PATIENT FLOW AND CAPACITY MANAGEMENT IN HEALTH SERVICES

by

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To my family,

For

Their love and support.

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ABSTRACT

Growing demand for health services provided by outpatient clinics and hospitals caused health institutions flow and capacity challenges. Health organizations' poor response to these challenges directly translate into negative patient outcomes and intensified downstream costs. In this study, we investigate dynamics and mechanisms that influence patient wait times and capacity strains and propose strategies and policies that can improve these issues in both ambulatory and inpatient care.

First, we investigate the access issue in a multidisciplinary memory clinic, which consists of three practices and six patient types. Considering patient flow and interactions, we develop an empirical simulation model to evaluate the effectiveness of access improvement strategies such as overbooking, repatriation (i.e., referring the patient back to primary care), and increasing provider hours. Our results suggest that despite the increasing wait times in the multidisciplinary memory clinic, increasing provider slots is not always an effective strategy. In fact, overbooking and reducing unnecessary follow-up visits can result in more significant performance improvements.

Second, we study the impact of long-stay patients (i.e., patients with discharge barriers that stay in the hospital for non-medical reasons) on flow and capacity. In particular, we focus on the patient flow between Intensive Care Unit (ICU), Step-down Unit (SDU), and Medical Unit (MU) and quantify the impact of long-stay patient volumes on wait time, length of stay (LOS), and 30-day readmission probability of other patients transitioning among these units. We find that larger proportion of long-stay patients in the MU results in shorter LOS for other patients in the MU, and longer wait time for patients leaving the ICU to MU.

Third, we examine existing patient grouping system based on the service lines at two hospitals within the same health system and propose a two-step clustering-classification approach to identify new patient clusters. Unlike existing 8 patient clusters (i.e., service lines), our results identified 11 patient clusters in Wilmington hospital and 15 patient clusters in Christiana hospital, indicating the need to further splitting some of the existing service lines such as internal medicine, general surgery, and neurological disorders.

1. INTRODUCTION

Among the 30 developed countries in the Organization for Economic Cooperation and Development (OECD), the United States has the highest health spending while it ranks near the bottom on common health measures (Kane 2012, Peterson and Burton 2009, Schroeder 2007). To this end, Schroeder (Schroeder 2007) proposed two focus areas that can impact health status in the US, improving the quality of care, and improving patient access to care. Granting the fact that quality of care in the US is no worse than that of other OECD countries (Schroeder 2007), access to care remains an ongoing issue in the US, especially among underserved populations (Bettenhausen et al. 2017, Land 2020, Mayer 2008, Schmidt et al. 2018).

Improving patient access to ambulatory services requires effective management of patient no-shows as well as patient follow-ups. Patient no-show negatively impacts provider productivity, clinic efficiency, healthcare costs, and patients access to care (Laganga and Lawrence 2007, Ratcliffe et al. 2012). Depending on the clinic type, no-show may vary from 3% to 80% (LaGanga and Lawrence 2012). Previous studies estimated patient no-show rates in different clinics. For instance, 55% in an outpatient clinic (Vikander et al. 1986), 13.6% up to 23.1% in an academic outpatient practice (Parikh et al. 2010), 18% in an Endoscopy clinic (Berg et al. 2013), 18% in primary care (Mehrotra et al. 2008), 15.8% in a Swiss university outpatient clinic (Lehmann et al. 2007), and 8.5% in an endocrinology clinic (Kim et al. 2018).

In addition to the no-show issue, outpatient clinics also deal with great volumes of follow-up visits. As reported in several studies, follow-up visits account for about 75% of specialist visits in England (Reeve et al. 1997), and nearly 50% of overall outpatient visits in the United States (Ackerman et al. 2014). It is believed that proportion of follow-up specialty visits can be handled through primary care, hence improve the access to specialty clinics (Ackerman et al. 2014, Mehrotra et al. 2011, Naiker et al. 2018). This proportion has been estimated anywhere between 5.6% to 48% (Ackerman et al. 2014, Hashim 2020, Reeve et al. 1997, U.S. 2013).

Although the literature supports the need for better no-show and follow-up management, there is no study to measure the impact of them on patient access to multidisciplinary clinics. Multidisciplinary practice models have gained popularity in recent years due to the potential advantages they have to offer, such as early diagnosis and cost savings, process efficiencies, and better health outcomes especially for patients with comorbidities (Bech-Azeddine et al. 2001, Hejl et al. 2002, Hodges et al. 2010, Høgh et al. 1999, Verhey et al. 1993, Wolfs et al. 2006).

In this study, we develop an empirical model of multidisciplinary memory clinic, considering different patient flows, no-shows, and follow-up patterns. We then evaluate the effectiveness of multiple access improvement strategies related to no-show, follow-up, and capacity management.

Similar to outpatient setting, inpatient flow can directly impact health outcomes, hospital costs, and patient satisfaction (Eriksson et al. 2017, Shi et al. 2018). In addition, proper bed allocation of hospital units and smoothing their occupancies shown to improve inpatient flow (Armony et al. 2015, Crilly et al. 2015, Hillier et al. 2006).

To estimate bed requirements, one needs to assess patient needs and their care complexities which can be extremely challenging due to the discretionary nature of diagnostics and treatment decisions (Lismont et al. 2016), clouding effect of overflowing activities (Lismont et al. 2016), as well as patient conditions and their health histories. As such, grouping similar patients is both critical and challenging. For that, bed allocation studies in both single-unit setting (Van Riet and Demeulemeester 2015, Rodrigues et al. 2018, Saghafian et al. 2015, Tierney and Conroy 2014) and cross-units setting (Bhattacharjee and Ray 2014, He et al. 2019) considered overall patient groups such as service lines.

In this study, we shed light on a special patient population, long-stay patients. These patients have long length of stays due to either complex care needs or discharge barriers. They comprise a fairly small portion of patient population but constitute majority of the patient days (e.g., 4.4% of patient population used 63% of the patient days (Naghib et al. 2010)). As such, it is important to investigate their impact on patient flow and hospital capacity. Due to the limited research in this realm and controversial findings regarding their impacts on flow and capacity (Lantz 2020, Woodger 2017, Woodger et al. 2018), this study aims to evaluate their impact on patient flow and hospital capacity from multiple perspectives.

In addition, we identify patient clusters using available data at the time of patient admission. Identified clusters can redefine existing service lines and inform reallocation of beds among them. They can also inform the hospital about potential anomality and guideline adherences.

2. LITERATURE REVIEW

Studies suggest that worse health outcomes are associated with poor access to both outpatient (Landon et al. 2005, Wu et al. 2001) and inpatient services (Eriksson et al. 2017, Shi et al. 2018). Also, historical patterns represent a constantly growing demand for both outpatient and inpatient services. In fact, demand for outpatient services has doubled within the past decade (Ackerman et al. 2014). Similarly, emergency visits and inpatient demands have been growing annually at annual rate of 2.3% (Slade et al. 2010). A more recent study suggest that the number of emergