to further break down the comparisons of time benchmarks. Throughout this subsection, statistical tests to be used in the analysis are identified and explained.

3.3.1 Comparison Groups

During this study period, there were many periods when the OZ was open and many when it was not, in an ad-hoc fashion, creating a natural experiment. As revealed by the independence analysis, the OZ did tend to operate during the daytime when demand was expected to be higher, but aside from this bias, the reasons for the specific periods that the OZ was open or closed were mainly staffing, and hence random and independent of the daily demand in the ED. These concurrent comparisons are preferable to a before-and-after comparison because of the rapidly changing nature of ED crowding and mitigation strategies. Two main types of comparisons are used in order to examine the OZ's functioning, referred to as "unit-level" and "patient-level," and all types of comparison show a separate analysis for each hospital site.

For unit-level comparisons, all data are used, and periods where the OZ is open are compared to periods when the OZ is closed. For patient-level comparisons, only data from OZ-open periods are used, and patients who enter the OZ are compared to those who do not. Table 4 and Table 5 summarize the data usage and comparison groups for each type of comparison. Patient-level results will be more representative of the OZ's effect on the patients who use it, and unit-level results will be more representative of its effect on the system as a whole.

Table 4 Data used for unit-level comparisons

OZ Status	Patient Enters OZ	Patient Does Not Enter OZ
OZ Open	Comparison group A	
OZ Closed	Comparison group B	N/A

Table 5 Data used for patient-level comparisons

OZ Status	Patient Enters OZ	Patient Does Not Enter OZ
OZ Open	Comparison group A	Comparison group B
OZ Closed	Data not used	N/A

3.3.2 Path Analysis

Patients are intended to travel through the ED in a specific sequence of steps. The major steps considered here are: reaching an ED bed, first contact with a registered nurse (RN), first contact with a medical doctor (MD), and discharge from the ED. Patients typically receive treatment in this order but the data indicate at least 20 distinct paths. Table 6 describes each of the major categories of possible paths through the ED and lists the specific treatment sequences that are included in each. The "Other" category represents a collection of treatment sequences that appeared very infrequently, e.g. MD – Discharge, which may be a reflection of patients who are not offloaded, but which occurs only six times at each hospital. Some 0.14% of the paths were noted to be erroneous records, as they included nonsensical implications such as receiving treatment after being discharged from the ED, and were excluded from consideration.

Table 6 Categories of paths taken through the ED by patients and the major treatment sequences included in them

ED Path	Treatment Sequences Included
Typical	ED Bed – RN – MD – Discharge
MD Before RN	ED Bed – MD – RN – Discharge
Treatment Before ED Bed	MD – ED Bed – RN – Discharge RN – ED Bed – MD – Discharge RN – MD – ED Bed – Discharge MD – RN – ED Bed – Discharge
No ED Bed	RN – MD – Discharge MD – RN – Discharge
Leave Without Being Seen (LWBS)	ED Bed – Discharge Discharge
Other	Various infrequent sequences

To consider the distribution of patients among the various possible paths through the ED, a chi-square test of independence was used to determine whether the distribution of paths differs between OZ comparison groups. The test estimates whether ED path and OZ group are independent variables.

Because chi-square tests are sensitive to large sample sizes (Bergh, 2015), a random sampling of approximately one fifth of the dataset was used for these tests. The resulting sample sizes were 2,436 overall and 1,234 during OZ-open periods at Hospital A, and 1,290 overall and 746 during OZ-open periods at Hospital B.

The chi-square test proposes the null hypothesis (H_0) that ED path and OZ group are not related in the population, and the alternative hypothesis (H_a) that ED path and OZ group are related in the population. The table of observed frequencies is summed from the data sampling, and is used to generate a table of expected frequencies by calculating each cell (r, c) as

$$\frac{Row\ r\ total * Column\ c\ total}{N}$$

where N represents the sum of all observed frequencies. The chi-square test statistic χ^2 is calculated by

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

summed across each cell in both tables, where O is the observed frequency and E is the expected frequency. The critical chi-square value is found using degrees of freedom $df = (number\ of\ ED\ paths - 1) * (number\ of\ OZ\ groups - 1)$ and a significance level of $\alpha = 0.05$.

In addition to testing the overall distribution of paths, each path's proportion of the distribution was tested independently. The two-proportion z-test compared the proportion of patients taking a given path when the OZ is open to the proportion taking it when the OZ is closed, as well as the proportions in and outside of the OZ. For these tests, the full dataset and not the one-fifth sampling was used.

The two-proportion z-test proposes the null hypothesis (H_0) that the difference between the population proportions is 0, and the alternative hypothesis (H_a) that the difference is not 0. The test statistic Z is calculated, using a pooled standard error, by

$$Z = \frac{\hat{p}_1 - \hat{p}_2 - 0}{\sqrt{p_0(1 - p_0)(\frac{1}{n_1} + \frac{1}{n_2})}}$$

where $\hat{p}_1$ and $\hat{p}_2$ are the proportions of patients taking a given path in each of the two OZ groupings, n_1 and n_2 are sample sizes for each OZ grouping, and p_0 is the combined proportion for the path across both OZ groupings. The critical value is found in the two-tailed Z-table using a significance level of $\alpha = 0.05$.

3.3.3 Time Analysis

The main statistical test used in this study is an unpaired two-sample t-test. The t-tests are used to compare average time intervals between subsets of the population. Although the dataset contained essentially the entire population of ambulance patients from the studied time period, the variances are not considered to be known, because of the susceptibility to timestamp entry error. The main comparisons, performed on the entire dataset, are presented numerically alongside supplementary data for median and standard deviation, to give an idea of data skew. Some skew is present in the data, however, it is valid to perform t-tests on skewed datasets with large sample sizes (Fagerland, 2012). The dataset is broken down into a variety of demographic and situational variables, and these comparisons are presented graphically in the form of 95% confidence interval charts for better comprehension, but are still functionally t-tests, where overlapping intervals within a given OZ group pairing implies that the null hypothesis is accepted. The t-test was chosen in favour of more complicated multivariate tests because the main interest is the difference between OZ groups, and it is not necessary to consider comparisons across multiple sets of variables or among variables with 3 or more groups.

The t-test proposes the null hypothesis (H_0) that the sample means are the same, and the alternative hypothesis (H_a) that they are different. The test statistic t is calculated by

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s^2(\frac{1}{n_1} + \frac{1}{n_2})}}$$

using a pooled sample variance

$$s^2 = \frac{\sum_{i-1}^{n_1}(x_i - \bar{x}_1)^2 + \sum_{j-1}^{n_2}\left(x_j - \bar{x}_2\right)^2}{n_1 + n_2 - 2}$$

where $\bar{x}_1$ and $\bar{x}_2$ are the sample means, and n_1 and n_2 are the sample sizes. The critical value is found in Student's two-tailed t-table using degrees of freedom $df = n_1 + n_2 - 2$ and a significance level of $\alpha = 0.05$.

The measurements used for the comparisons of means are time benchmarks in each patient's journey through the ED. Many organizations will instead or additionally report on these benchmarks using a 90th percentile measurement, but here means are used for ease of analysis of a large volume of comparisons and variable stratifications. Of the benchmarks that are recorded in the data, four were selected for examination (Table 7). Note that the "Time to ED Bed" benchmark counts only the reaching of a regular ED bed, not an OZ bed.

Table 7 Time intervals in the ED journey that were chosen for examination and why they were chosen

Measurement	Time Interval	Reason for Choosing
Offload Time	Arrival–Being offloaded from ambulance	To assess changes in AOD
Time to ED Bed	Arrival–Being assigned an ED bed	To assess whether patients wait longer for an ED bed
Time to MD	Arrival–First time seen by an MD	To assess whether patients' time to treatment is impacted
ED Length of Stay	Arrival–Departure	To assess whether patients stay longer in the ED

A number of variables are considered, both demographic (Table 8) and situational (Table 9). The main dataset is broken down according to these variables, but for each one, only the comparisons between the OZ groupings described above are performed. Note that the majority of ambulance calls for children are directed to a children's hospital in the area, and so there are very few records in the dataset for such patients. Age groups younger than 15, totalling 23 records, are disregarded due to their scarcity.

Table 8 Demographic variables that the OZ comparisons are stratified into

Variable	Variable Groups
Sex	Male, Female
Age Group	15–24, 25–34, 35–44, 45–54, 55–64, 65–74, 75–84, 85+
CTAS (most to least acute)	1, 2, 3, 4, 5
Clinical Impression	See Table 3

Table 9 Situational variables that the OZ comparisons are stratified into

Variable	Variable Groups	
	Hospital A	Hospital B
Ambulance Patient Volume (arrivals/day, where each hospital has values specific to its own traffic levels)	<20, 20–22, 23–25, 26–28, 29–31, 32–34, 35–37, 38–40, 41–43, 44–46, 47+	<9, 9–10, 11–12, 13–14, 15–16, 17–18, 19–20, 21–22, 23–24, 25–26, 27+
Day of Week	Mon, Tue, Wed, Thu, Fri, Sat, Sun	

The data are broken down by only one variable stratification at a time. This is because most of the variables do not break down into similarly sized groups, and so once the data are broken down by two or more variables at once, sample sizes that are too small to reliably test begin to occur. Comparisons broken down by variable stratifications are displayed together in the same chart for brevity and comprehension, but the only comparisons made should be between the OZ groupings; it is not statistically valid to compare between variable stratification groups in these charts.

These data and methods were adapted to focus on effects in the system caused by ED staff behaviour for a special interest publication by the Journal of the Operational Research Society (Elliott et al., 2020).

CHAPTER 4 RESULTS AND DISCUSSION

4.1 Introduction

In the analysis, the sequence of treatment steps as well as the timeframe for various steps in the ED journey are examined. In each case, a type of OZ versus non-OZ comparison is made. Treatment paths are analyzed in terms of the overall distribution of paths as well as each individual path's proportions. For the time-based analysis, comparisons are broken down into unit-level or patient-level, and then further into a number of descriptive variables.

Results that are relevant to the discussion are presented in this section. That is to say, mainly the statistically significant results are shown. In some cases, results that are not significant are found to be relevant for discussion, because they reflect on the OZ process—for example, showing that the OZ does not delay the time it takes to be seen by a physician, because contrary to the initial concept, it was reported that staff were seeing patients in the OZ.

Simple comparisons of two means are shown in the form of two-sample t-tests, summarized in tables. Comparisons that are further broken down by variable are shown graphically in the form of confidence intervals, for better comprehension.

4.2 Conditions in the ED Pre-OZ

To provide an estimate of what conditions were in each hospital prior to the OZ being introduced, Table 10 shows a general summary of performance during periods when the OZ is off, and compares each pair of means using two-sample t-tests.

Table 10 OZ-closed time benchmarks compared between the hospital sites

Benchmark (minutes)	Mean ± St. Dev.		Median (IQR)		T-test p-value
	Hosp. A	Hosp. B	Hosp. A	Hosp. B	
Offload Time	50.7 ± 76.3	49.3 ± 72.6	31 (35)	35 (34)	0.466
Time to ED Bed	54.3 ± 77.4	60.2 ± 71.2	25 (52)	32 (60)	0.001
Time to MD	97.3 ± 88.6	112 ± 91.7	70 (98)	85 (112)	<0.001
Length of Stay	507 ± 537	586 ± 531	355 (416)	438 (497)	<0.001

The hospitals have a similar average offload time, but Hospital B takes longer to reach the other benchmarks.

4.3 Treatment Path Analysis

The chi-square test of independence was performed to see whether the distribution of paths taken through the ED would change between OZ-open and OZ-closed states, as well as between in-OZ and out-of-OZ states during periods when the OZ was running. The test data are not shown here, as displaying the information in the form of proportions is more intuitive for comprehensive, but the full tests can be seen in the Appendix.

Table 11 shows the unit-level comparison of path proportions at both hospitals alongside the chi-square p-value result, and Table 12 shows the same but for the patient-level comparisons. The unit-level comparison of path distributions is different at both hospitals, but the patient-level comparison is different only at Hospital A. Furthermore, each individual path was tested using two-proportion z-tests, one each for the path's proportional share of the OZ-open/OZ-closed populations and another for the in-OZ/out-of-OZ populations. The pairs of proportions tested are the same ones listed in Table 11 and Table 12, and a * symbol has been added to pairs where the z-test found a significant difference.

Table 11 Unit-level comparison of possible paths through the ED at both hospitals, where the overall distribution of path frequency is compared with a chi-square test of independence, and * denotes pairs of proportions that were found to be different as determined by a two-proportion z-test

Path Description	Hospital A (%)		Hospital B (%)	
	OZ Open	OZ Closed	OZ Open	OZ Closed
Typical	36.2 *	41.9 *	37.4 *	47.6 *
MD Before RN	43.4	42.3	32.6 *	35.2 *
Treatment Before ED Bed	11.6 *	7.9 *	20.4 *	11.3 *
No ED Bed	6.0 *	4.1 *	6.6 *	2.7 *
LWBS	2.0 *	2.9 *	1.9	2.3
Other	0.85	0.88	1.1	1.0
Chi-square p-value	<0.001		<0.001	

Table 12 Patient-level comparison of possible paths through the ED at both hospitals, where the overall distribution of path frequency is compared with a chi-square test of independence, and * denotes pairs of proportions that were found to be different as determined by a two-proportion z-test

Path Description	Hospital A (%)		Hospital B (%)	
	In OZ	Out of OZ	In OZ	Out of OZ
Typical	33.5 *	38.5 *	37.2	37.5
MD Before RN	42.3	44.4	32.1	33.2
Treatment Before ED Bed	13.9 *	9.6 *	21.4 *	18.5 *
No ED Bed	7.6 *	4.5 *	6.4	7.0
LWBS	1.5 *	2.3 *	1.8	2.7
Other	1.2 *	0.59 *	1.1	1.1
Chi-square p-value	0.012		0.689	

4.4 Comparison of Time Benchmarks

4.4.1 Unit-Level Comparisons

Table 13 through Table 16 show results for status-level (i.e. OZ-open versus OZ-closed) comparisons at both hospital sites, not stratified by any demographic or situational variables. The same general patterns are apparent at both sites, but with varying differences between sample means. Median and interquartile range (IQR) are shown in each table as well to provide a sense of skew, however the p-value shown applies only to the comparison of means. At times when the OZ is open, patients are offloaded from the ambulance an average of 5.8 minutes (11.4%) faster at Hospital A and 14.8 minutes (30.0%) faster at Hospital B than at times it is closed. Patients reach an ED bed an average of 4.2 minutes (7.7%) slower at Hospital A and 18.6 minutes (30.9%) slower at Hospital B at times when the OZ is open. Patients stay in the ED an average of 61 minutes (12.0%) longer at Hospital A and 55 minutes (9.4%) longer at Hospital B at times when the OZ is open. At both sites, there is no difference in the time it takes for patients to see an MD for OZ-open versus OZ-closed periods. Interestingly, for length of stay at Hospital B, the mean is larger, yet the median appears to be smaller when the OZ opens.

Table 13 General statistics and results of unit-level t-tests for mean of offload time at both hospitals

Offload Time (minutes)	Hospital A		Hospital B	
	OZ Open	OZ Closed	OZ Open	OZ Closed
Mean ± St. Dev.	44.9 ± 51.6	50.7 ± 76.3	34.5 ± 37.6	49.3 ± 72.6
Median (IQR)	32 (30)	31 (35)	27 (23)	35 (34)
T-test p-value	<0.001		<0.001	

Table 14 General statistics and results of unit-level t-tests for mean of time to ED bed at both hospitals

Time to ED Bed (minutes)	Hospital A		Hospital B	
	OZ Open	OZ Closed	OZ Open	OZ Closed
Mean ± St. Dev.	58.5 ± 77.9	54.3 ± 77.4	78.8 ± 81.8	60.2 ± 71.2
Median (IQR)	27 (62)	25 (52)	48 (92)	32 (60)
T-test p-value	0.005		<0.001	

Table 15 General statistics and results of unit-level t-tests for mean of time to MD at both hospitals

Time to MD (minutes)	Hospital A		Hospital B	
	OZ Open	OZ Closed	OZ Open	OZ Closed
Mean ± St. Dev.	96 ± 160	97.3 ± 88.6	110.6 ± 88.2	112.1 ± 91.7
Median (IQR)	67 (88)	70 (98)	87 (112)	85 (112)
T-test p-value	0.665		0.517	

Table 16 General statistics and results for unit-level t-tests for mean of length of stay at both hospitals

Length of Stay (minutes)	Hospital A		Hospital B	
	OZ Open	OZ Closed	OZ Open	OZ Closed
Mean ± St. Dev.	568 ± 684	507 ± 537	641 ± 637	586 ± 531
Median (IQR)	345 (413)	355 (416)	378 (690)	438 (497)
T-test p-value	<0.001		<0.001	

In general, when data were stratified by variable, results tended to follow similar patterns to those above. For some stratifications, the reduced sample sizes and thus greater uncertainties ended up eliminating the statistical significance of an apparent difference between means. The following results were selected to highlight interesting deviations from the previous patterns, or differences between the hospital sites. Stratifications where the pattern of results differed from the main results in Table 13 through Table 16, but which are not presented for discussion here, can be found in the Appendix.

Figure 2 and Figure 3 show comparisons at Hospital A, stratified by patient sex. The former compares time to offload, and the latter compares time to bed. Only male patients have a reduction in offload time during periods when the OZ opens, while only female patients are delayed in reaching a bed when the OZ opens. Figure 4 shows comparisons for length of stay at Hospital B, stratified by patient sex. Only female patients have a longer length of stay when the OZ opens.

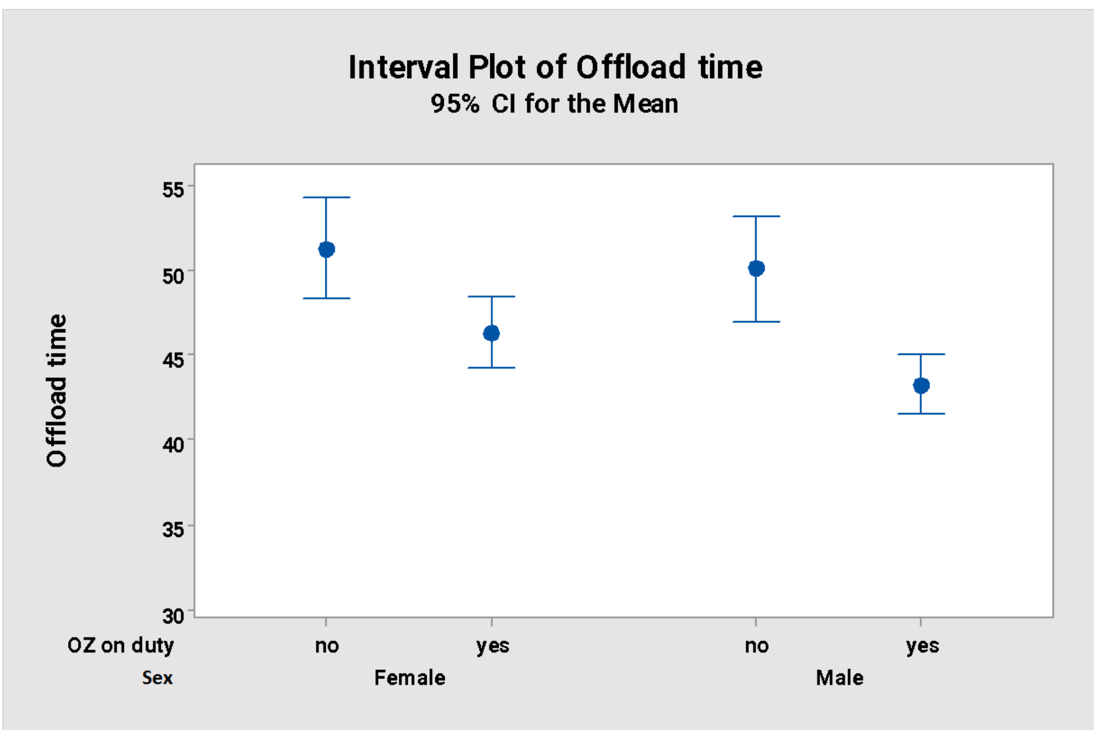

Figure 2 Means and 95% confidence intervals for offload time at Hospital A, representing a unit-level comparison stratified by patient sex

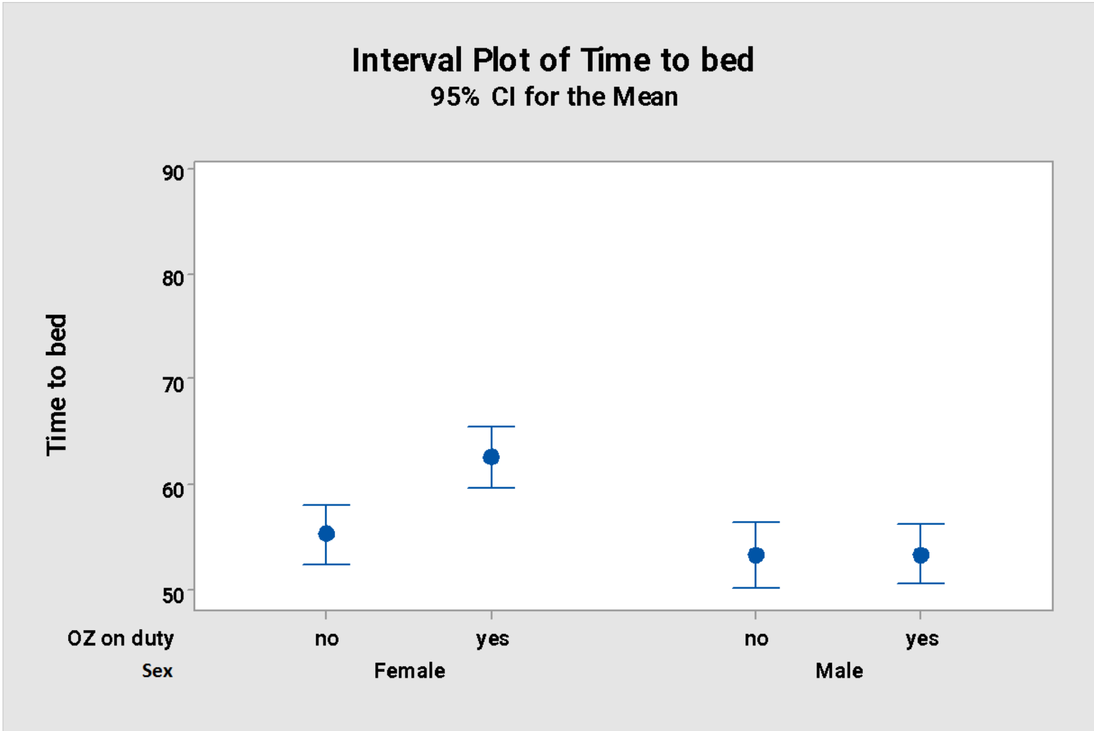

Figure 3 Means and 95% confidence intervals for time to ED bed at Hospital A, representing a unit-level comparison stratified by patient sex

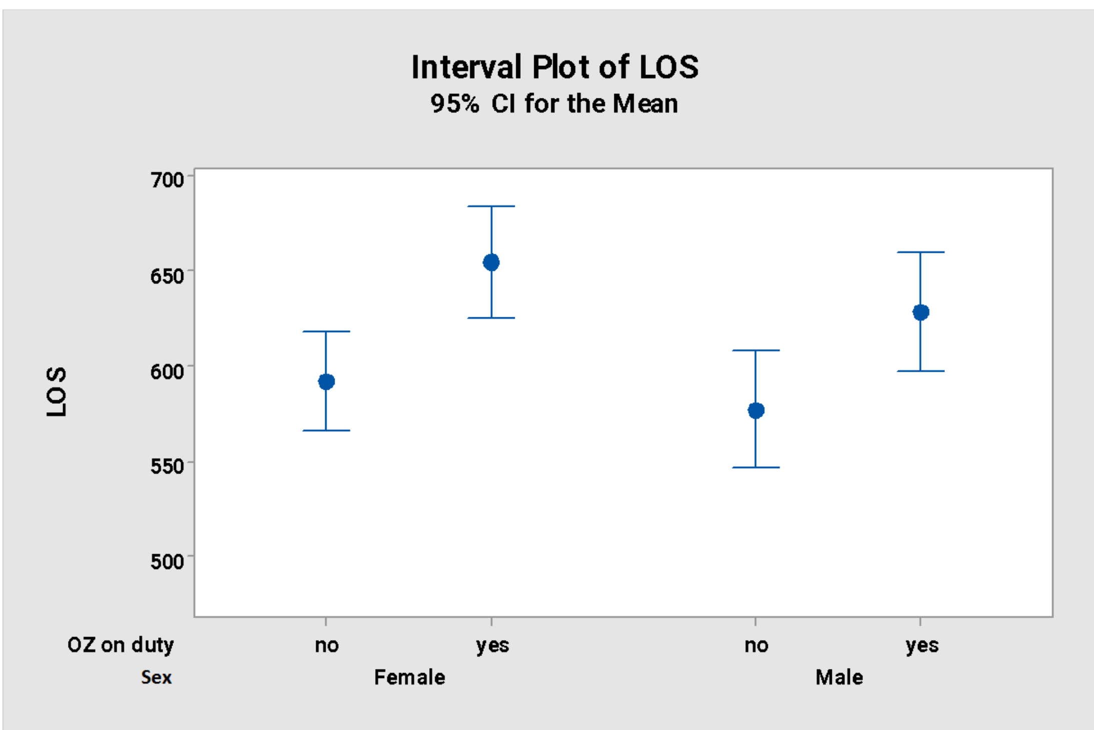

Figure 4 Means and 95% confidence intervals for length of stay at Hospital B, representing a unit-level comparison stratified by patient sex

Figure 5 and Figure 6 show comparisons for offload time at both hospital sites, stratified by patient age groups. While Hospital A shows reduced offload times for a range of higher patient ages from 55 to 84 when the OZ is open, Hospital B shows reduced offload times for all patients outside of the 35 to 54 range. Figure 7 shows comparisons for time to reach an ED bed at Hospital A, where only patients 85 years and over are delayed in reaching a bed when the OZ is open.

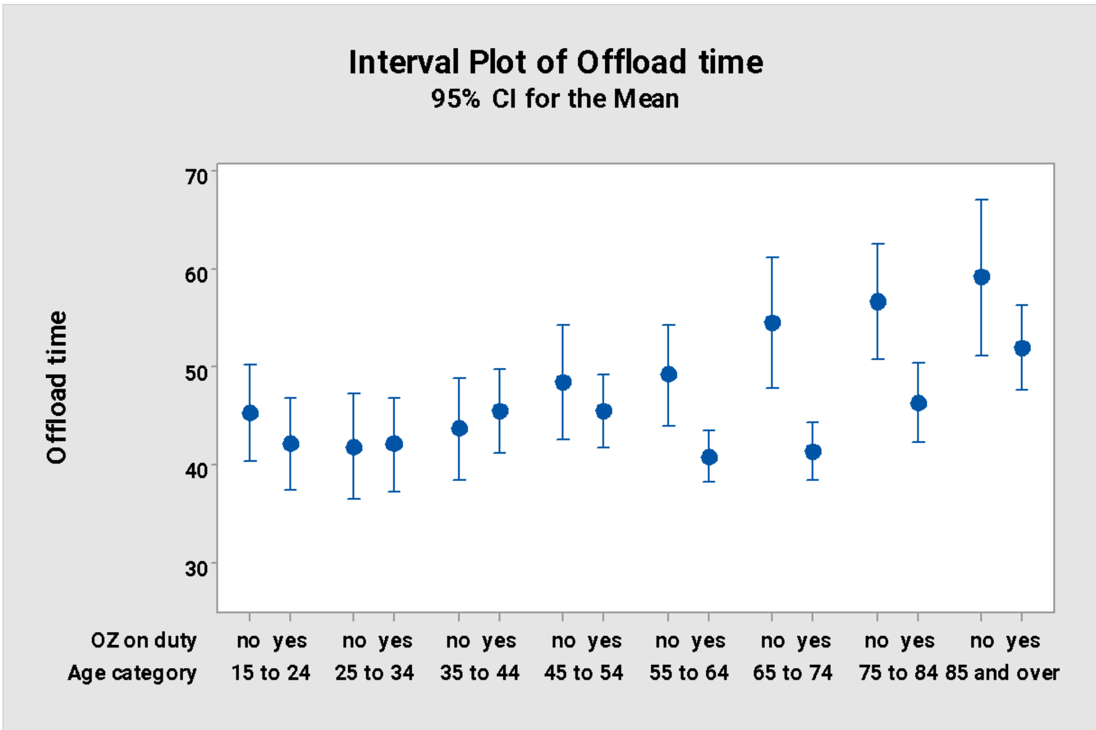

Figure 5 Means and 95% confidence intervals for offload time at Hospital A, representing a unit-level comparison stratified by patient age group

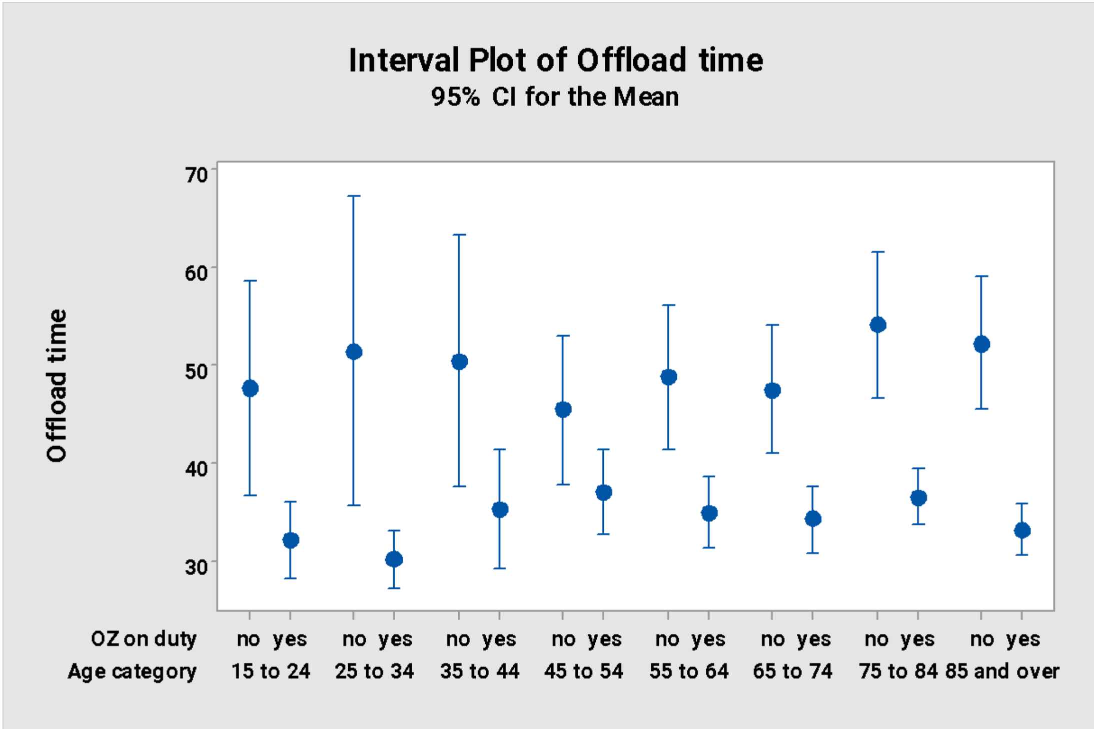

Figure 6 Means and 95% confidence intervals for offload time at Hospital B, representing a unit-level comparison stratified by patient age group

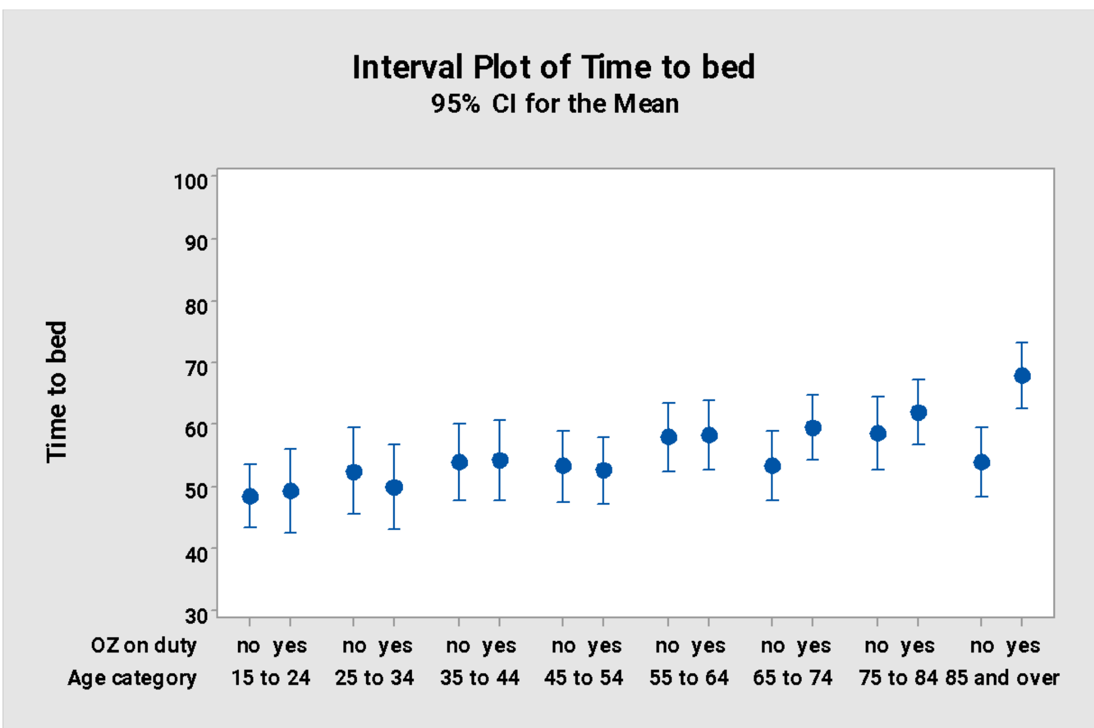

Figure 7 Means and 95% confidence intervals for time to ED bed at Hospital A, representing a unit-level comparison stratified by patient age group

Figure 8 through Figure 13 show comparisons for offload time, time to reach an ED bed, and length of stay at both hospital sites, stratified by patient CTAS. At Hospital A, patients with CTAS 3 have reduced offload time when the OZ is open, and at Hospital B, patients with CTAS 2, 3, and 4 have reduced offload time. At both sites, patients with CTAS 2 and 3 take longer to reach a bed when the OZ is open, and patients with CTAS 3 have a longer length of stay.

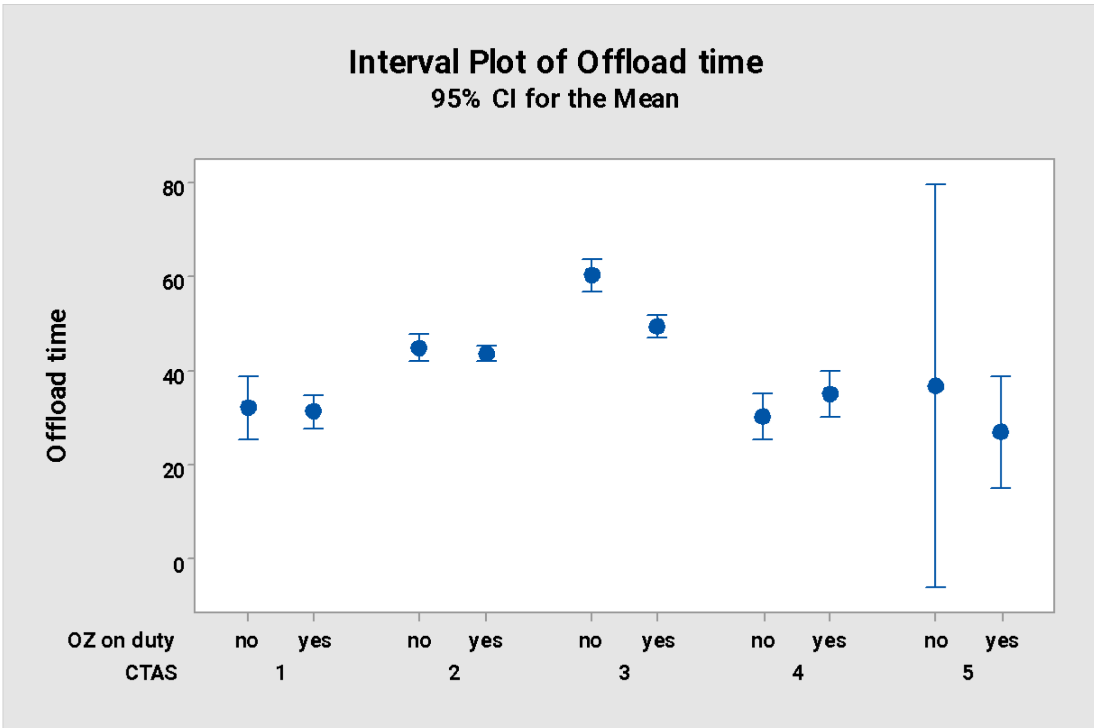

Figure 8 Means and 95% confidence intervals for offload time at Hospital A, representing a unit-level comparison stratified by patient CTAS

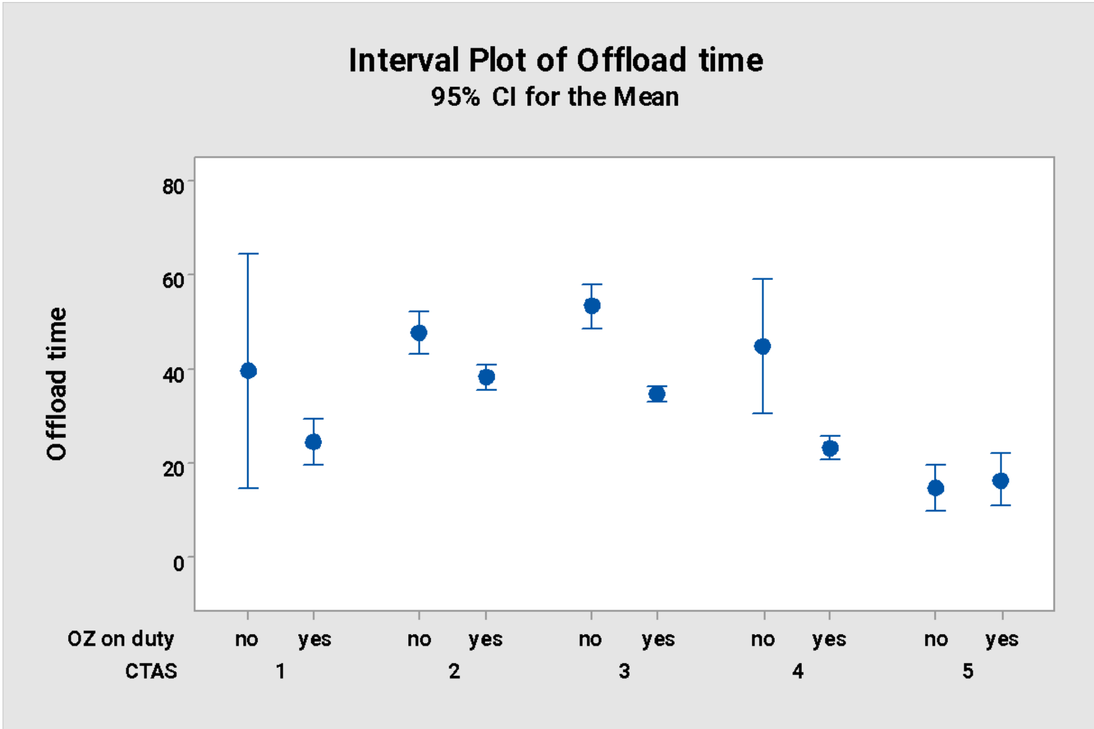

Figure 9 Means and 95% confidence intervals for offload time at Hospital B, representing a unit-level comparison stratified by patient CTAS

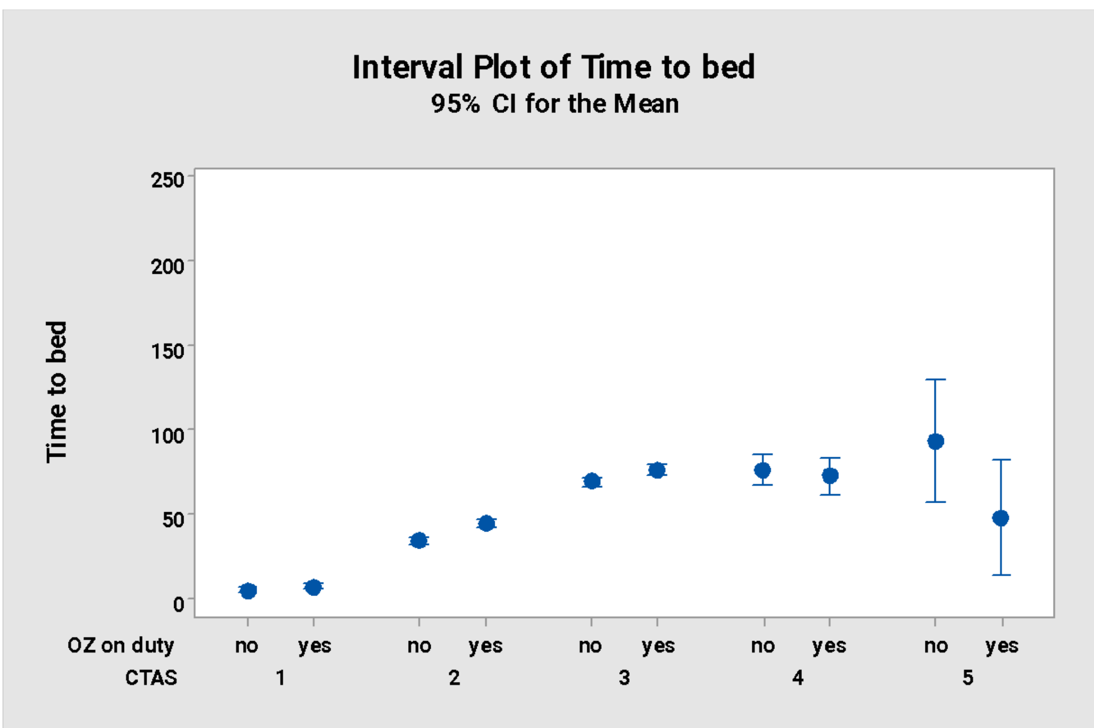

Figure 10 Means and 95% confidence intervals for time to ED bed at Hospital A, representing a unit-level comparison stratified by patient CTAS

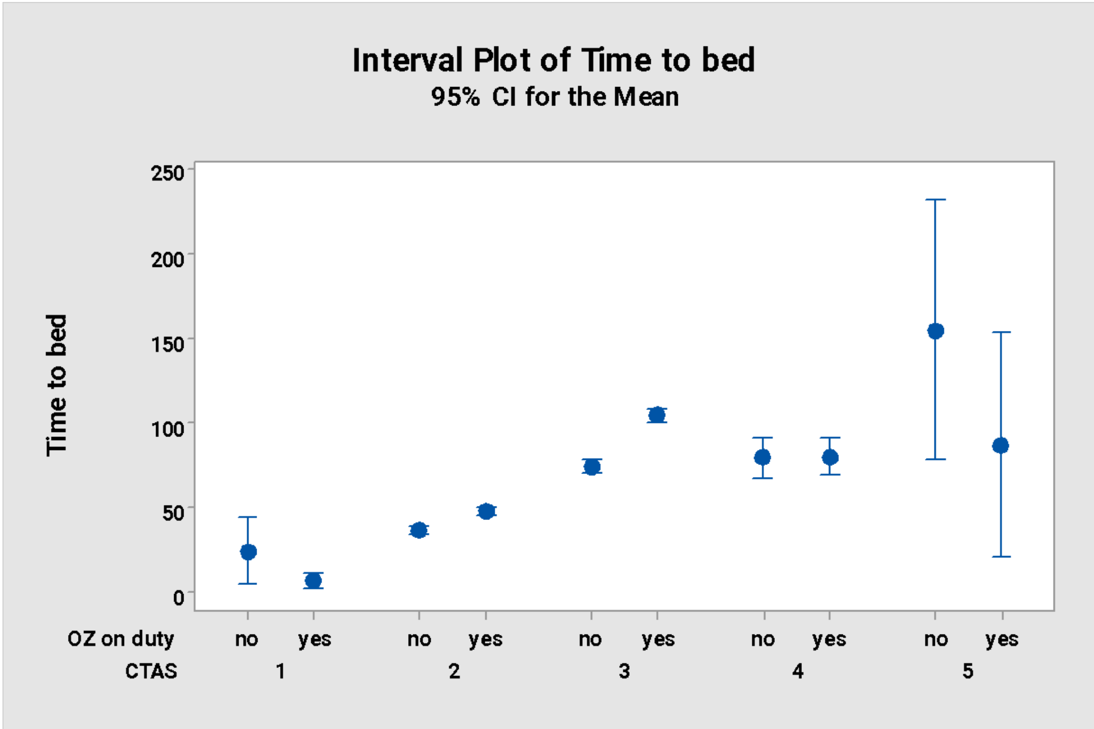

Figure 11 Means and 95% confidence intervals for time to ED bed at Hospital B, representing a unit-level comparison stratified by patient CTAS

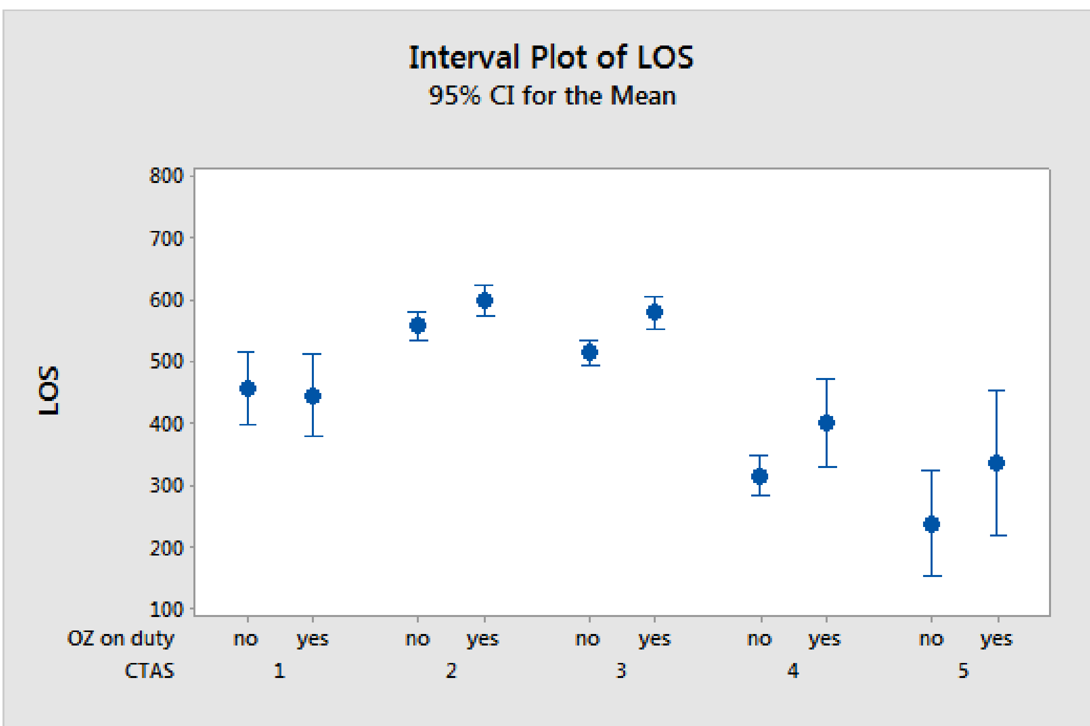

Figure 12 Means and 95% confidence intervals for length of stay at Hospital A, representing a unit-level comparison stratified by patient CTAS

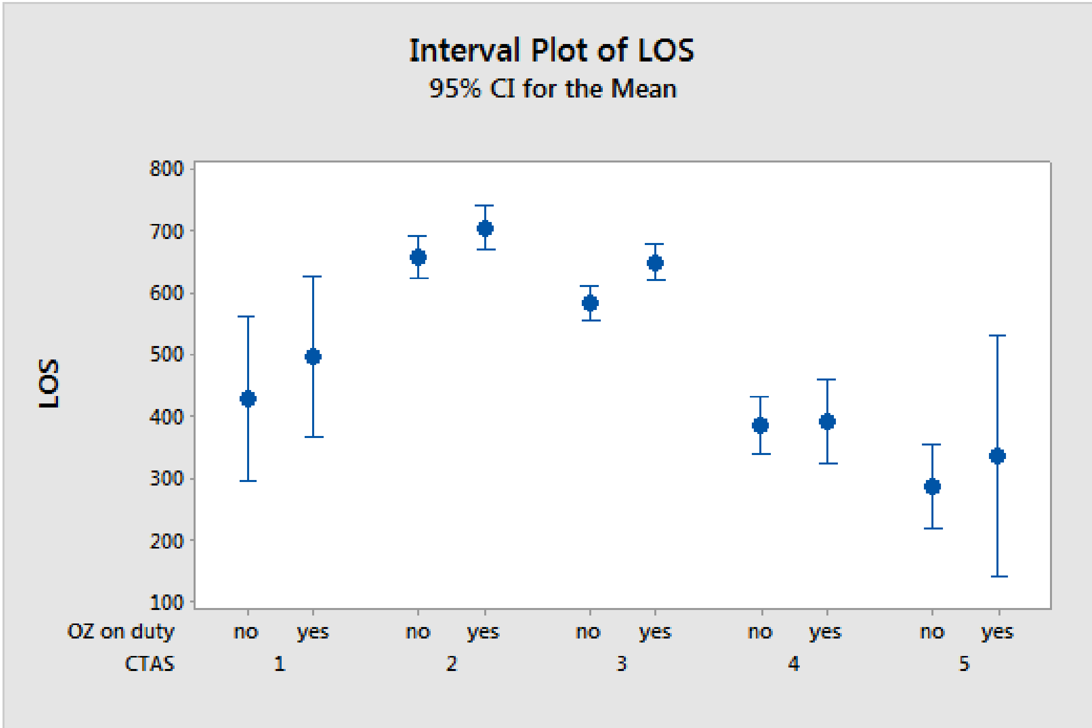

Figure 13 Means and 95% confidence intervals for length of stay at Hospital B, representing a unit-level comparison stratified by patient CTAS

Figure 14 shows comparisons for time to reach an ED bed at Hospital B, stratified by patient's clinical impression. Patients with fainting, general malaise, gastrointestinal/genitourinary, respiratory, or trauma conditions take longer to reach a bed. Figure 15 shows comparisons for length of stay at Hospital A. Patients with gastrointestinal/genitourinary or psychological conditions have a longer length of stay while those with "complex" conditions have a shorter length of stay.

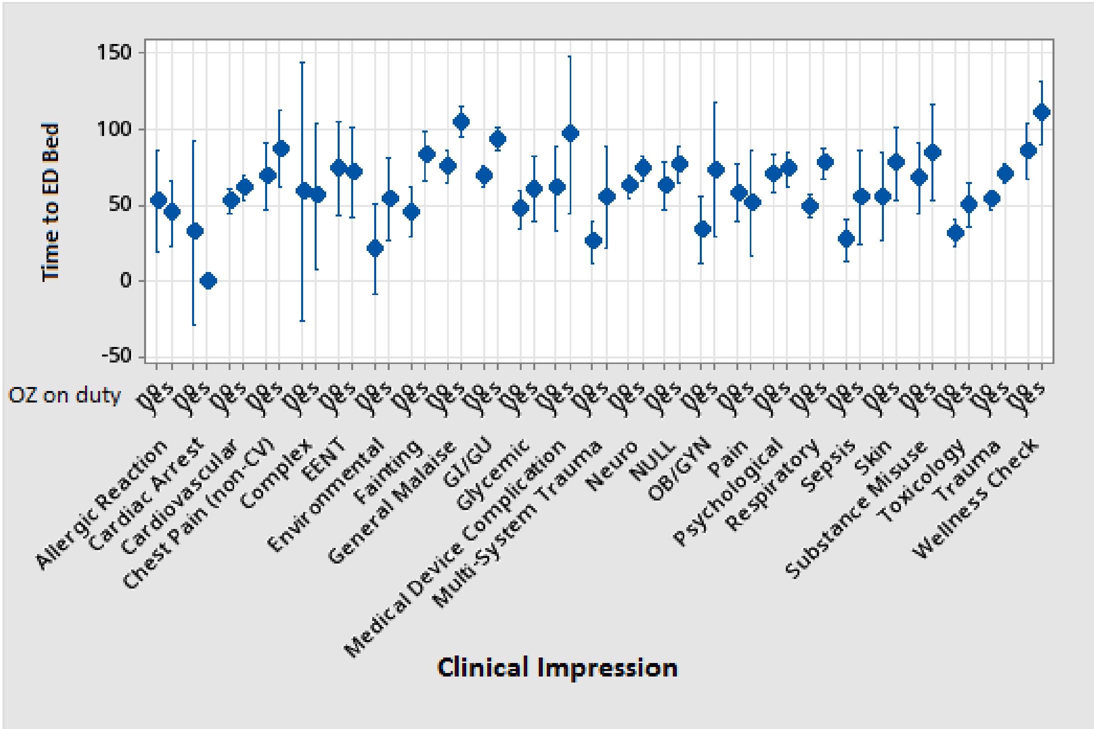

Figure 14 Means and 95% confidence intervals for time to ED bed at Hospital B, representing a unit-level comparison stratified by patient clinical impression

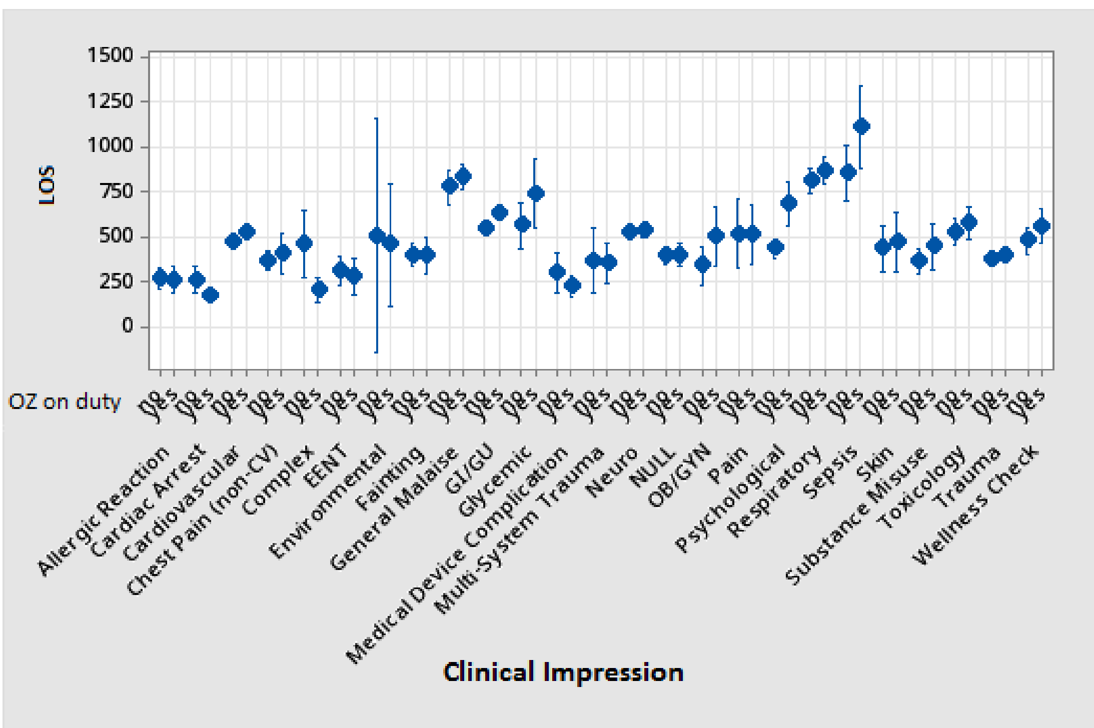

Figure 15 Means and 95% confidence intervals for length of stay at Hospital A, representing a unit-level comparison stratified by patient clinical impression

Figure 16 through Figure 21 show comparisons for offload time and time to reach an ED bed at both hospital sites, as well as time to reach an MD at Hospital B and length of stay at Hospital A, stratified by day of the week. When the OZ is open at Hospital A, no particular days show a difference in offload time or time to reach an ED bed, in contrast to the overall results for this hospital, although there is a longer length of stay on Sundays. When the OZ is open at Hospital B, all weekdays have reduced offload time, every day but Thursday has a longer time to reach an ED bed, and Saturday has a shorter time to reach an MD.

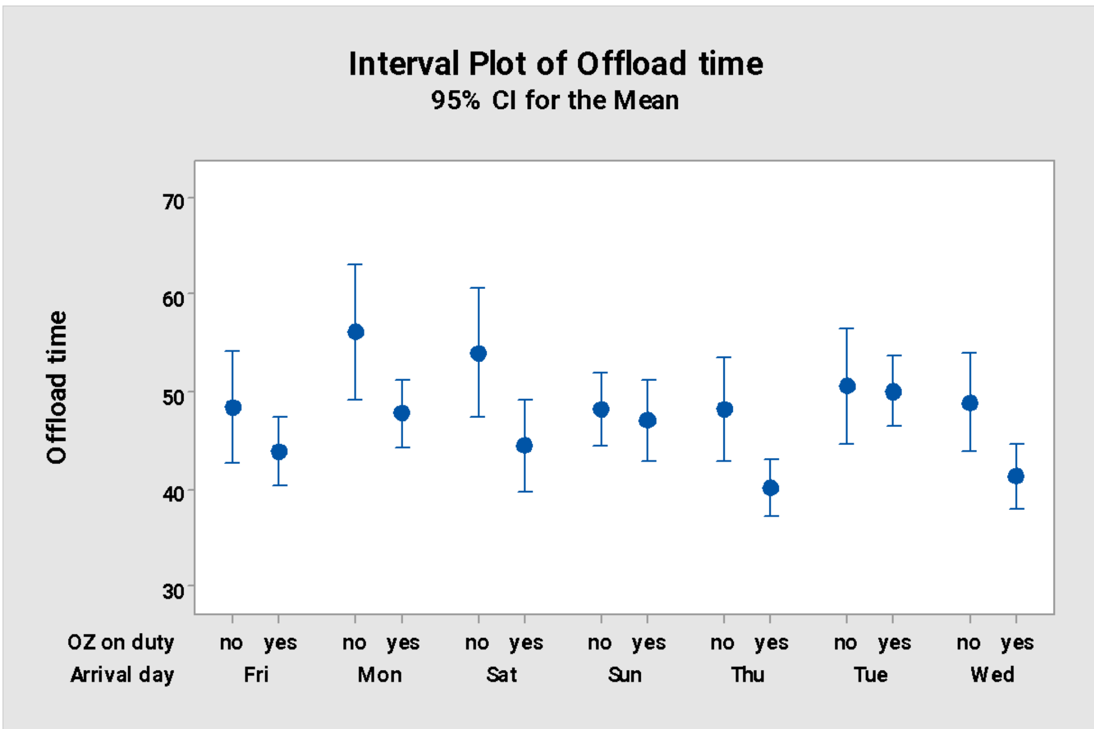

Figure 16 Means and 95% confidence intervals for offload time at Hospital A, representing a unit-level comparison stratified by day of week

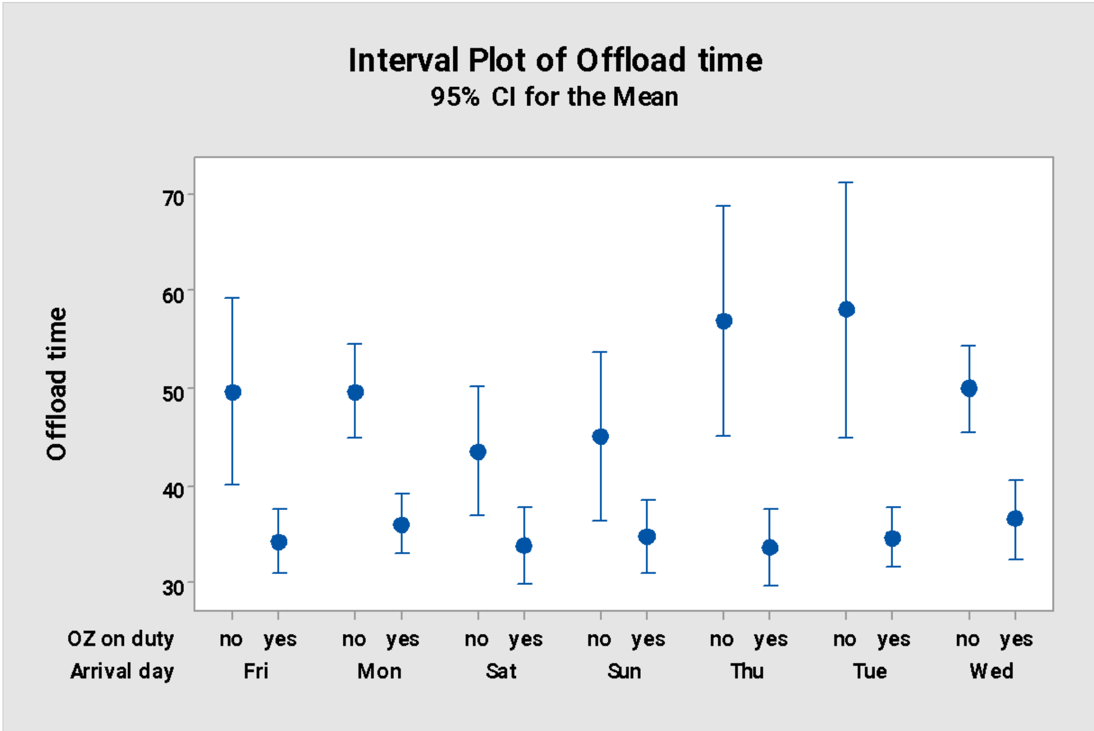

Figure 17 Means and 95% confidence intervals for offload time at Hospital B, representing a unit-level comparison stratified by day of week

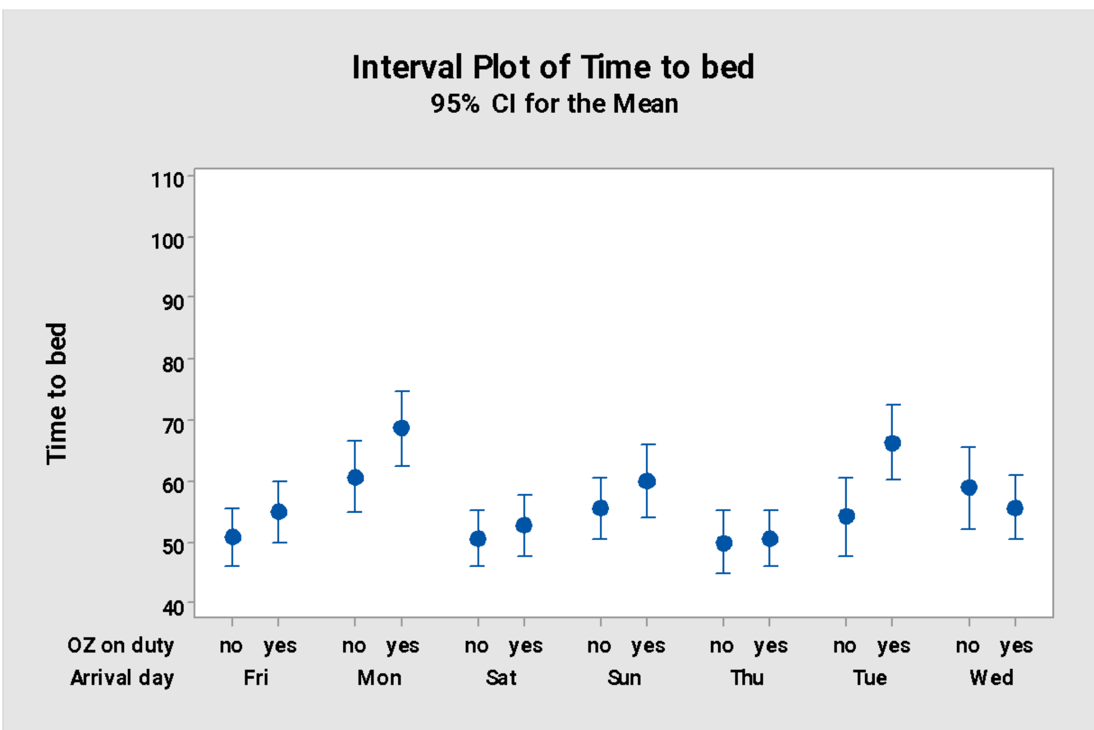

Figure 18 Means and 95% confidence intervals for time to ED bed at Hospital A, representing a unit-level comparison stratified by day of week

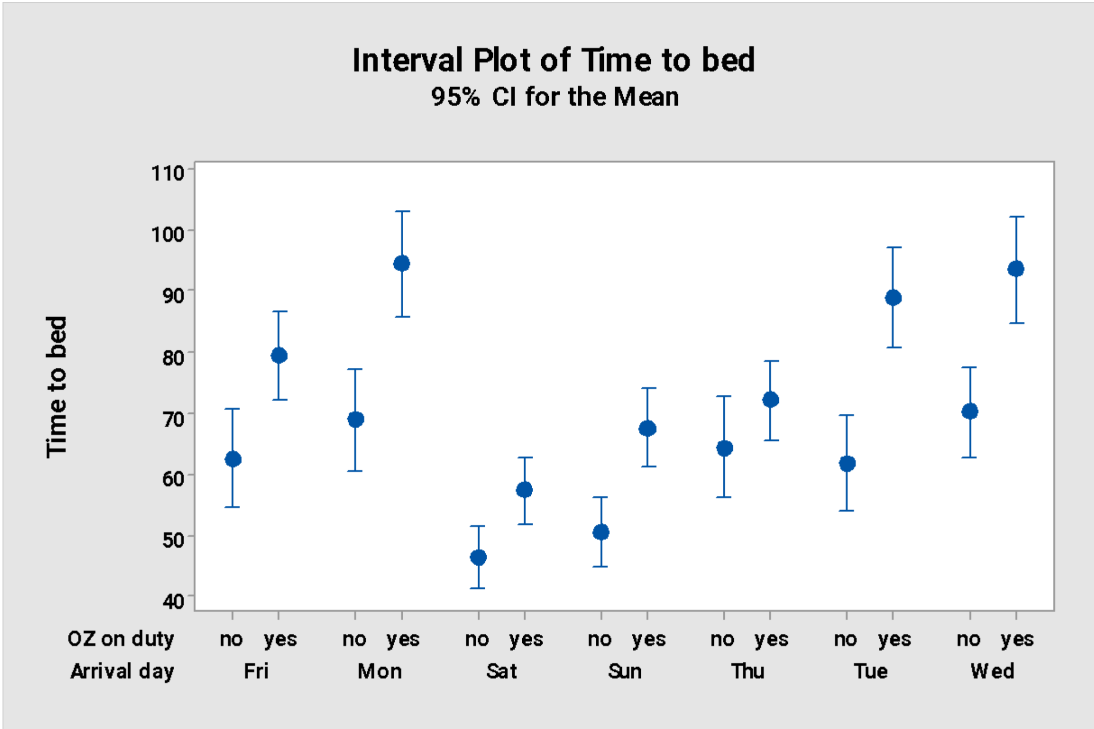

Figure 19 Means and 95% confidence intervals for time to ED bed at Hospital B, representing a unit-level comparison stratified by day of week

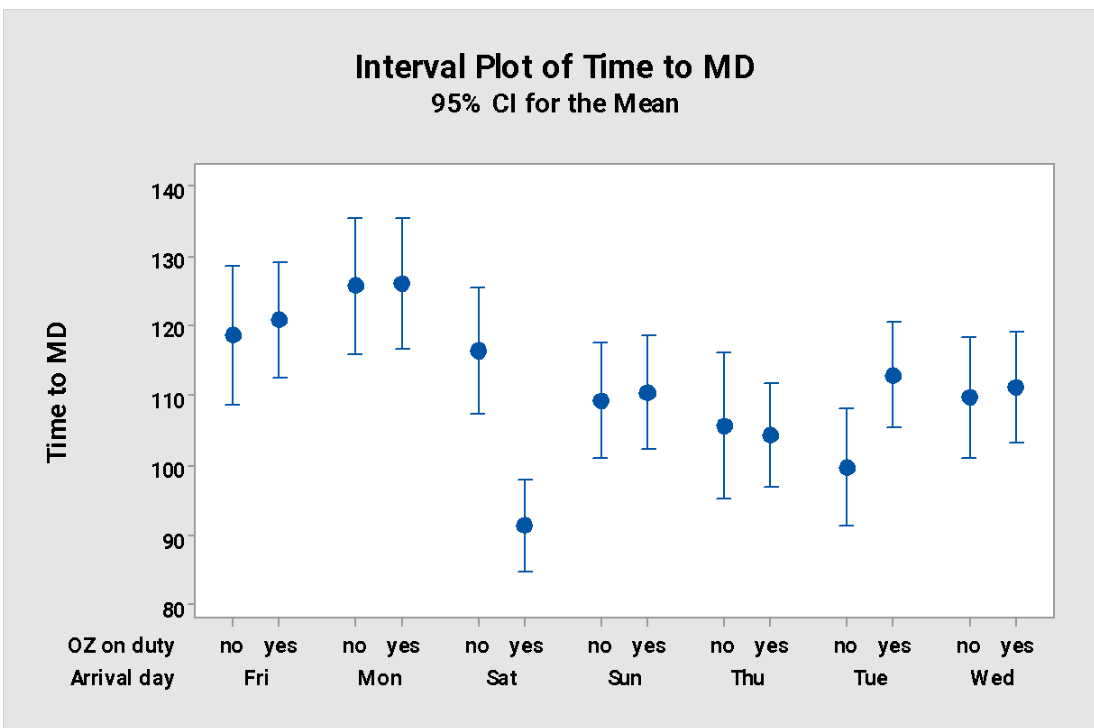

Figure 20 Means and 95% confidence intervals for time to MD at Hospital B, representing a unit-level comparison stratified by day of week

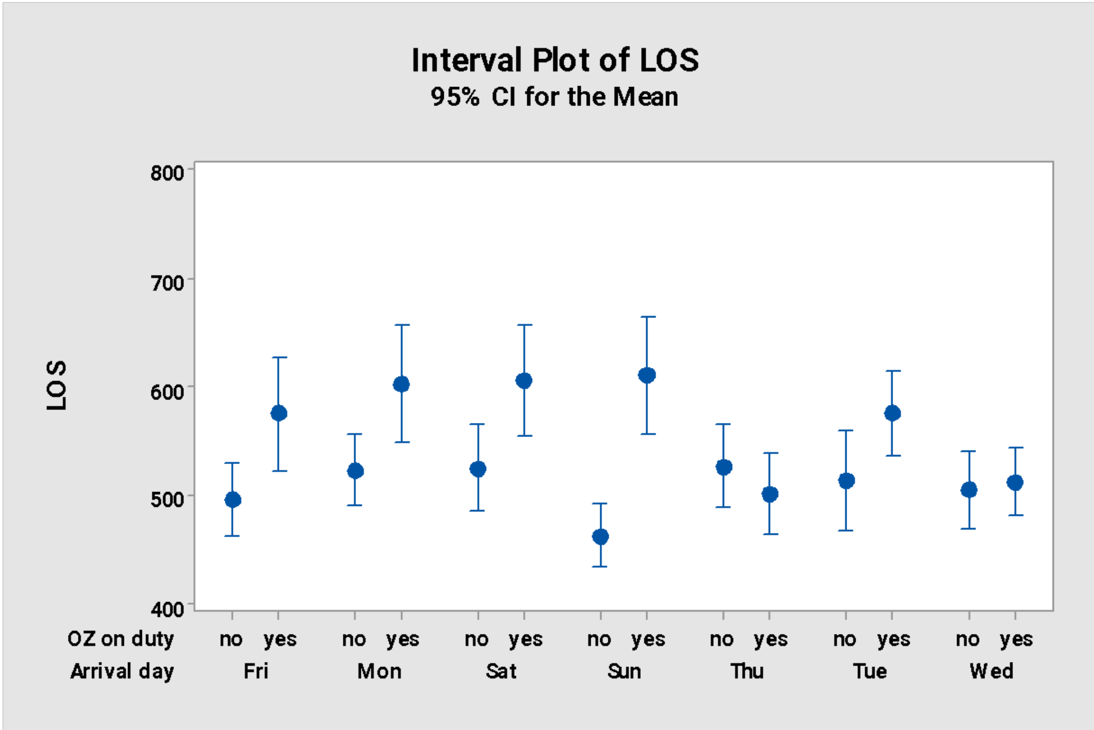

Figure 21 Means and 95% confidence intervals for length of stay at Hospital A, representing a unit-level comparison stratified by day of week

Figure 22 through Figure 25 show comparisons for time to reach an MD at both hospital sites, as well as offload time and time to reach an ED bed at Hospital B, stratified by daily ambulance arrival volumes. When the OZ is open at Hospital A, time to reach an MD is reduced on days with 26 to 28 arrivals. When the OZ is open at Hospital B, offload time is reduced on days with 13 to 24 arrivals, the time to reach an ED bed is longer on days with less than 9 arrivals, 15 to 16 arrivals, or 21 to 26 arrivals, and the time to reach an MD is reduced on days with 19 to 20 arrivals but increased on days with 21 to 22 arrivals or 25 to 26 arrivals.

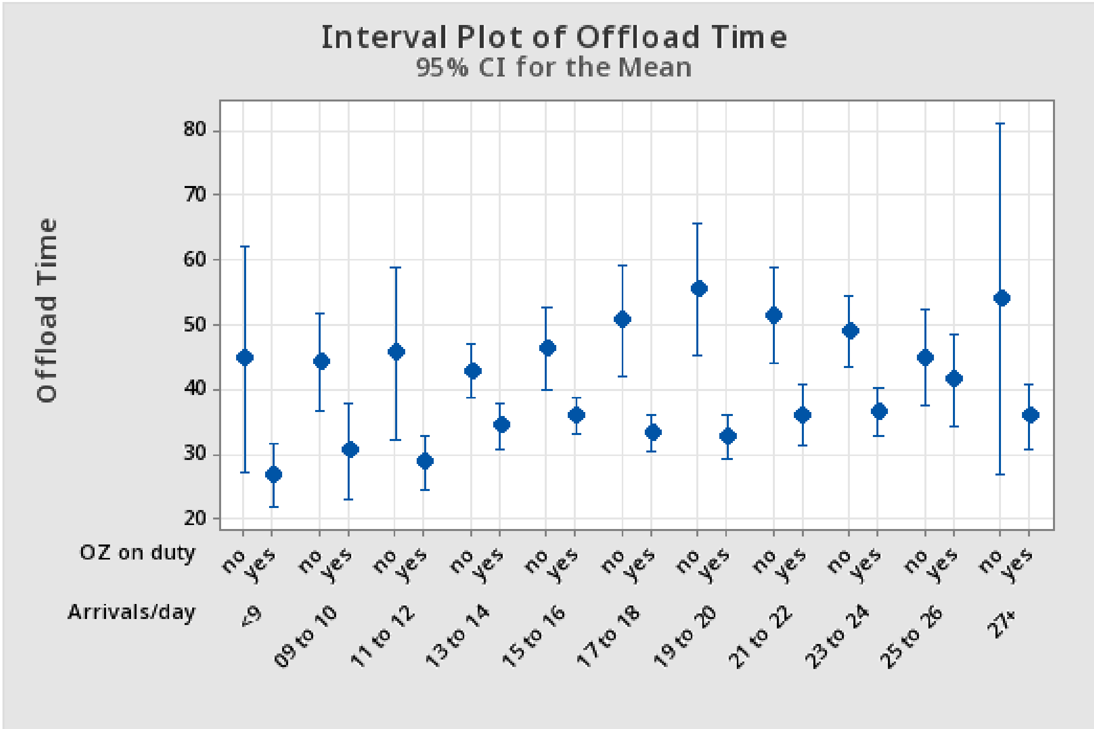

Figure 22 Means and 95% confidence intervals for offload time at Hospital B, representing a unit-level comparison stratified by daily ambulance arrivals

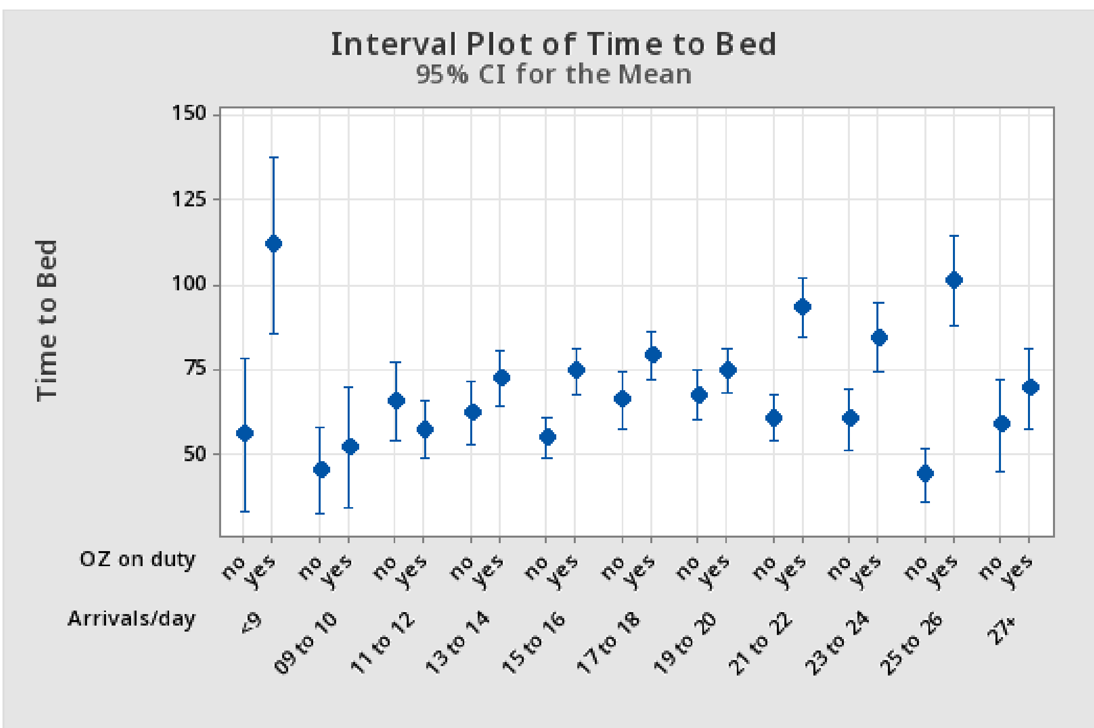

Figure 23 Means and 95% confidence intervals for time to ED bed at Hospital B, representing a unit-level comparison stratified by daily ambulance arrivals

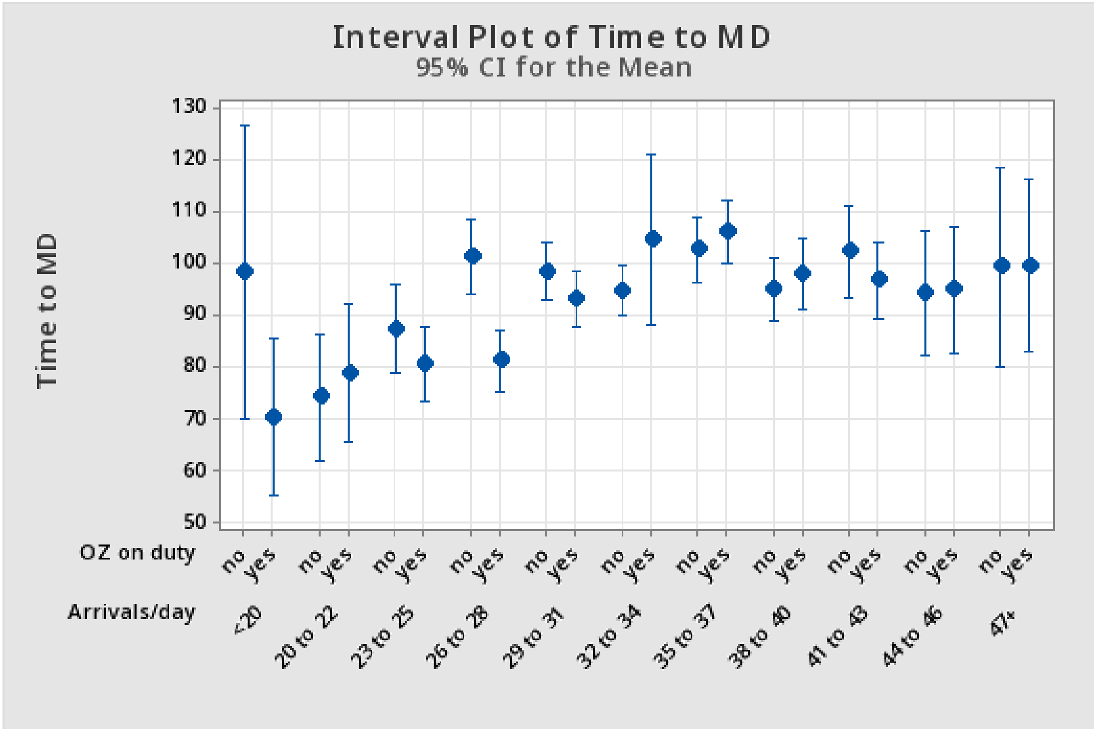

Figure 24 Means and 95% confidence intervals for time to MD at Hospital A, representing a unit-level comparison stratified by daily ambulance arrivals

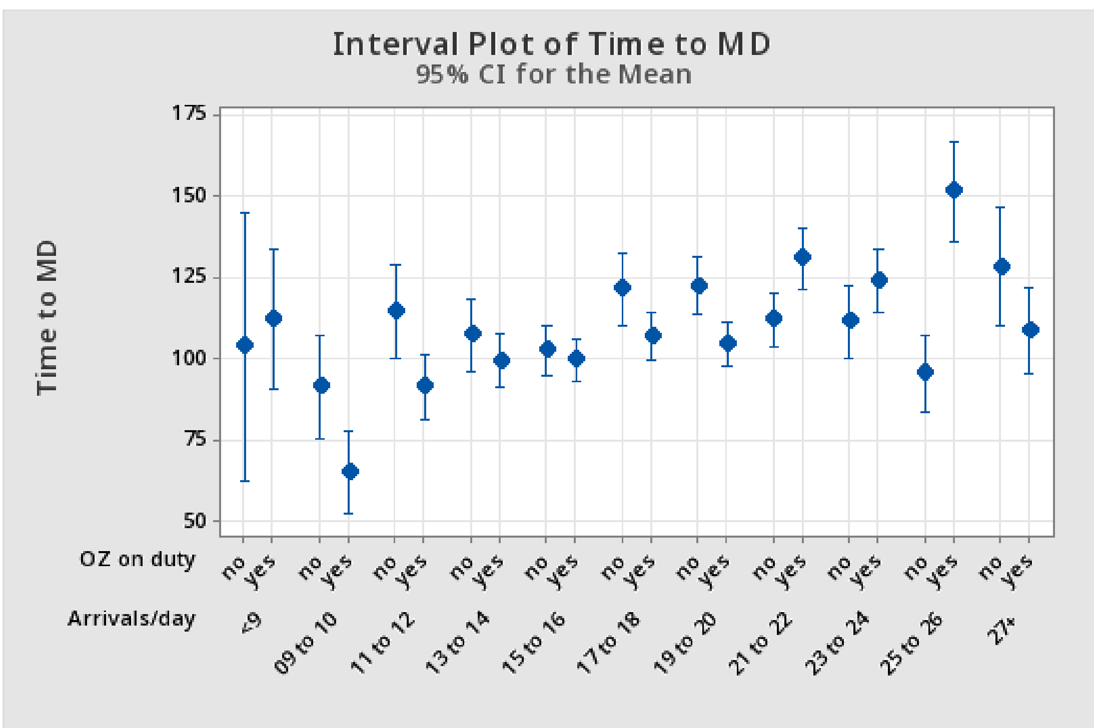

Figure 25 Means and 95% confidence intervals for time to MD at Hospital B, representing a unit-level comparison stratified by daily ambulance arrivals

4.4.2 Patient-Level Comparisons

Some general tests were first performed to characterize patients who are selected for the OZ during OZ-open days (Table 17 through Table 22). At both hospitals, male and female patients are selected equally frequently, and patients in the OZ are on average approximately 1.8 years older than those not in the OZ. At Hospital A, patients chosen for the OZ have a slightly higher acuity than those not selected, but there is no difference at Hospital B. For each hospital, every individual clinical impression category was tested against the population proportion using one-sample z-tests to see whether that clinical impression is selected for the OZ more or less often than typical, and the statistically significant results are included here. At Hospital A, cardiovascular conditions are more likely to be selected, and substance misuse conditions less likely. At Hospital B, wellness checks are less likely to be selected.

Table 17 Two-proportion z-tests on proportion of each sex that is selected for the OZ at both hospitals

Sex	**Proportion in OZ (%)**	
	Hospital A	**Hospital B**
Male	45.5	61.6
Female	46.5	64.4
Z-test p-value	0.434	0.094

Table 18 Two-sample t-tests on mean of age of patients within and outside the OZ at both hospitals

In OZ	**Mean of Age**	
	Hospital A	**Hospital B**
Yes	61.8	59.7
No	60.1	57.9
T-test p-value	0.002	0.012

Table 19 Two-sample t-tests on mean of CTAS of patients within and outside the OZ at both hospitals

In OZ	Mean of CTAS	
	Hospital A	Hospital B
Yes	2.525	2.682
No	2.601	2.688
T-test p-value	<0.001	0.800

Table 20 One-proportion z-test comparing proportion of cardiovascular patients who are selected for the OZ to the general proportion of patients selected for the OZ at Hospital A

Clinical Impression	Proportion in OZ (%)
Cardiovascular	51.0
Entire Patient Population	46.1
Z-test p-value	0.012

Table 21 One-proportion z-test comparing proportion of substance misuse patients who are selected for the OZ to the general proportion of patients selected for the OZ at Hospital A

Clinical Impression	Proportion in OZ (%)
Substance Misuse	33.8
Entire Patient Population	46.1
Z-test p-value	0.029

Table 22 One-proportion z-test comparing proportion of wellness check patients who are selected for the OZ to the general proportion of patients selected for the OZ at Hospital B

Clinical Impression	Proportion in OZ
Wellness Check	0.518182
Entire Patient Population	0.635813
Z-test p-value	0.012

Table 23 through Table 26 show results for patient-level (i.e. in OZ versus out of OZ) comparisons at both hospital sites, not stratified by any demographic or situational variables. Median and IQR are shown to give a sense of skew, but the p-value shown applies only to the comparison of means. The same general patterns are apparent at both sites. Patients who pass through the OZ are offloaded from the ambulance an average of 9.6 minutes (19.3%) faster at Hospital A and 8.8 minutes (21.7%) faster at Hospital B than patients who do not pass through the OZ. At both sites, there is no difference in the time it takes to reach an ED bed, to see an MD, or for overall length of stay.

Table 23 General statistics and results of patient-level t-tests for mean of offload time at both hospitals

Offload Time (minutes)	**Hospital A**		**Hospital B**	
	In OZ	**Out of OZ**	**In OZ**	**Out of OZ**
Mean ± St. Dev.	40.1 ± 44.4	49.7 ± 57.4	31.7 ± 36.2	40.5 ± 39.9
Median (IQR)	30 (26)	33 (35)	26 (22)	30 (24)
T-test p-value	<0.001		<0.001	

Table 24 General statistics and results of patient-level t-tests for mean of time to ED bed at both hospitals

Time to ED Bed (minutes)	**Hospital A**		**Hospital B**	
	In OZ	**Out of OZ**	**In OZ**	**Out of OZ**
Mean ± St. Dev.	58.6 ± 77.9	58.3 ± 77.9	79.4 ± 82.0	77.7 ± 81.5
Median (IQR)	27 (61)	27 (62)	49 (92)	46 (91)
T-test p-value	0.902		0.559	

Table 25 General statistics and results of patient-level t-tests for mean of time to MD at both hospitals

Time to MD (minutes)	**Hospital A**		**Hospital B**	
	In OZ	**Out of OZ**	**In OZ**	**Out of OZ**
Mean ± St. Dev.	92.8 ± 85.1	99 ± 204	110.2 ± 85.3	111.5 ± 93.1
Median (IQR)	67 (83)	67 (92)	88 (111)	85 (112)
T-test p-value	0.108		0.681	

Table 26 General statistics and results of patient-level t-tests for mean of length of stay at both hospitals

Length of Stay (minutes)	Hospital A		Hospital B	
	In OZ	Out of OZ	In OZ	Out of OZ
Mean ± St. Dev.	563 ± 657	571 ± 706	649 ± 644	626 ± 625
Median (IQR)	352.5 (394)	341 (432)	380 (685)	375 (694)
T-test p-value	0.668		0.309	

In general, when data were stratified by variable, results tended to follow similar patterns to those above. For some stratifications, the reduced sample sizes and thus greater uncertainties ended up eliminating the statistical significance of an apparent difference between means. The following results were selected to highlight interesting deviations from the previous patterns, differences between the hospital sites, or differences from what was observed in the status-level section. The only variable entirely omitted from this section is comparisons stratified by sex, as their patterns simply mirrored the unstratified status-level comparisons. Stratifications where the pattern of results differed from the main results in Table 23 through Table 26, but which are not presented for discussion here, can be found in the Appendix.

Figure 26 and Figure 27 show comparisons for offload time at both hospital sites, stratified by patient age groups. At Hospital A, patients in the age ranges of 45 to 54 and 75 and over have reduced offload time when passing through the OZ, and Hospital B shows similar results, with age ranges of 45 to 54 and 85 and over having reduced offload time.

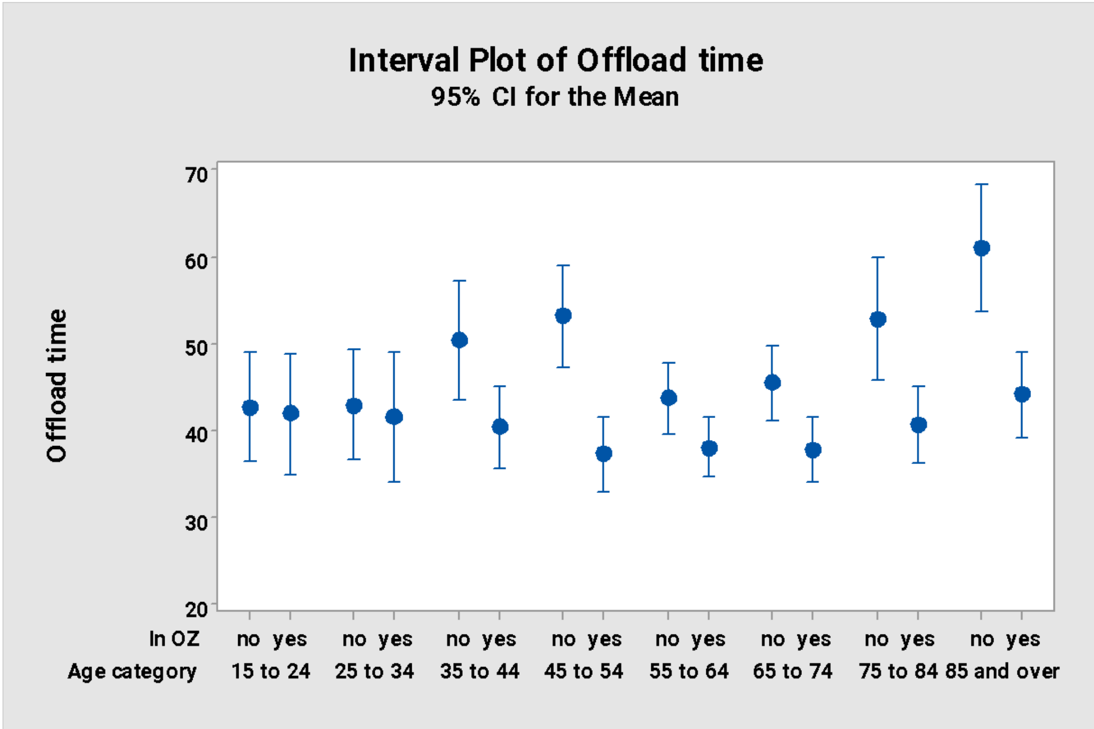

Figure 26 Means and 95% confidence intervals for offload time at Hospital A, representing a patient-level comparison stratified by patient age group

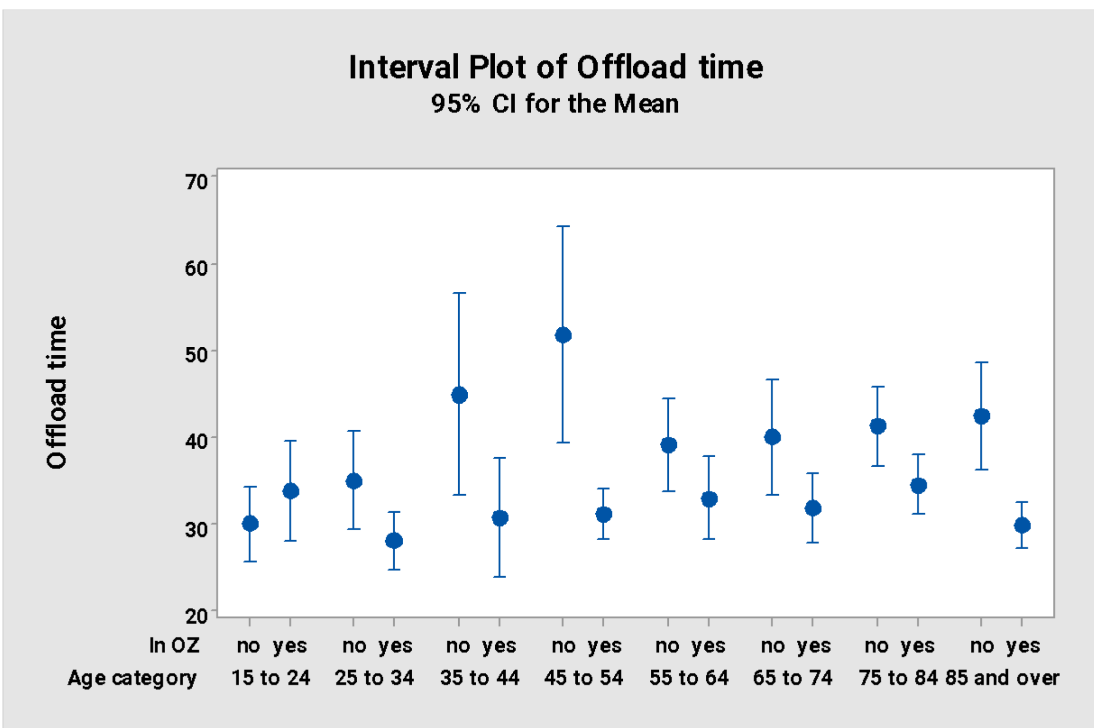

Figure 27 Means and 95% confidence intervals for offload time at Hospital B, representing a patient-level comparison stratified by patient age group

Figure 28 and Figure 29 show comparisons for offload time at both hospitals, stratified by patient CTAS. At Hospital A, patients with CTAS 3 and 4 have a reduced offload time when they pass through the OZ, and at Hospital B, patients with CTAS 2 and 3 have reduced offload time. Figure 30 shows comparisons for time to reach an ED bed at Hospital A, where patients with CTAS 2 are delayed in reaching a bed when passing through the OZ. Figure 31 shows comparisons for length of stay at Hospital B, where patients with CTAS 1 have a much longer length of stay when passing through the OZ.

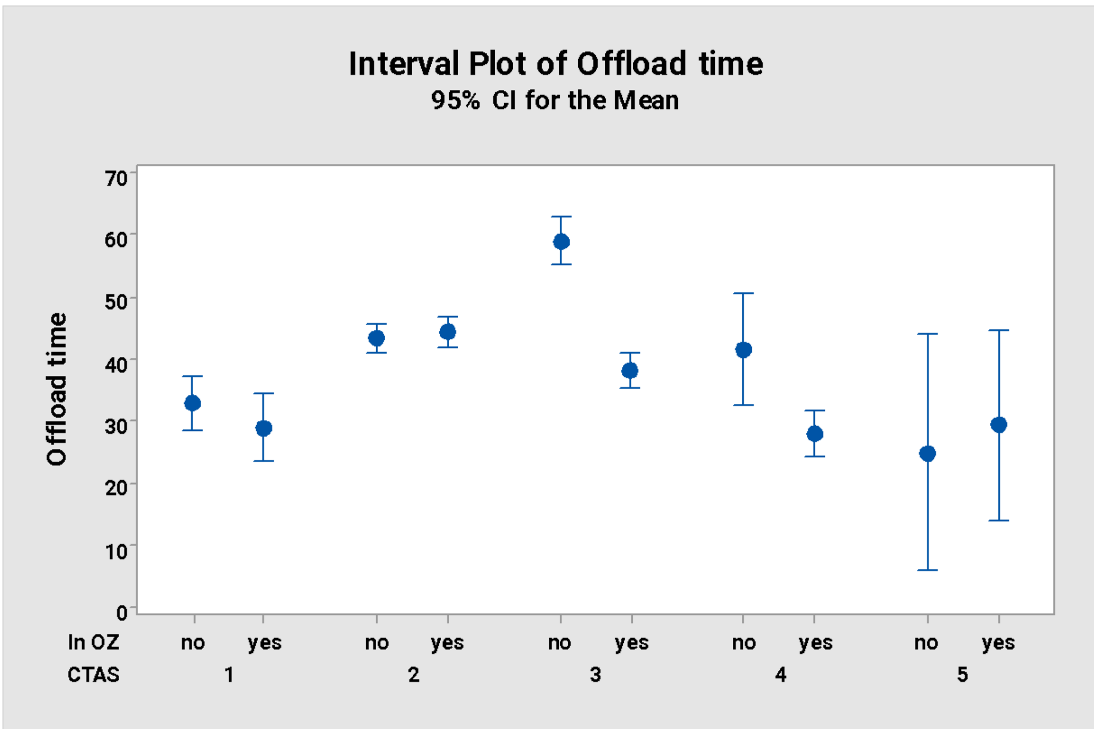

Figure 28 Means and 95% confidence intervals for offload time at Hospital A, representing a patient-level comparison stratified by patient CTAS

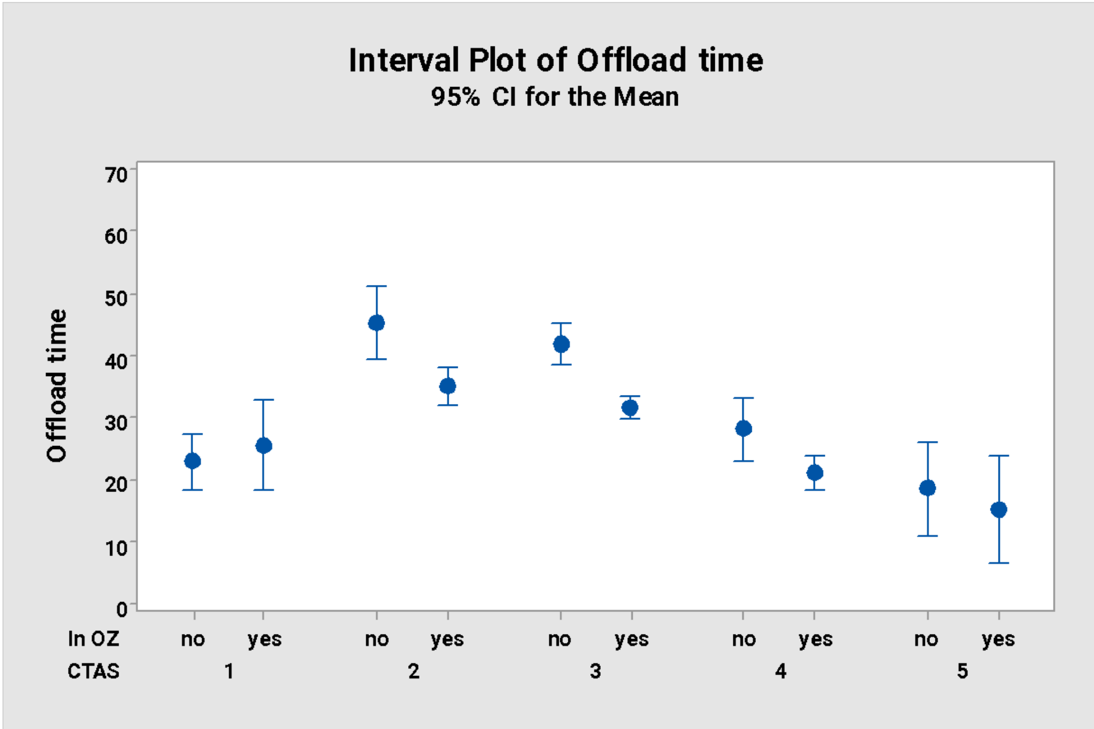

Figure 29 Means and 95% confidence intervals for offload time at Hospital B, representing a patient-level comparison stratified by patient CTAS

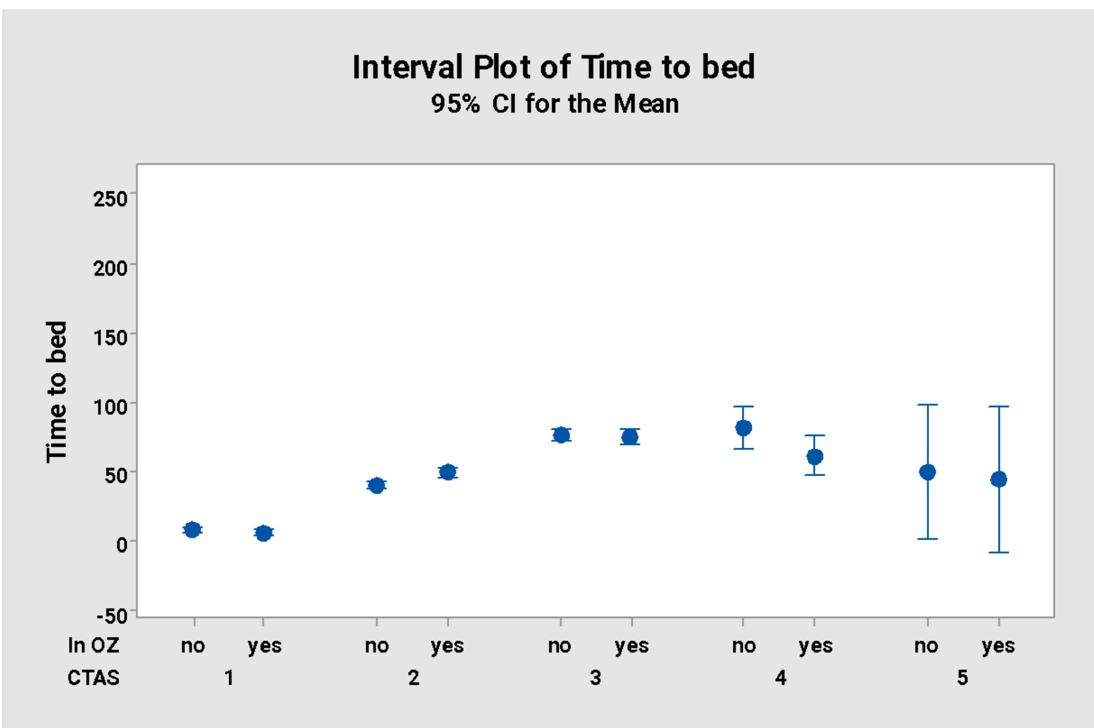

Figure 30 Means and 95% confidence intervals for time to ED bed at Hospital A, representing a patient-level comparison stratified by patient CTAS

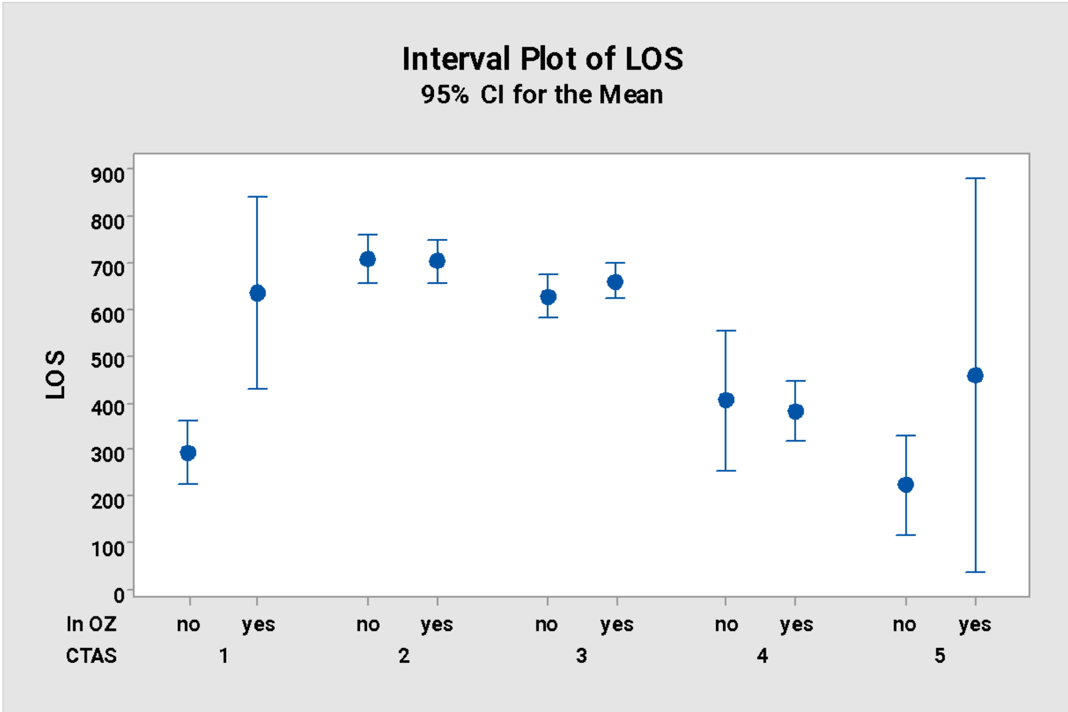

Figure 31 Means and 95% confidence intervals for length of stay at Hospital B, representing a patient-level comparison stratified by patient CTAS

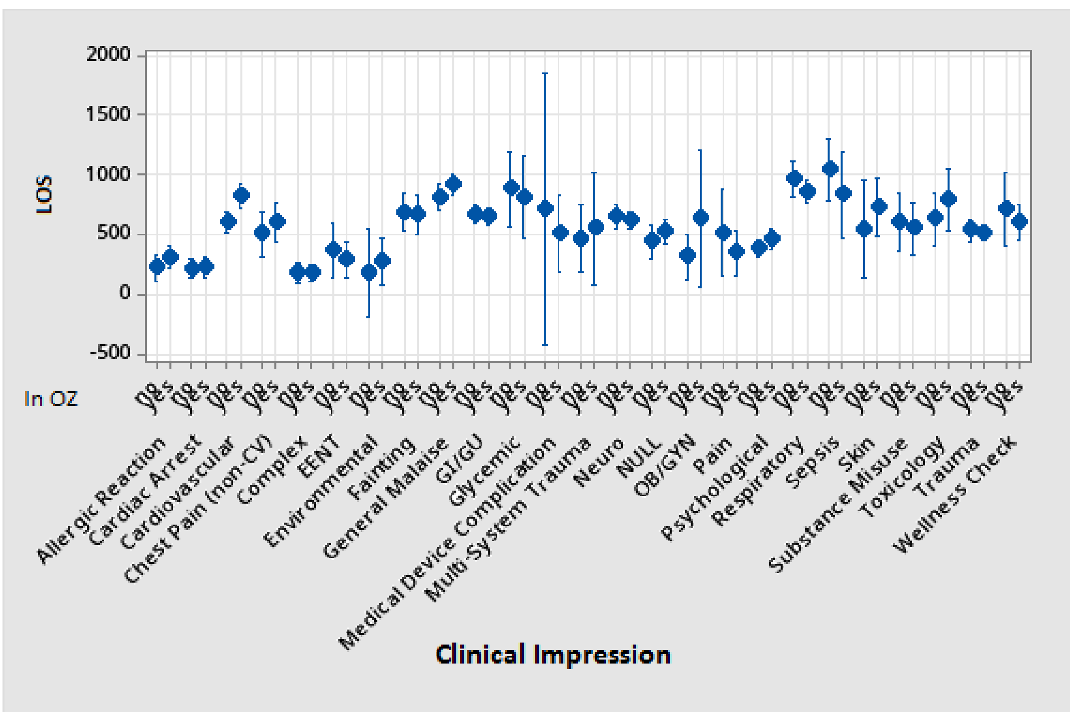

Figure 32 Means and 95% confidence intervals for length of stay at Hospital B, representing a patient-level comparison stratified by patient clinical impression

Figure 32 shows comparisons for length of stay at Hospital B, where patients with cardiovascular conditions have a longer length of stay after passing through the OZ.

Figure 33 through Figure 36 show comparisons for offload time at both hospital sites, as well as time to reach an ED bed and time to reach an MD at Hospital B, stratified by day of the week. At Hospital A, patients passing through the OZ on Friday, Saturday, Sunday, or Tuesday have reduced offload time. When patients pass through the OZ at Hospital B, Wednesday, Friday, and Sunday have reduced offload time, and Friday has both reduced time to reach an ED bed and time to reach an MD.

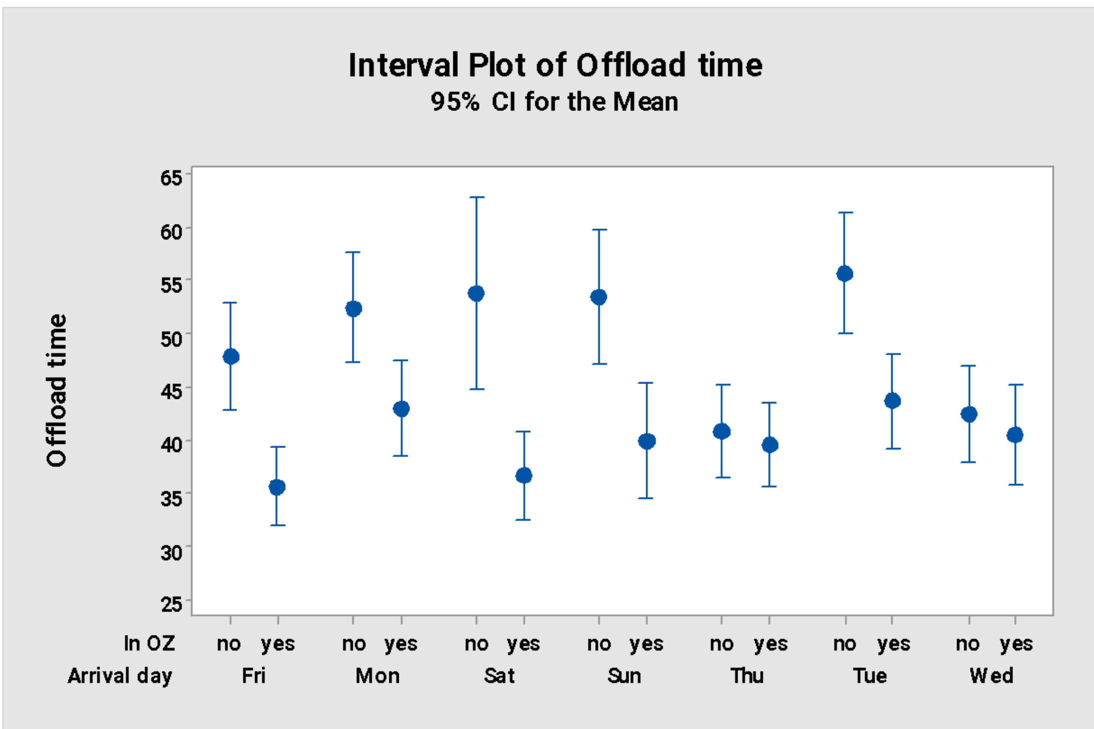

Figure 33 Means and 95% confidence intervals for offload time at Hospital A, representing a patient-level comparison stratified by day of week

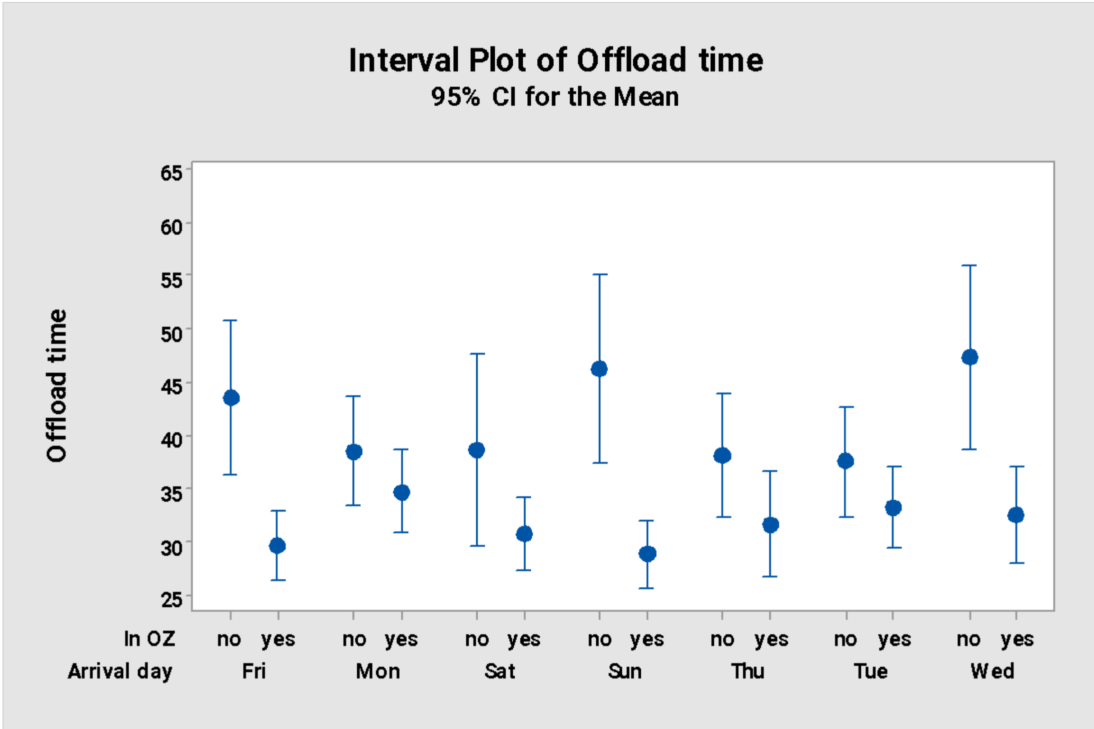

Figure 34 Means and 95% confidence intervals for offload time at Hospital B, representing a patient-level comparison stratified by day of week

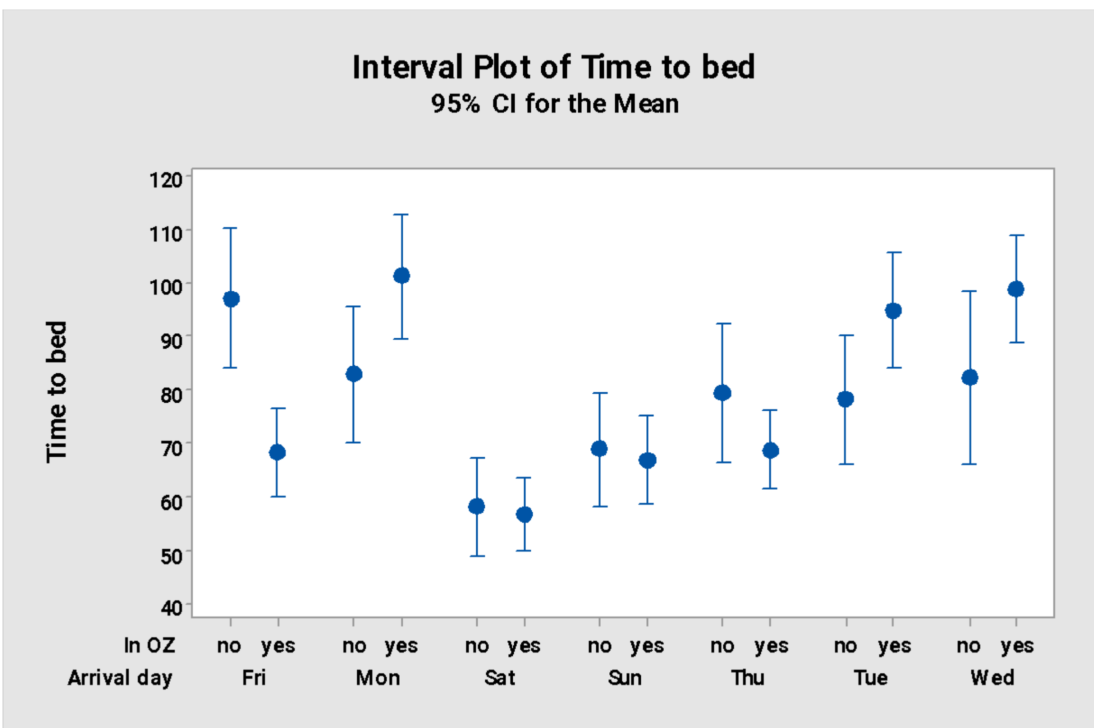

Figure 35 Means and 95% confidence intervals for time to ED bed at Hospital B, representing a patient-level comparison stratified by day of week

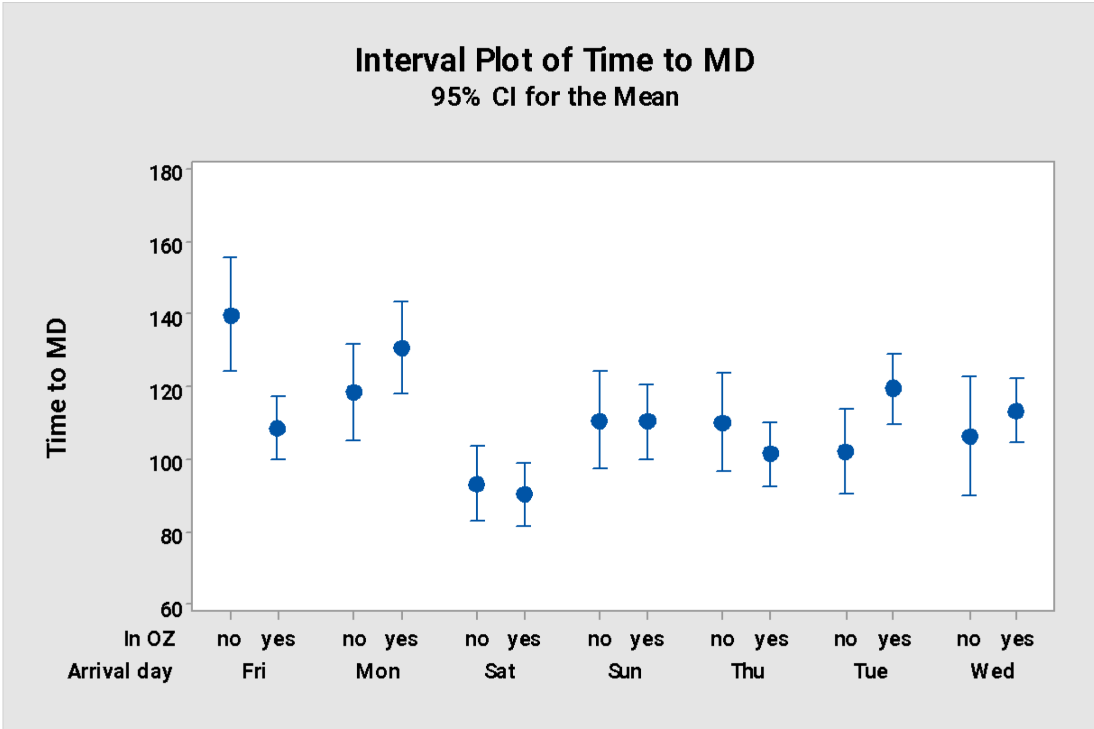

Figure 36 Means and 95% confidence intervals for time to MD at Hospital B, representing a patient-level comparison stratified by day of week

Figure 37 through Figure 39 show comparisons for offload time at both hospital sites, as well as time to reach an ED bed at Hospital A, stratified by daily arrival volumes. When patients pass through the OZ at Hospital A, offload time is reduced on days with 29 to 34 arrivals or 38 to 43 arrivals, and time to reach an ED bed is increased on days with 35 to 37 arrivals but reduced on days with 38 to 40 arrivals. When patients pass through the OZ at Hospital B, offload time is reduced on days with 23 to 26 arrivals.

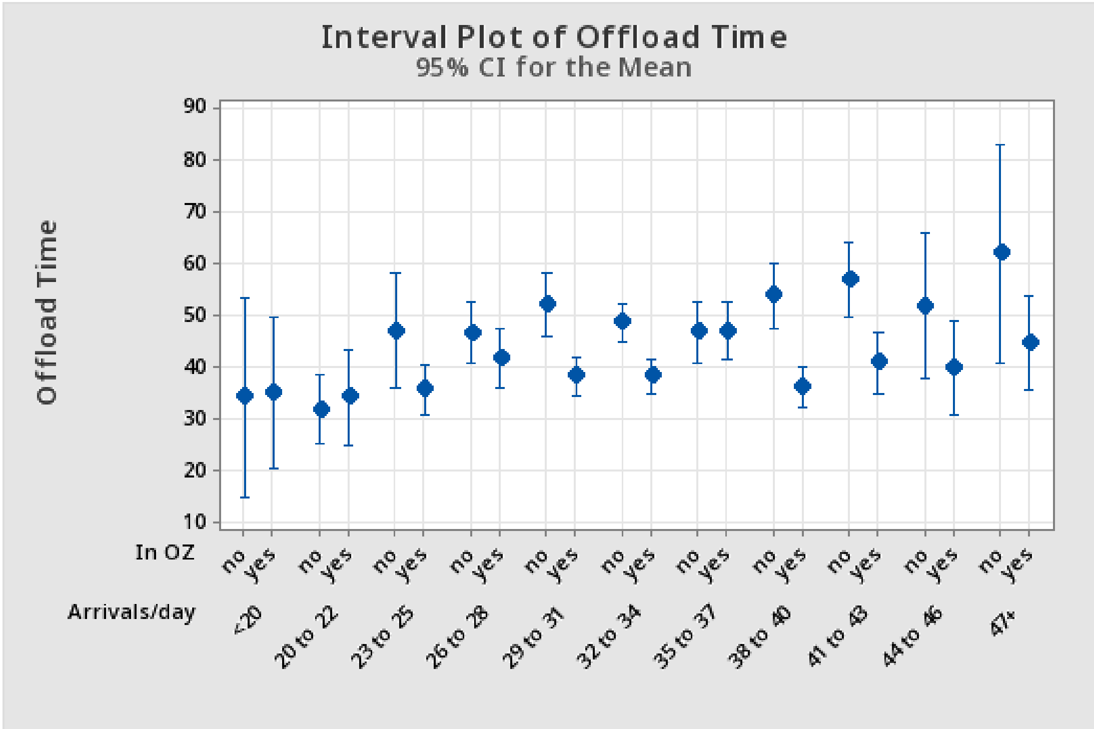

Figure 37 Means and 95% confidence intervals for offload time at Hospital A, representing a patient-level comparison stratified by daily ambulance arrivals

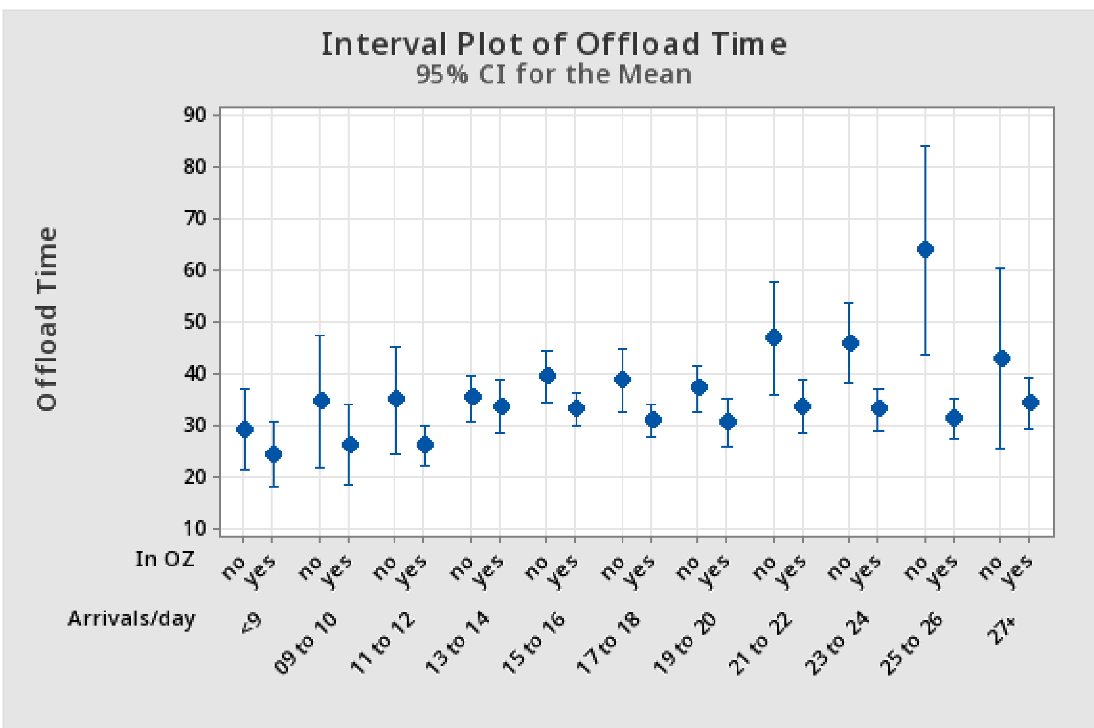

Figure 38 Means and 95% confidence intervals for offload time at Hospital B, representing a patient-level comparison stratified by daily ambulance arrivals

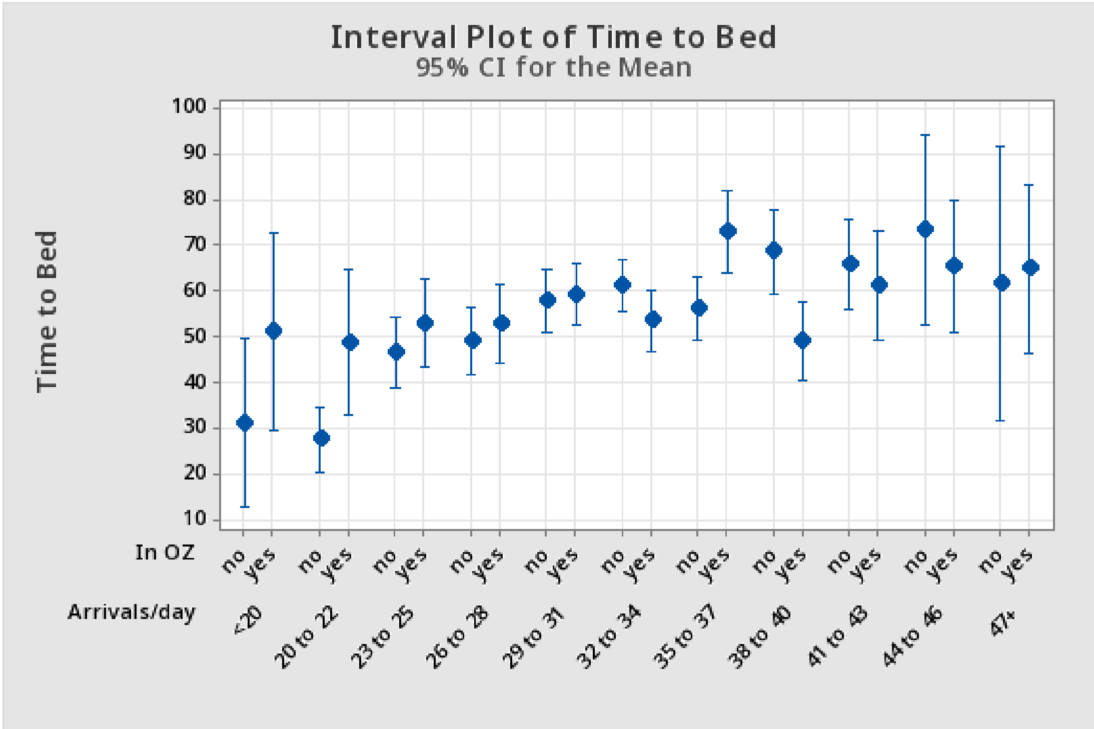

Figure 39 Means and 95% confidence intervals for time to ED bed at Hospital A, representing a patient-level comparison stratified by daily ambulance arrivals

4.5 Discussion

Examining the results laid out in the previous subsections provides insight as to how the OZ is used at each hospital, how different types of patients interact with it, and how it affects the overall flow of the ED. Contrasting the results of unit-level versus patient-level comparisons provides insight as to the systemic versus the individual patient effects of the OZ. Table 27 shows a summary of the main findings that will be expanded on throughout the discussion.

Table 27 Summary of main findings at each hospital

Section of Results	Main findings	
	Hospital A	Hospital B
Pre-OZ State	Experiencing crowding	Experiencing crowding more severely; More likely to use hallway admissions
Characteristic of Patients Selected for the OZ	Slightly older; Slightly higher acuity	Slightly older
Path Analysis	Patients treated in the OZ; Hallways admissions sometimes occur; OZ reduces likelihood of LWBS	Patients treated in the OZ and in hallways; Hallway admissions still common when OZ open
Unstratified Time Analysis	Offload time reduced primarily for patients who use the OZ	Offload time reduced primarily for patients who use the OZ; Ratio of ED to OZ beds may impact results; Issue with ED boarding
Time Analysis Stratified by Patient Age	Best offload time improvement for ages 55–84	Best offload time improvement for ages <35 and >54
Time Analysis Stratified by Patient CTAS	OZ is used to more freely allocate patients based on acuity; CTAS 2 most likely to be treated in OZ	OZ is used first-come-first-served to alleviate ambulances ASAP; CTAS 2 and 3 patients most likely to be treated in OZ or hallway; OZ may be used for less urgent CTAS 1 cases
Time Analysis Stratified by Patient Clinical Impression		OZ is used to begin lengthy testing processes; Patients with low-needs conditions are left in OZ longer and are delayed in reaching an ED bed
Time Analysis Stratified by Day of Week	Some effects apparent from weekly staffing schedules and demand patterns	Some effects apparent from weekly staffing schedules and demand patterns

Section of Results	Main Findings	
	Hospital A	Hospital B
Time Analysis Stratified by Ambulance Arrival Volume	Possible relationship between OZ size and number of arrivals that can be managed	Possible relationship between OZ size and number of arrivals that can be managed; Hallway admissions become more common after a certain arrival threshold is reached; Time to reach an MD is negatively impacted at highest level of demand

4.5.1 Pre-OZ State

To begin, the baseline statistics on each hospital's OZ-closed performance (Table 10) can indicate the system state when the OZ was introduced. Both hospitals have the same performance in terms of offload time, around 50 minutes. This figure is already above the target of 30 minutes, and it should be noted that the true mean is likely even higher, since OZ-closed periods are on average less busy than when the OZ is opened. This result confirms that, as expected, both hospitals were dealing with crowding that impacted their ability to accept incoming ambulance arrivals.

After patients are offloaded and before they reach an ED bed, a few intermediary steps occur: triage, registration, and physical transportation into the ED. According to discussions with hospital workers during the course of this study, these steps typically take only a few minutes. Hospital B takes 5.9 minutes longer than Hospital A to place patients in an ED bed, which would be unexpected if they have the same offload times. This margin is small enough that it could be explained by process differences or longer transportation distances. However, it could also be a systemic consequence of accepting patients into the ED before a bed is available for them.

Patients at Hospital B also wait 14.8 minutes longer to see an MD and have a 79 minute longer ED length of stay than those at Hospital A, indicating that they generally face a larger burden on their ED resources. In this case, it would be expected for their offload times to be impacted as well, so the result that the hospitals have a similar offload time supports the idea that patients at Hospital B are being offloaded before a bed is available to them, either to wait or to begin treatment in an undesignated area such as a hallway. This scenario will be referred to throughout the discussion as "hallway admissions."

4.5.2 Characteristics of Patients Selected for the OZ

The tests characterizing patients who are selected for the OZ (Table 17 through Table 22) can provide some insight, but it must be considered that the non-OZ population comprises high-acuity patients who enter the ED right away, low-priority patients who must wait with ambulance paramedics when the OZ is full, and minimal acuity patients who are directed to the walk-in waiting room. Since CTAS 2 and 3 account for the bulk of the population (87.6% across both hospitals), the very high- and very low-acuity cases should not have a strong effect. OZ patients tend to be slightly older than non-OZ patients, which may be related to which acuities and conditions are more common at different ages, but may also be due to older patients being moved for their comfort. Hospital A's OZ patients have a slightly higher acuity than those who do not use the OZ, indicating that the OZ may be relied on as a place where higher-acuity patients have more security and access to better resources in case their condition declines. The acuity for each group is the same at Hospital B, so they more likely allocate patients on a first-come-first-served basis, either as policy or out of necessity due to their higher burden of demand.

With cardiovascular conditions being more commonly selected at Hospital A, note that cardiac arrest is a different category and is not included in this group. More than half of cardiovascular patients are initially tagged as "not yet diagnosed," so this may be a condition where staff feel that bringing a patient into the OZ to order tests before they take up an ED bed is the most efficient use of resources. Substance misuse conditions are less commonly selected here, possibly because this condition often requires quick treatment. There are a number of high-acuity conditions that require quick treatment and would be expected to show different proportions as well, but they tend to be rarer, so it could be that their sample sizes are too small to register significance. Wellness checks are less likely to be selected at Hospital B, possibly because this type of condition is generally low-acuity and may be one of the best types of patients to redirect to the walk-in waiting room. It is unclear why there are different condition selection patterns at each hospital, but it may be due to demographics of the local area, or simply due to the large number of condition types breaking the data into much smaller sample sizes with higher uncertainty levels.

4.5.3 Path Analysis

Looking at the sequence of treatment steps analyses in Table 11 and Table 12 reveals a change in ED staff's behaviour and decision-making. At both hospitals, when the OZ is open, the typical path for treating patients becomes less frequent. Physicians are more likely to treat patients before they are assigned a bed and sometimes discharging them before ever being placed in a bed. This result implies that when the OZ is open, care providers are treating patients in the OZ. This is a concern because when patients are being treated in the OZ, they stay in an OZ bed longer, and offload delay will return when arriving ambulances find the OZ full.

The patient-level comparison at Hospital A reflects that it is primarily OZ patients who are treated before reaching an ED bed, although it does appear to also occur for non-OZ patients who are admitted to hallways. Hospital B shows high rates of occurrence for the Treatment before ED Bed path, and with almost no differences in any of its patient-level tests, it would seem that both OZ and non-OZ patients travel through the ED in a similar way, with OZ patients being only slightly likelier to begin treatment before reaching an ED bed. This result shows that hallway admissions are a common occurrence at Hospital B, occurring frequently even when the OZ is available.

A few other points of interest can be noted here. The only place where a change in the "MD before RN" path occurs is in Hospital B's unit-level tests. Since this path becomes less common, it could show that when the OZ is open, MDs are stretched more thinly and start to take longer to see some patients. At Hospital A, the LWBS path becomes less frequent in both comparisons. Whether this is because patients are better satisfied with their care, or because they feel uncomfortable leaving in a more heavily supervised setting, it is a positive in terms of patient care outcomes.

4.5.4 Unstratified Time Analysis

At both hospital sites, the OZ reduces offload time on both the unit level (OZ-open/OZ-closed) (Table 13) and the patient level (in-OZ/out-of-OZ) (Table 23). The estimates for the means in the unit-level analyses may be biased by the higher likelihood of the OZ being open during higher traffic periods, however, as discussed in the data independence analysis, this bias does not make the statistical significance of the difference between means less likely to be true.

In considering patient offload time, an ideal result would be to find a difference at the unit level but not the patient level, because it would indicate that the OZ benefits all ambulance patients and not just the ones selected for the OZ. The results described here, where there is a difference at both levels, is a moderate success, where patients selected for the OZ are more likely to see a benefit. This result is likely a reflection of the anecdotally reported scenario where the OZ fills up and AOD again becomes an issue.

In the unit-level test (Table 13), the estimated difference between means is greater at Hospital B (30.0% reduction in offload time) than Hospital A (11.4% reduction in offload time). This discrepancy is unintuitive considering that the path analysis showed Hospital B as being likely to admit patients into hallways, which would lower the expected offload time during OZ-closed periods, and likely to treat patients within the OZ, which would cause the OZ to fill up and become less useful. To show a difference at the unit level, it is likely that Hospital B is not replacing hallway admissions with OZ admissions but rather is continuing to allow hallways admissions while the OZ is functioning. The greater difference between means may also be a reflection of better results from the OZ due to the ratio of OZ beds to general ED capacity.

These main results were used to estimate the number of AOD hours avoided as a result of the OZ program (Table 28). The number of actual AOD hours was found using the calculated average offload times for OZ-on and OZ-off periods, with 30 minutes removed from each patient record, so that these figures reflect the amount of time beyond the typical target offload interval. The number of AOD hours that would have occurred during the same time period if there had been no OZ was estimated by using the OZ-off average offload time and applying it to all patient records during the period. The estimated AOD hours avoided is the difference between these figures. These results are important to consider because in a resource-constrained system, every hour of AOD avoided is an hour that goes back into coverage to maintain response times in the community.

Table 28 Actual AOD hours reflected in the dataset, an estimate of AOD hours that would have occurred during the same time period with no OZ in place, and an estimate of AOD hours avoided as a result of the OZ

Hospital	Actual AOD Hours	Estimated AOD Hours If No OZ	Estimated AOD Hours Avoided
A	3,501	4,081	580
B	1,161	2,044	883

It is difficult to put these numbers into context due to the rapidly increasing severity of AOD. Carter et al. reported in 2015 that EHS had recently estimated AOD across all of Nova Scotia to total 2,900 hours annually. Using more recent data from the Office of the Auditor General of Nova Scotia (2023), reports of average AOD and number of offloads can be used to estimate 50,733 hours at QEII and 25,319 hours at DGH during 2022. The data in Table 28 reveal an estimated reduction in AOD of 14.2% at Hospital A and 43.2% at Hospital B, but it cannot be guaranteed that similar rates of effectiveness would occur with the much higher levels of AOD present in recent years.

At both hospital sites, the OZ reduces time to reach an ED bed on the unit level (Table 14) but not the patient level (Table 24). This result would indicate that the OZ causes all ambulance patients, whether they enter the OZ or not, to be delayed in reaching a bed. However, this result may be partly or entirely caused by the OZ operation hours bias. Once again, the unit-level test shows a greater difference between means at Hospital B (30.9% slower to reach a bed) than Hospital A (7.7% slower to reach a bed). This discrepancy could be taken to mean that Hospital B is more likely to have something beyond just bias causing the difference, because if it was just bias, it would not be expected to see larger differences for both the offload time and the time to ED bed comparisons. Rather, it could be a result of OZ patients being delayed by starting treatment within the OZ, or general delays from admitting more patients than there are beds for.

An examination of the waiting time between steps, which can be estimated by the difference between time benchmark means, can further support some of the discussion points above. Table 29 shows the wait time from exiting an ambulance to being placed in an ED bed, as calculated from means found in Table 23 and Table 24. At Hospital A, patients not selected for the OZ wait an average of 8.6 minutes between exiting the ambulance and being placed in an ED bed, which is a reasonable amount of time to spend on the typical intermediary processes of triage, registration, and physical transportation between locations. Patients selected for the OZ wait an average of 18.5 minutes, with their wait time representing the same intermediary processes as well as any time spent in the OZ. At Hospital B, however, these figures are 37.2 minutes and 47.7 minutes respectively. Long waits for patients who do not use the OZ are further evidence of patients being admitted to the hallway, and long waits overall indicate that this hospital tends to admit more patients than it has the resources to process in order to alleviate ambulances.

Table 29 Time from exiting ambulance to reaching an ED bed for patients in and out of the OZ, at both hospital sites

In OZ	**Time From Exiting Ambulance to Reaching ED Bed (minutes)**	
	Hospital A	**Hospital B**
Yes	18.5	47.7
No	8.6	37.2

At both hospital sites, neither unit-level (Table 15) nor patient-level tests (Table 25) showed a difference in the time it takes to be seen by an MD. This result is promising in terms of patient outcomes, but it is unintuitive considering previous results showed delays in reaching a treatment bed. It can be taken as further evidence that some patients are receiving treatment within OZ or in the hallways, before officially reaching an ED bed. It might also be expected, given that treatment within the OZ or in the hallway represents an overburdening of stated ED resources, that time to reach an MD would be delayed as staff are stretched over a greater patient burden. Since there is no difference in this measure, it may be the case that a considerable amount of ED capacity is being used by patients who have concluded treatment and do not require much if any ED resources as they wait to be discharged or transferred, as is a commonly-cited phenomenon in the literature.

Finally, at both hospital sites, the OZ reduces patients' ED length of stay on the unit level (Table 16) but not the patient level (Table 26), indicating that the OZ causes all ambulance patients, whether they enter the OZ or not, to have a longer length of stay. Patients stay an average of 61 minutes longer at Hospital A and 55 minutes longer at Hospital B. This difference could come from the OZ operation hours bias, extra time spent in the OZ, longer wait times due to more patients being brought in at once, or any combination of the three. If it is reflective of increased ED utilization rates by ambulance patients, then there could be ramifications for walk-in patient waiting times.

An interesting occurrence in the unit-level comparison at Hospital B (Table 16) is that the mean for length of stay increases when the OZ opens, while the median appears to decrease. This could be interpreted to mean that while length of stay decreases for most patients, there is an increase in the number of outliers with very long stays, inflating the mean value. This interpretation is supported by the IQR also being larger when the OZ is open. This pattern is not apparent in the patient-level comparison, which means that it applies both to those using the OZ and those not using it. Given that time to reach an MD shows no difference when the OZ is open, and does not have a similar effect with the medians, it can be assumed that the effects seen in length of stay are rooted in something occurring after first contact with a physician. One possibility is that with more patients being admitted to the ED at a given time, their treatments take longer to administer, however this would more likely lengthen all patients' stays rather than reduce the stay for some and increase it for others. Another possibility is that during the daytime, when the OZ is most often open, is when there is the greatest bottleneck in admitting patients to other hospital wards, resulting in a larger number of ED boarders with overly long stays during these periods. If so, it is unclear why this pattern would appear only at one of the hospitals. Perhaps Hospital B generally has more of a bottleneck in this area, which in turn feeds into their already-discussed issues with crowding. This could also be a motivator for the practice of hallway admission and treatment within the OZ/hallways; if ED capacity is taken up by patients not requiring treatment, then patient flow could be restored by finding additional places to treat those who do need it.

4.5.5 Time Analysis Stratified by Patient Sex

Looking at the unit-level tests that are stratified by patient sex (Figure 2 through Figure 4), there are a few differences from the main result patterns, however, the patient-level tests follow the same patterns as the main results. This result would likely indicate that any differences in the processing of male and female patients come from the main ED ward and not from selection biases in the OZ.

4.5.6 Time Analysis Stratified by Patient Age

It is interesting to note that in the tests for offload time stratified by patient age groups, the unit-level (Figure 5 and Figure 6) and patient-level (Figure 26 and Figure 27) results are quite incongruous with each other. A few test result combinations have already been discussed: when a difference exists at both the unit level and the patient level, the OZ benefits mostly those who use it, and when a difference exists at the unit level but not the patient level, the OZ benefits all ambulance patients. These figures introduce some new results combinations. When a difference exists at the patient level but not the unit level, it tends to be because the OZ benefits those who use it while further delaying those who do not use it, resulting in the OZ-open group balancing out the OZ-closed group in the unit-level test. When there is no difference in either test, as long as it does not appear to be due to high uncertainty, it can be interpreted to mean that the patients in this group were already high priority and the OZ is not able to further improve their delay. The results where some or all patients benefit and none are further delayed—that is to say, the results that include a difference in the unit-level test—would be the more preferred outcomes. Hospital A achieves these outcomes for patients aged 55–84 and Hospital B achieves them for patients under 35 and over 54. The difference between the hospitals' performance may be due to different patient demographics, or due to Hospital B being more likely to admit patients to the hallway. It could also be further indication that Hospital A is more intentional with the types of patients they allocate to the OZ while Hospital B is forced to respond to excessive demand by allocating on a first-come-first-served basis.

Also of note in Hospital A's age group analysis is that in the unit-level comparisons, patients aged 85+ are the only ones to show a longer time to reach an ED bed when the OZ is open (Figure 7), possibly because they normally cannot be prioritized very highly but when the

OZ opens they can be placed there and left to wait longer than usual with the pressure of needing to free an ambulance no longer applicable.

4.5.7 Time Analysis Stratified by Patient CTAS

The comparison of unit-level (Figure 8 and Figure 9) and patient-level (Figure 28 and Figure 29) results can bring insight to the tests for offload time stratified by patient CTAS, as well. At Hospital A, CTAS 1, 2, and 5 are already high priority, and at Hospital B, CTAS 1 and 5 are already high priority, and so these groups are not benefited by the OZ. In the context of patient offloading, a CTAS 5 is considered "high priority" for transferring in that they can often either be directed to wait in the walk-in patient area (the "Direct to Chairs" policy), or expedited to an ED ward reserved for concerns that are quick to resolve. At Hospital A, CTAS 3 patients, and at Hospital B, CTAS 2 and 3 patients, are mostly only benefited by the OZ when they are selected to use it. For CTAS 4, Hospital A shows that patients in the OZ benefit while those outside it are delayed, and Hospital B shows that all patients benefit from the OZ. These patterns are summarized in Table 30. The results can be placed into context as informed by the discussion surrounding previous results. At Hospital A, the OZ seems to be used as a way to be more flexible with patient allocation, allowing staff to more freely deprioritize lower-acuity patients and reserve capacity for higher-acuity patients. At Hospital B, the OZ seems to be an extension of the hallway admission practice, allowing them to free as many ambulances as possible. Another observation from these results is that because Hospital B uses this extra capacity to bring in CTAS 2 patients, while Hospital A was already prioritizing CTAS 2 patients highly enough that the OZ does not benefit them, it further hints that Hospital B struggles more with balancing overall demand and resources. This could be the underlying reason that they are generally more prone to allowing hallway admissions and beginning treatments before the patient reaches an ED bed.

At both hospital sites, CTAS 2 and 3 patients take longer to reach an ED bed when the OZ is open (Figure 10 and Figure 11), however, only CTAS 2 patients at Hospital A have a difference between those who use the OZ and those who do not (Figure 30). The unit-level differences may just be from the OZ operation hours bias, but the patient-level difference could be due to the severity of CTAS 2 conditions that tempt staff to treat these patients within the OZ when they do end up having to use it. The lack of patient-level difference at

Hospital B, when considered alongside its unit-level differences, would indicate that CTAS 2 and 3 patients who are admitted to either the OZ or to a hallway are all slowed due to competing for ED resources and/or being treated outside of a proper ED bed. With CTAS 4 patients having improved offload times but no differences in the time to reach an ED bed, it seems that the OZ capacity allows more CTAS 4 patients to be offloaded but they are less likely to begin treatment in undesignated areas and are simply waiting for a bed.

Table 30 The OZ's effect on offload time for patients in and out of the OZ, at both hospital sites

CTAS	**OZ's Effect on Offload Time**	
	Hospital A	**Hospital B**
1	No change—already high priority	No change—already high priority
2	No change—already high priority	Reduced only when selected for OZ
3	Reduced only when selected for OZ	Reduced only when selected for OZ
4	Reduced when selected for OZ, increased when not selected for OZ	Reduced for all patients
5	No change—"Direct to Chairs" policy	No change—"Direct to Chairs" policy

At both hospital sites, CTAS 3 patients have a longer length of stay during periods when the OZ is open (Figure 12 and Figure 13), with all ambulance patients being affected regardless of whether they use the OZ. While this result may simply be an effect of their longer wait for an ED bed and/or the OZ operation hours bias, it is still a concern to note. CTAS 3 patients represent about half of all ambulance arrivals, so their increased utilization of the ED could present serious ramifications for other patients' wait times.

An unexpected result is found in the patient-level comparisons for length of stay at Hospital B (Figure 31). Here, despite a low sample size leading to high uncertainty levels, the CTAS 1 patients who use the OZ have a much longer length of stay than those who do not use the OZ, with an estimated difference of over 300 minutes. This phenomenon is particularly strange because this group is not delayed in reaching an ED bed nor in beginning their treatment, only in their overall stay; this would seem to indicate a difference in the types of conditions that go directly to the ED versus those afforded a brief detour first. Perhaps conditions that are serious enough to be deemed CTAS 1, yet still not so urgent that they go immediately to an ED bed, are more vaguely-presenting conditions that are more likely to take some time to test and diagnose, in contrast to some of the other high-acuity events like trauma and heart attacks that are quickly identifiable. Another factor could be cases of extreme acuity being transferred quickly to the ICU, where their little-to-no time in the ED would artificially lower the mean for other non-OZ patients.

4.5.8 Time Analysis Stratified by Patient Clinical Impression

For analysis of clinical impressions, it's important to recall that these conditions come in groups of vastly different sizes. The top 7 categories are trauma, gastrointestinal/genitourinal, neurological, cardiovascular, respiratory, general malaise, and psychological, after which point the frequencies of other types of complaints drop off sharply. These 7 categories together make up about 76.5% of all visits while the remaining 18 categories make up 23.5%. When doing comparisons stratified by clinical impression, the majority of those that show a significant difference are ones for these top 7 conditions, and they just reflect the same patterns discussed in the non-stratified data. However, there are a few interesting phenomena to note.

Firstly, although it has already been apparent that differences in time to see an MD are very uncommon among the stratified tests, it is particularly encouraging to note no clinical impression at either hospital site showed a difference in this respect, indicating that conditions of all types are given appropriate attention regardless of what other process differences the OZ may cause.

Cardiovascular patients at Hospital B are shown to have a longer length of stay if they are placed in the OZ (Figure 32). This clinical impression is one of the largest groups, and while a difference for it might not be remarkable in another of the tests, this one is notable because it is the only condition at either hospital to show a difference in length of stay at the patient level, and because it contrasts with the results of the unstratified tests where no difference was shown. It may be that cardiovascular patients who are more acutely ill have conditions that are easier to diagnose, while less acute cardiovascular conditions are vaguer and require more testing to identify. It is also an important observation to note because as one of the largest groups of patients, their increased utilization of the ED could have ramifications for other patients' wait times.

Patients with fainting conditions at Hospital B take longer to reach an ED bed when the OZ is open (Figure 14). This result is notable since it is one of the only uncommon conditions to show a difference in any of the clinical impression tests. This may be because a fainting condition is an ideal case to bring into an OZ or hallway area—their treatment frequently amounts to resting, so it is not an issue for these areas to be lacking in staff or equipment. When the OZ opens and more capacity becomes available at Hospital B, as long as a more urgent case doesn't need attention, then patients with fainting may be a common choice to offload in order to free the ambulance without introducing as much additional demand for care to the ED.

Unexpectedly, the "complex" condition—which is not an official hospital term but a term used in this paper for patients who had multiple seemingly-unrelated conditions—shows a shorter length of stay at Hospital A during times when the OZ is open (Figure 15). It is unintuitive that a complex condition could be resolved in less time when the ED tends to be busier. However, given that the OZ is generally open in the daytime, this difference could be due to certain testing and diagnostic services being unavailable during the night, causing "complex" conditions to take longer to diagnose and treat at that time.

4.5.9 Time Analysis Stratified by Day of Week

It is strange to note that at Hospital A, no differences appear in the unit-level tests for offload time stratified by day of the week (Figure 16). In the patient-level tests (Figure 33) a number of differences do exist. Since Wednesdays and Thursdays show no difference in either test, these days appear to be the best-balanced in terms of demand and resources, while the other days require some patients to be delayed in order for others to be expedited. This pattern could be a result of weekly staffing schedules. This hospital's unit-level tests for time to reach an ED bed (Figure 18) also show no differences, contrasting with the unstratified test result, but this may be due to the small difference that was estimated between OZ-open and OZ-closed means, making smaller patient groups less likely to show a difference due to higher uncertainty. Another odd result for this site is a longer length of stay when the OZ is open on Sundays (Figure 21). Since this applies both to patients within and outside of the OZ, it could be that this day is generally busier and/or tends to be understaffed.

At Hospital B, the unit-level tests (Figure 17) show reduced offload time on weekdays only, indicating that weekends are less busy and/or better staffed. A lack of clear pattern in the patient-level tests (Figure 34) for offload time could indicate variability in traffic. These two ideas are supported by the tests for time to reach an ED bed as well (Figure 19 and Figure 35), where no clear patterns emerge aside from noting that values associated with weekend days are among the lowest in each figure. The tests for time to reach an MD, however, show more consistency among values (Figure 20 and Figure 36), which may be a sign that despite potentially disorganized arrival processes, most patients still receive treatment on a predictable timescale. Two notable differences, however, are patients seeing an MD faster on Saturdays when the OZ is open, and patients who use the OZ seeing an MD faster on Fridays. The former would more likely be related to better staffing during busier hours on Saturday, since it affects all patients, and the latter may be related to ED demand, since especially high-demand days would cause both the OZ and the hallway to fill up and cause non-OZ patients (which comprises both hallway patients and patients remaining in ambulances) to be overall more delayed in being seen.

4.5.10 Time Analysis Stratified by Ambulance Arrival Volume

While some of the large confidence intervals in these figures make it difficult to be sure of what patterns are occurring, there are still some interesting observations to note. At both sites, lower-volume days are less likely to have any differences caused by the OZ, which makes sense as they are days where resources can keep up with demand easily. Although Hospital A has nearly double the ambulance arrivals of Hospital B, the patient-level charts (Figure 37 and Figure 38) show that both hospitals begin to fill their OZ and see AOD recur when daily arrival volumes reach the mid-to-upper 20s. This alignment would make sense given that the hospitals both used an OZ with a capacity of six. However, this cannot be claimed with certainty, because the comparative outcomes could have been affected by each hospital's level of hallway admissions.

Hospital A shows some interesting results in the patient-level comparisons for offload time (Figure 37) and time to reach an ED bed (Figure 39). At around 35 patients per day, there is a single test where there is no difference in offload time, and there is a reversal of trends in the tests for time to reach a bed. This change could reflect a point at which the hospital asks on-call staff to come in.

The unit-level tests for Hospital A reveal another occurrence where a difference exists in time to reach an MD (Figure 24). This reduction in time to reach treatment for all patients when the arrival volume is around 26–28, which is just before the OZ's effects become apparent in the patient-level tests, and could represent a brief window of demand-to-resource balance where staff are able to stretch themselves to treat a few extra patients within the OZ sooner than they would otherwise be seen.

The unit-level test for time to reach an ED bed at Hospital B (Figure 23) shows that patients reach a bed more slowly on the lowest volume days with <9 arrivals, which is counterintuitive. It could be that staff begin admitting low-acuity patients to the OZ before arrival volumes rise, to keep ED space free for high-acuity cases, and when arrivals remain low there is no incentive to clear the OZ.

The pattern in unit-level comparisons at Hospital B (Figure 22) is for differences between offload time for patients in and out of the OZ to increase to a peak at around 19–20 patients per day, and decrease thereafter. This arrival volume could represent a point where, when the OZ is not available, staff begin to grow concerned about ambulances waiting and begin admitting patients to the hallway. This idea is supported by the unit-level test for time to reach an ED bed (Figure 23), where patients begin to be delayed in reaching a bed after around 20 arrivals per day, and the unit-level test for time to reach an MD (Figure 25), where at around 20–21 patients per day there is a switch from reduced to increased time to see an MD. At the high end of the range of arrival volumes, 25–26 patients per day, patients who do not enter the OZ see a delayed time to reach treatment. This point could be where both the OZ and the hallways tend to be full and any further patients arriving by ambulance have no choice but to remain outside the ED. As this is the only result in the study where time to reach an MD is negatively impacted by the OZ, it is a sign of caution against overburdening ED resources in the pursuit of reducing offload time.

In contrast to the two cases presented in this thesis, Crilly et al. (2019) found that the use of an offload nurse in an Australian trial resulted in marginal reductions in offload time, time to be seen, and length of stay. Their pre-trial measurements (medians of 26 minutes for offload time and 24 minutes for time to be seen) can be contrasted with values in this paper (medians of 31 and 35 minutes for offload time and 70 and 85 minutes for time to be seen) to show that AOD and ED crowding were more severe issues at both of the Halifax sites. This difference in initial conditions may be why the Australian study found that offload time reductions were able to translate into reductions in time to be seen and length of stay. Its effectiveness may also be related to the hours of operation (24/7) or the size (not reported) of their offload area. They also found that there was more benefit for low-acuity patients, while the Halifax sites showed more benefit for moderate- and moderately high-acuity patients. It is unclear whether the Australian hospital has an analog to Halifax's "Direct to Chairs" policy; if not, it may be that their offload program benefits low-acuity patients due to filling a similar functional role to this policy.

CHAPTER 5 CONCLUSION

This study used statistics and data analysis techniques which assessed the functionality of the OZ at two locations. The data were able to shed light on the ED conditions that the OZ was introduced to, the ways in which it was used by the ED staff, the downstream effects on patients' journeys through the ED, and the overall effectiveness of the OZ. These results provide a formal evaluation of the effectiveness of a patient consolidation tactic, which has been pointed out in literature reviews as a gap in the body of knowledge.

The main finding of this study is that it is mainly patients within the OZ itself who benefit, but to some extent those who do not enter the OZ have improved offload time as well. If it is mainly patients within the OZ who benefit, then this is a confirmation of Carter et al.'s (2015) finding that the OZ would tend to fill up and AOD would then return. In spite of that, however, there is still a net improvement in AOD, with an estimated 580 hours avoided in Hospital A and 883 hours avoided at Hospital B over the course of one year. These results can be leveraged by the hospital to bring higher-acuity patients into the ED where resources will be available if their condition worsens, and to allow more ambulances to return to service than would otherwise occur.

Another main finding is that the actual use of the OZ delays patients in reaching an ED bed, and in conditions of overwhelming demand, potentially in accessing treatment. According to the OZ's original protocols for use, this should not occur—patients should wait the same amount, only in a different location. However, when patients are more often treated within the OZ and in hallways, they are increasingly delayed in reaching an ED bed. This apparent trade-off between delay in offload and disturbances in patient flow must be carefully balanced should any organization choose to implement a similar system. There does however appear to be some leeway in overburdening the stated capacity of the ED before treatment times are affected, and this may be due to some of the ED capacity being occupied by patients who do not require resources and are simply awaiting ED discharge.

In almost all cases, patients' wait to see a physician was not affected by the functioning of or by their entry to the OZ. This result addresses an important gap in the body of literature on AOD by showing that an offload program of this type, where more patients are introduced into the ED than it normally holds, will not negatively impact patients' access to treatment. The exception, as stated above, is in conditions of overwhelming demand, which might not be the fault of the OZ itself but simply the natural consequences of an imbalance between demand and resources.

Recalling discussion from Chapter 2 that framed the AOD issue in terms of queuing theory, the state of overwhelming demand can be described as when $\lambda \geq \mu$. If the OZ beds are used for treatment, the OZ can compensate for blocking by adding extra treatment space when ED beds are occupied by boarders, but ultimately it does not affect either λ or μ, and so the throughput of the ED will be the same. An OZ of infinite capacity would eliminate AOD, but wait times for treatment and to be admitted to other parts of the healthcare system would be unchanged. Therefore, the OZ should be represented strictly as a way to accommodate the ambulance arrival queue in a way that improves paramedic performance, and not as a way to address the root of the problem which lies in ED crowding, ED boarding, and hospital understaffing.

While many observations in the variable stratifications differed by hospital and led to an understanding of how each hospital operated their OZ, one interesting commonality between them was found in the analysis by arrival volume. Despite being EDs of different size with different burdens of demand, both sites began to top out the benefits of the OZ at around the same rate of patient arrivals volumes, from the mid-20s per day. There are too many other factors affecting these outcomes to be sure, but it may be that each added OZ bed provides a reliable safety net for 4 or 5 patients' worth of demand, allowing the minimum beneficial OZ size to be estimated based on known demand levels. The relationship between demand levels and effective OZ size has been explored in some modelling work but not in empirical studies. These initial results should be investigated with further empirical and/or modelling research to develop a general guideline for the development of an effective OZ.

One of the unexpected pieces of insight in this analysis was being able to piece together a rough idea of how the hospitals differed in the way they operated their OZs. In contrasting their methods and results, some lessons can be noted for future OZ implementations.

At Hospital A, which had been facing moderate crowding conditions, the OZ served as a tool for more flexible patient allocation and processing. Depending on the minute-to-minute demands being faced, it could be used as: a place to begin emergency treatment of high-acuity cases during periods of overwhelming demand; a place to begin lengthy testing processes for ambiguous conditions without having to occupy an official ED bed for as long as they otherwise would; a place to host moderate-acuity patients in a more secure environment where resources are more accessible in case their condition worsens; or even as a more comfortable environment for older patients to wait. For the most part, the use of the OZ represented a reallocation of patients to spaces that best suited the types of resources they need, and did not seem to increase the burden on the ED's resources, resulting in patients' wait time for treatment and overall length of stay being generally unaffected. This is not the original intended function of the OZ, but nonetheless could present a number of benefits for patient outcomes and ED patient flow.

At Hospital B, which had been facing more severe crowding and ED boarding, staff were already offsetting boarders by admitting patients to the hallway, and the OZ seemed to be used as an extension of this practice. The nature of the demand on their resources necessitated both the OZ and the hallway admissions to occur on a first-come-first-served basis, and for the patients therein to begin treatment before reaching an ED bed. Because the OZ admissions were in addition to and not a replacement for the hallway admissions, the most high-volume of periods could result in increased competition for ED beds and access to staff, leading to delays in treatment and longer stays in the ED.

Clearly, the OZ is not a universal solution that can just be thrown at any struggling ED. Aside from the previously discussed aspect of finding an effective OZ-to-ED size ratio, there are considerations to be made for how human behaviour affects the system. While the OZ concept presented clear benefits on paper, the practical outcome is affected by actors in the system who may respond to situations in unanticipated ways. For one, even if there is policy in place to not initiate treatment in the OZ, some individuals may not be able to reconcile this with seeing people in need with nothing but policy preventing them from being helped. This appears to be especially true as demand on the department increases. Behaviour pre-existing in the system should also be considered, such as at Hospital B, where an already-established practice of admitting and treating patients in hallways could have made it more likely for staff to end up using the OZ in a similar way. All of these considerations can help to explain why previous trials of OZ-style concepts have shown mixed results in practice. Of note in this regard are the projects implemented across Ontario, where details like working hours, maximum staff-to-patient ratio, and specific duties were left up to the region to decide, and consequently the results varied greatly from place to place. As well, in comparison to a formal evaluation of a similar offload program trial (Crilly et al., 2019), it seems that pre-OZ demand levels and interactions with pre-existing ED flows/policies may be highly influential to the OZ's results.

The above interpretations and conclusions are subject to a few limitations in the study. As discovered in the data independence analysis, there is a bias in the OZ's open hours, where the OZ is more likely to be open during the daytime when patient arrivals are higher, which may skew the results of unit-level comparisons. However, this bias is self-limiting if the hospitals attempt to schedule staff levels corresponding to demand levels. As well, for comparisons where the OZ reduces offload time, this bias actually makes the results more convincing than if it were an unbiased dataset. Uncertainty due to this bias can sometimes be clarified by cross-referencing with a corresponding patient-level comparison, where there is no data bias.

It is also important to note that the dataset comes with an inherent source of unreliability because data are recorded by employees working in a busy and high-stress environment, making them susceptible to entry errors or belated timestamping. Measures were taken to remove erroneous material from the dataset, but it cannot be guaranteed that all errors were identified, nor is there a way to estimate the rate or severity of remaining errors.

Finally, a few blind spots in the data left gaps in the analysis that would have been useful to include. Because the hospitals record only the time at which a patient first sees an RN or MD, there is no way of estimating how much time the ED staff actually spend attending to a given patient, and so the only way to approximate resource utilization is with a patient's overall length of stay. Because there have been some signs that some patients continue to stay in the ED without occupying staff resources as they await their departure, it would have been interesting to have more granular data to reveal an accurate picture of staff utilization. As well, data for walk-in patients were unavailable for this study, leaving questions as to the impact of the OZ on ED journey benchmarks for walk-in patients. Both of these gaps in analysis would be valuable to address in future research.

Another avenue to build upon this work would be to consider the various use-cases for the OZ that were noted in this analysis—namely as emergency treatment capacity, as an area for patients awaiting test processing, and the originally intended concept as a waiting room where no treatment occurs—and incorporate them into simulation or queuing modelling that could seek to find the most effective use of extra beds. These could be modelled alongside the original OZ concept as well as a "discharge zone" to address patients who occupy ED space while waiting to be transferred.

As mentioned previously, a potential relationship between ambulance arrival rates and effective OZ capacity could be investigated. Because this variable stratification presented an indication of the arrival rate beyond which AOD returned, it may also be a way to build on the work by Laan et al. (2016) regarding patient selection criteria, by determining practical advice for ED staff to make patient selection decisions that ensure the OZ functions as intended.

Finally, to build on the current assortment of empirical work related to OZ trials, which tend to focus on hospital-side effects and extrapolate how the results might translate to the ambulance side, studies could be devised which directly assess time savings and improvement in ambulance coverage for EHS as a result of hospital-side AOD interventions.

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Appendix

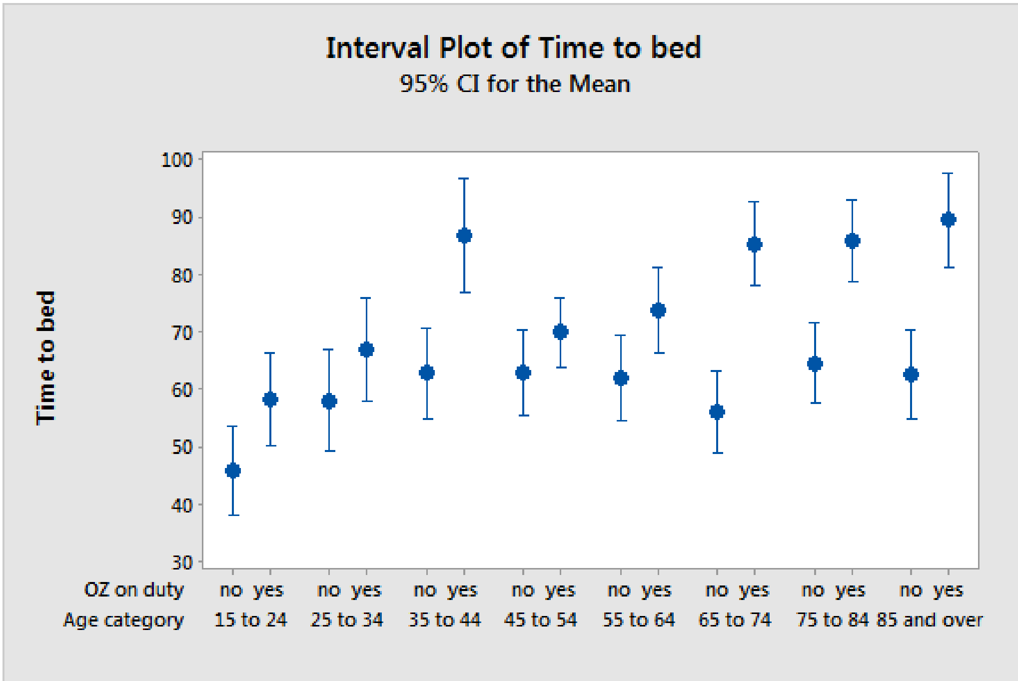

Figure A1 Means and 95% confidence intervals for time to ED bed at Hospital B, representing a unit-level comparison stratified by patient age group

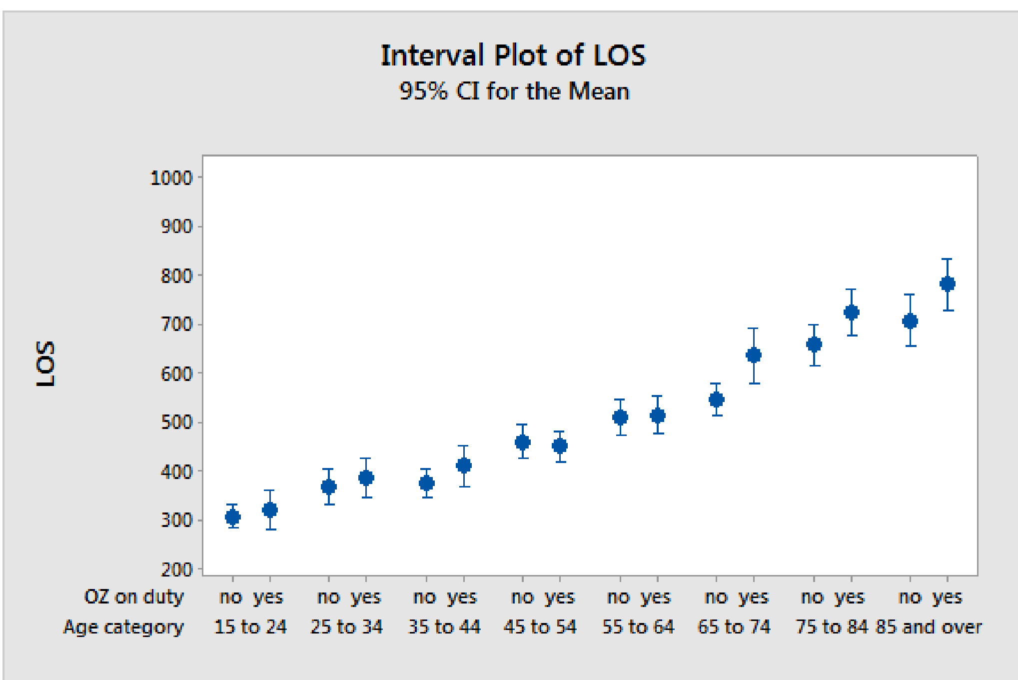

Figure A2 Means and 95% confidence intervals for length of stay at Hospital A, representing a unit-level comparison stratified by patient age group

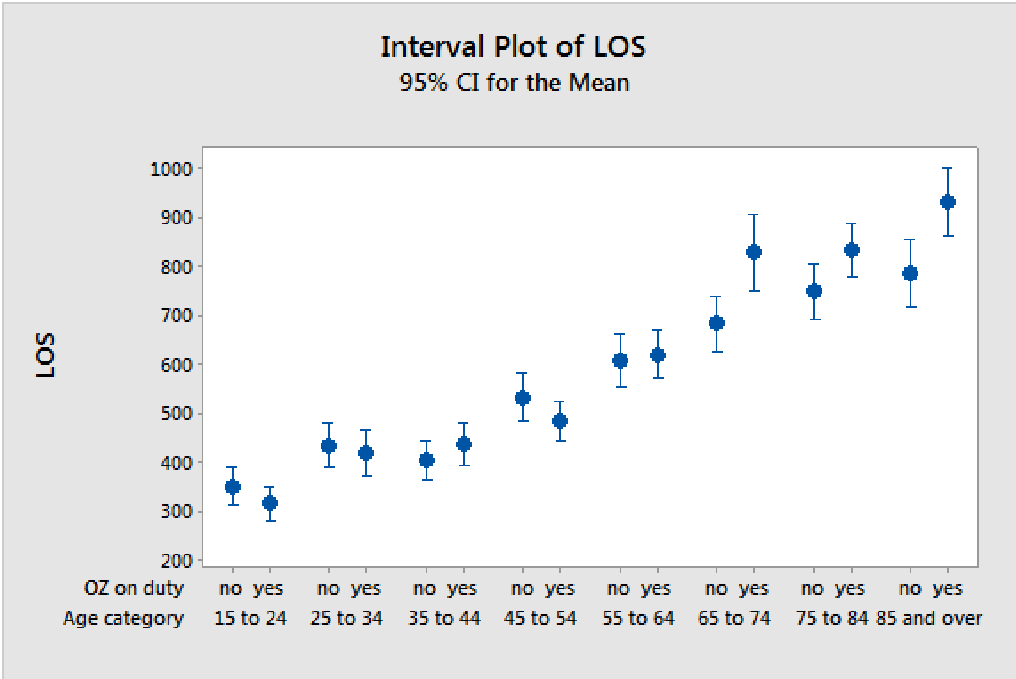

Figure A3 Means and 95% confidence intervals for length of stay at Hospital B, representing a unit-level comparison stratified by patient age group

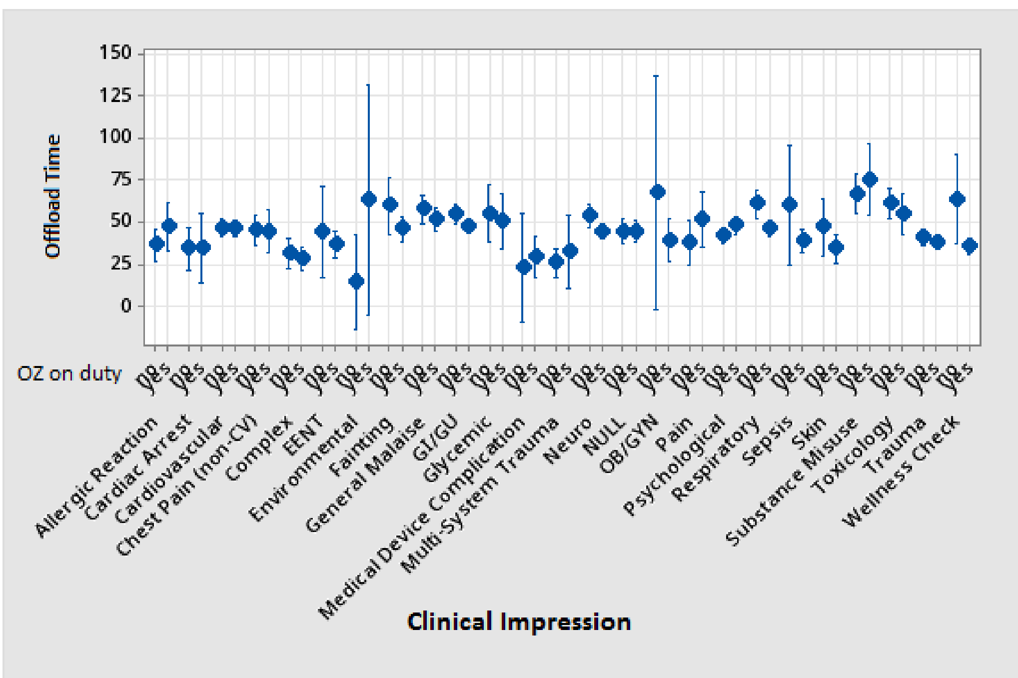

Figure A4 Means and 95% confidence intervals for offload time at Hospital A, representing a unit-level comparison stratified by patient clinical imp.

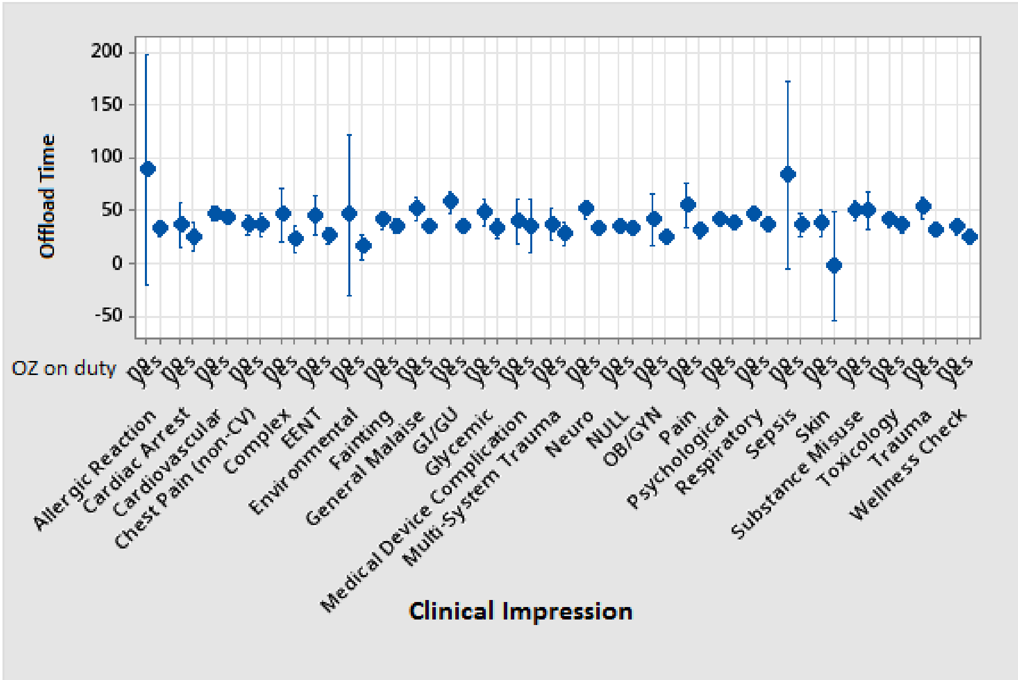

Figure A5 Means and 95% confidence intervals for offload time at Hospital B, representing a unit-level comparison stratified by patient clinical imp.

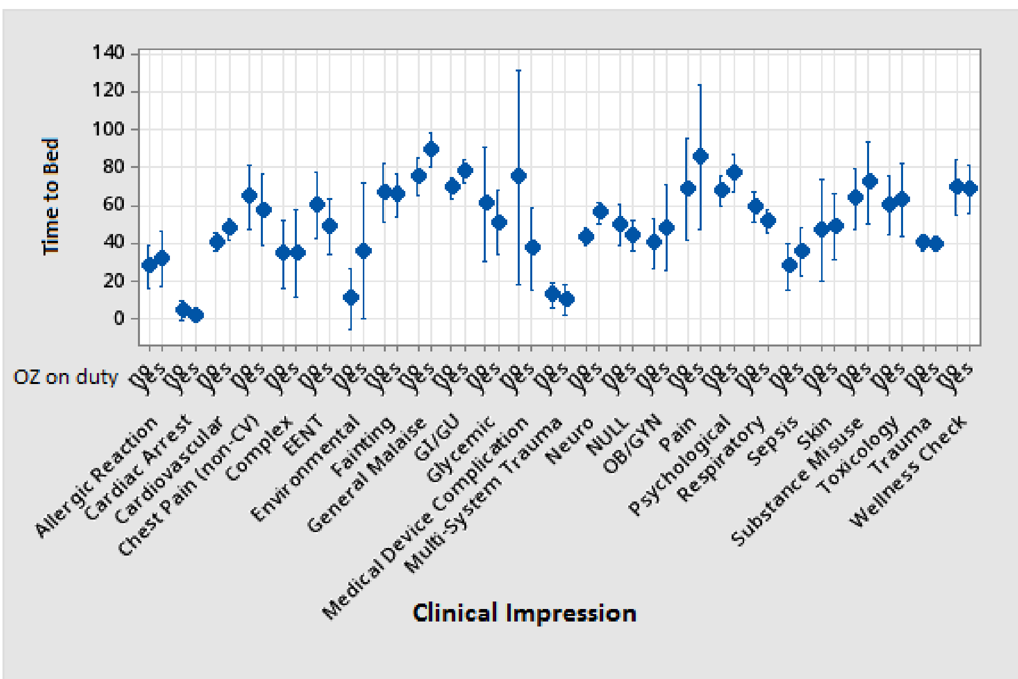

Figure A6 Means and 95% confidence intervals for time to ED bed at Hospital A, representing a unit-level comparison stratified by patient clinical imp.

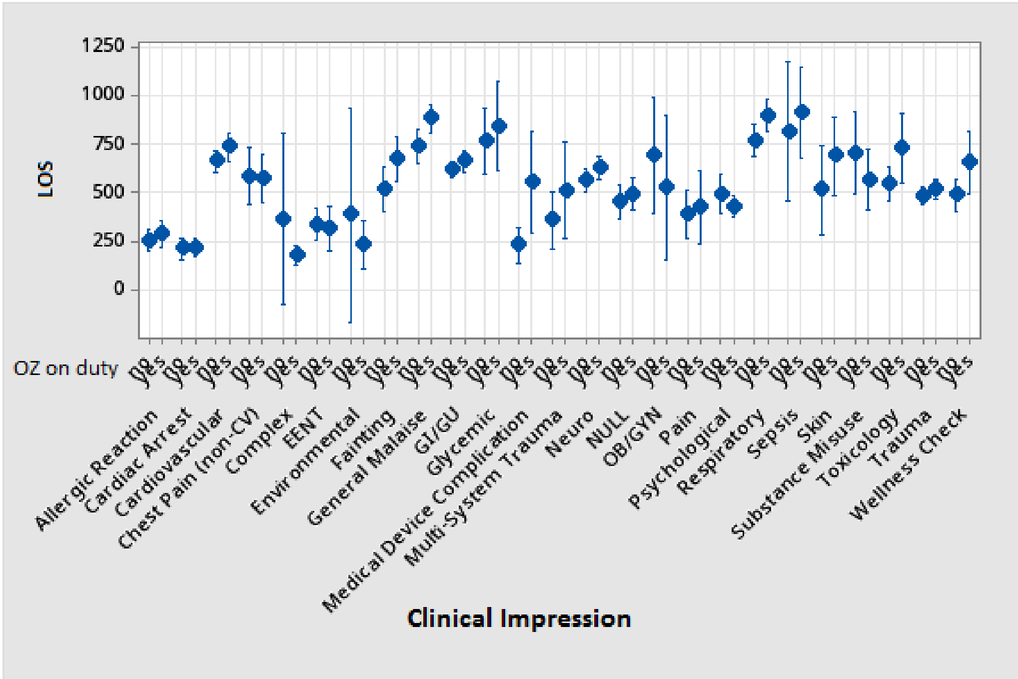

Figure A7 Means and 95% confidence intervals for length of stay at Hospital B, representing a unit-level comparison stratified by patient clinical imp.

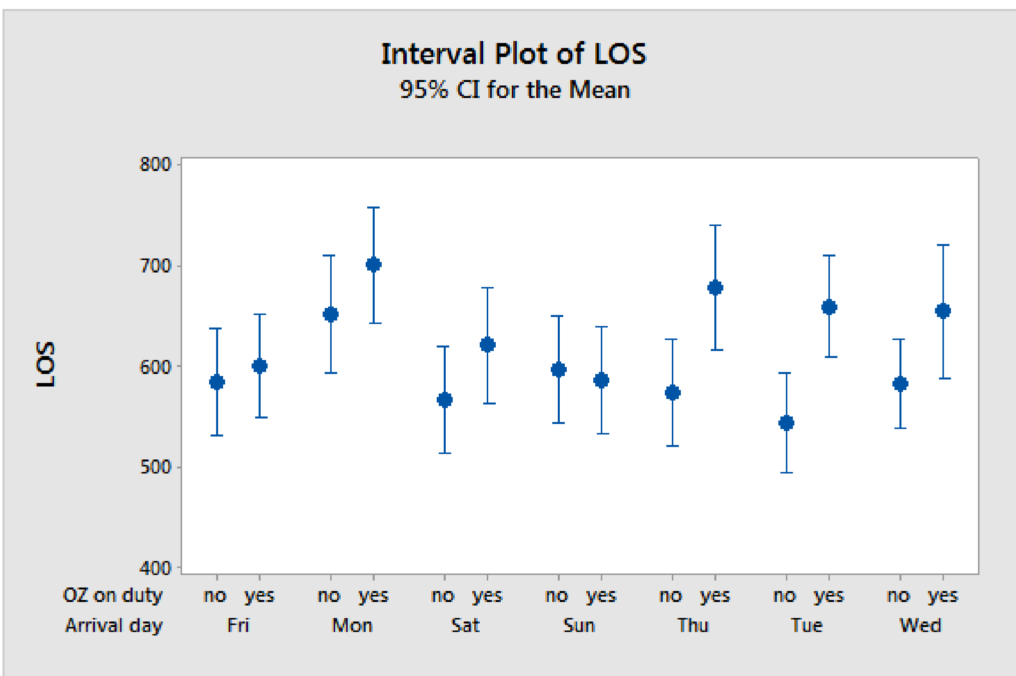

Figure A8 Means and 95% confidence intervals for length of stay at Hospital B, representing a unit-level comparison stratified by day of week

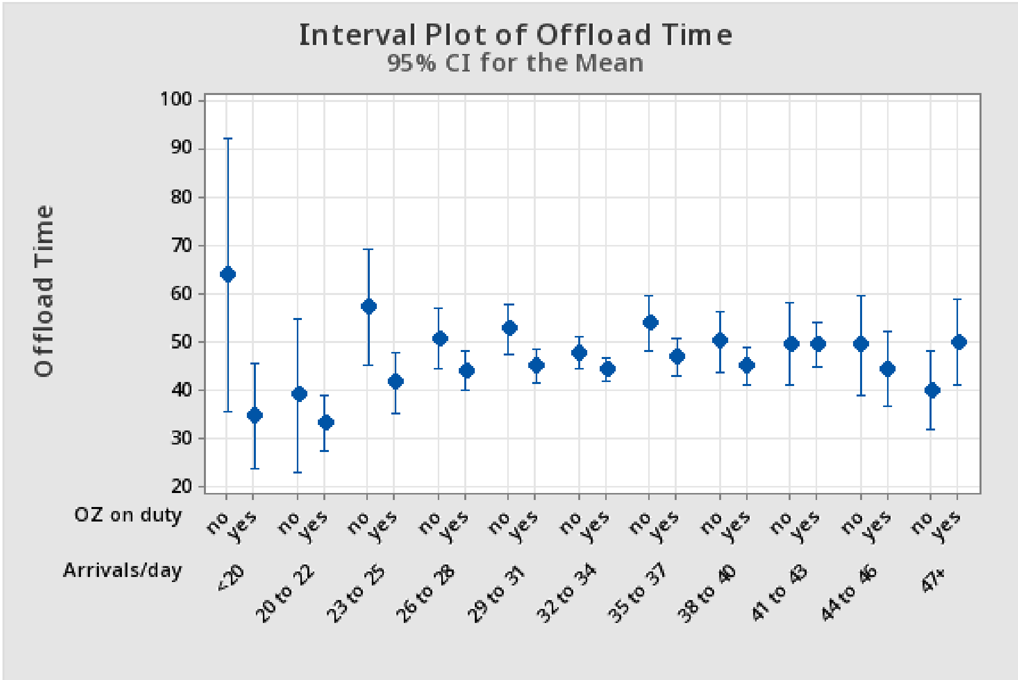

Figure A9 Means and 95% confidence intervals for offload time at Hospital A, representing a unit-level comparison stratified by daily arrival volume

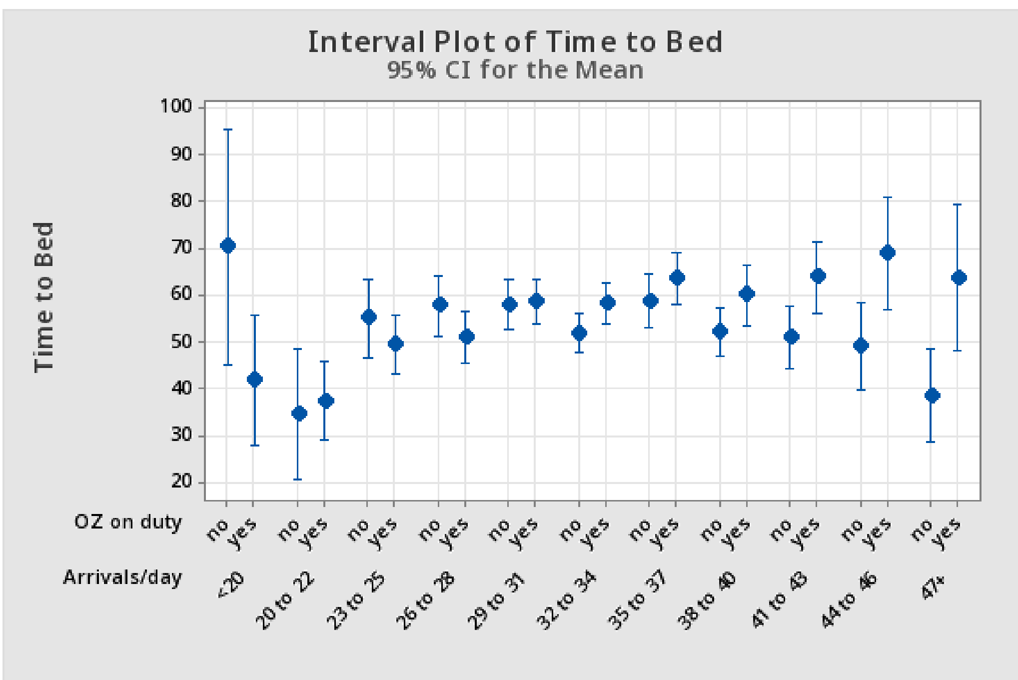

Figure A10 Means and 95% confidence intervals for time to ED bed at Hospital A, representing a unit-level comparison stratified by daily arrival volume

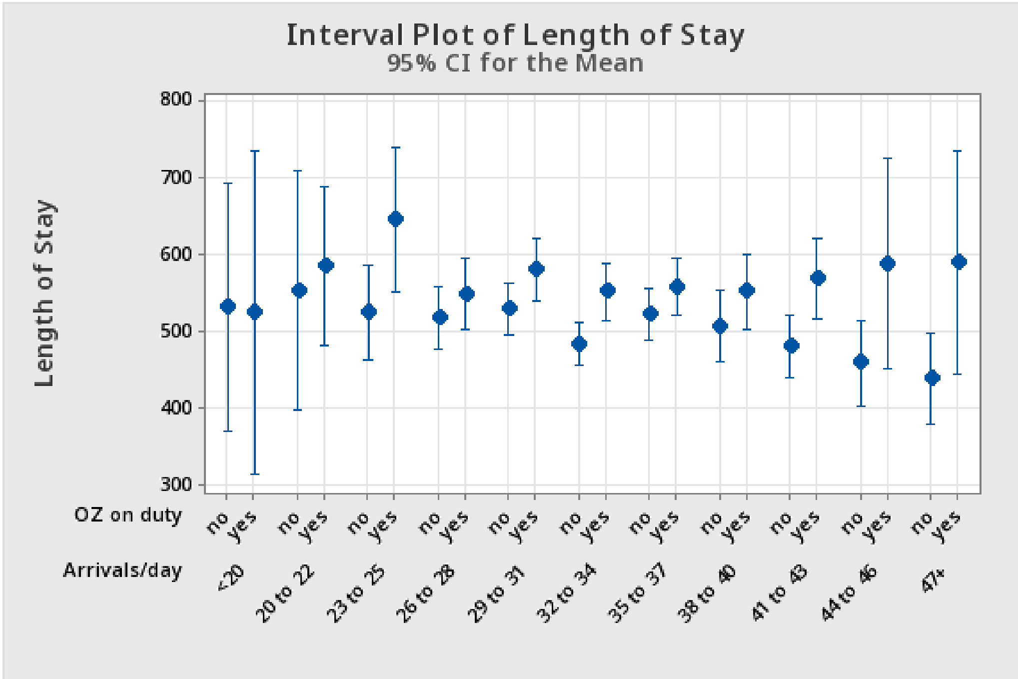

Figure A11 Means and 95% confidence intervals for length of stay at Hospital A, representing a unit-level comparison stratified by daily arrival volume

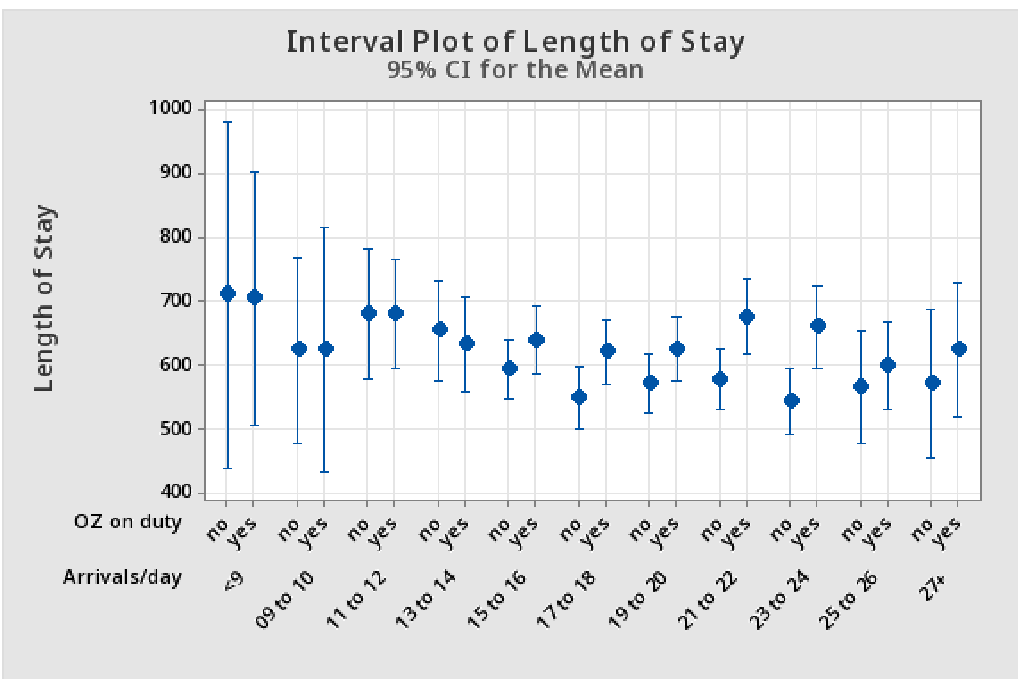

Figure A12 Means and 95% confidence intervals for length of stay at Hospital B, representing a unit-level comparison stratified by daily arrival volume

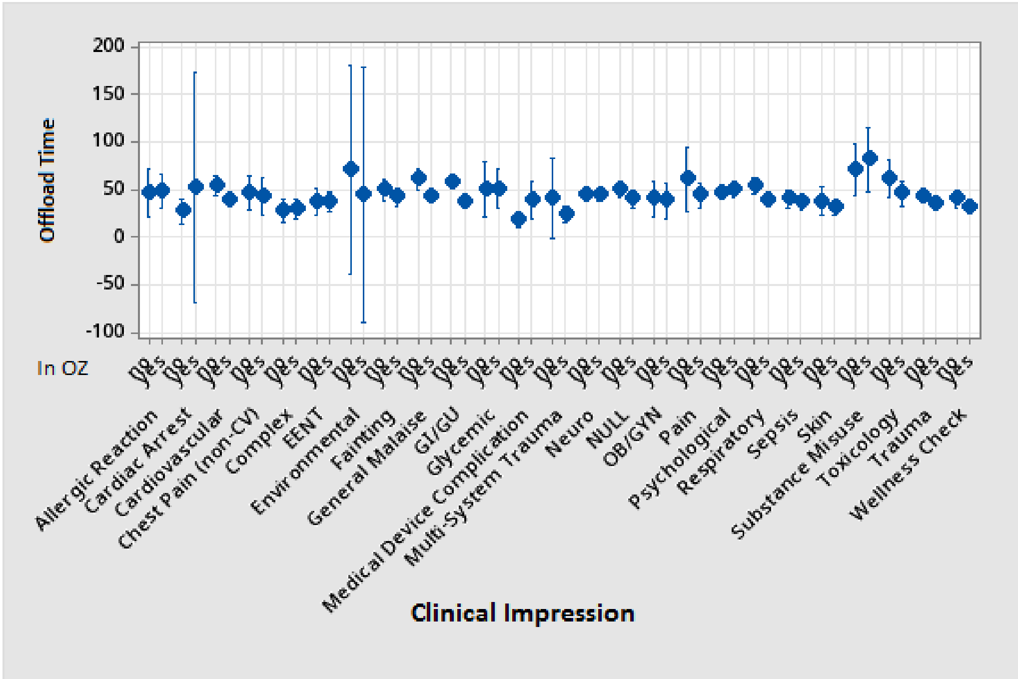

Figure A13 Means and 95% confidence intervals for offload time at Hospital A, representing a patient-level comparison stratified by patient clinical imp.

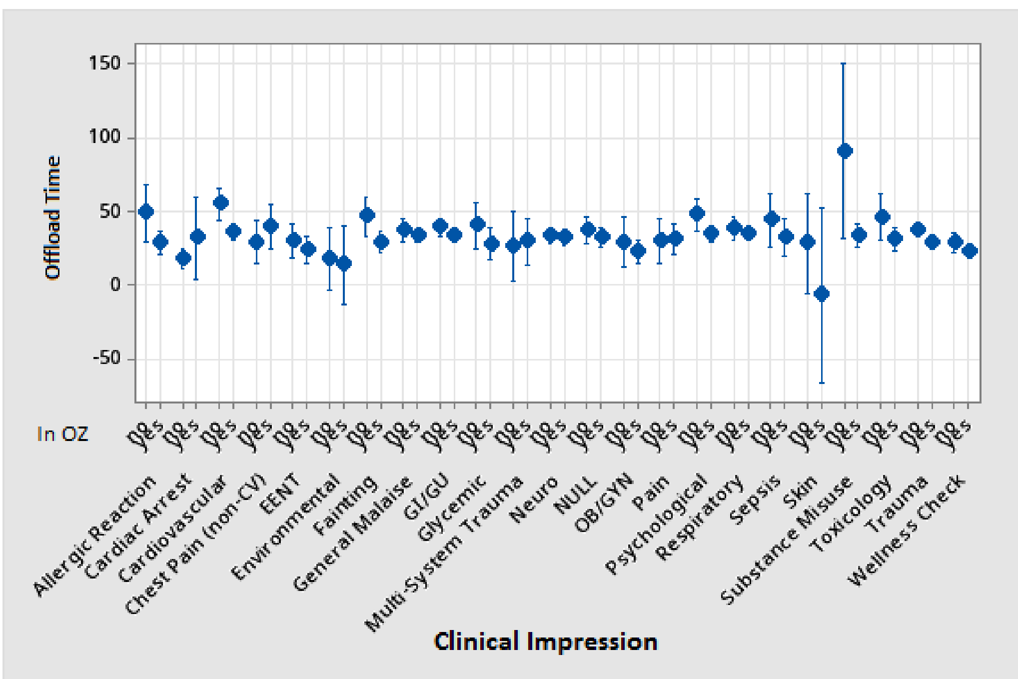

Figure A14 Means and 95% confidence intervals for offload time at Hospital B, representing a patient-level comparison stratified by patient age group

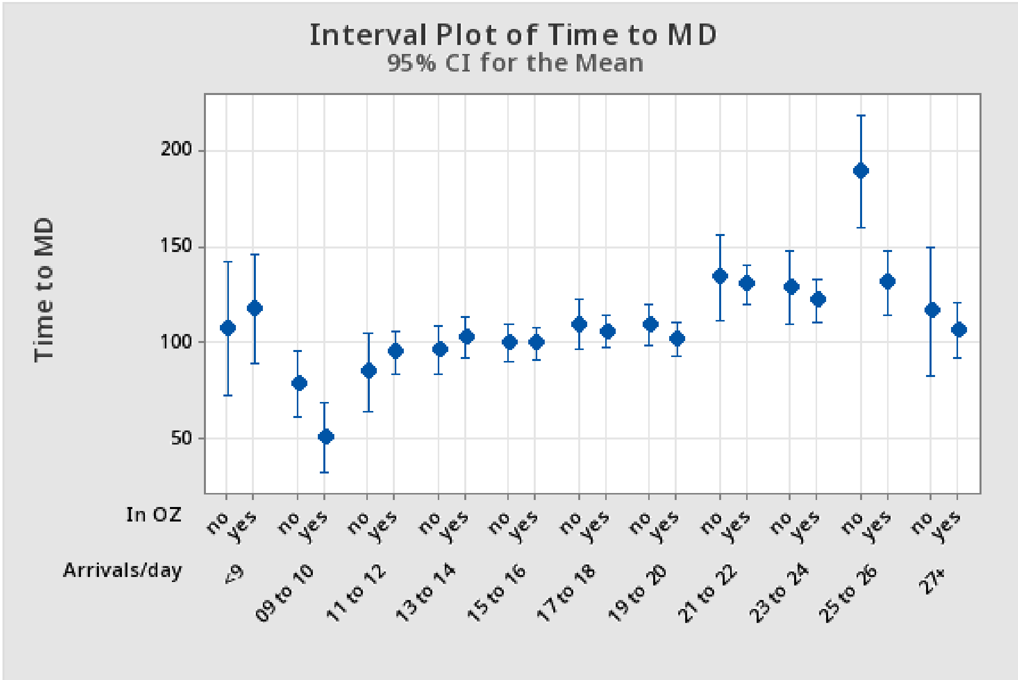

Figure A15 Means and 95% confidence intervals for time to MD at Hospital B, representing a patient-level comparison stratified by daily arrival volume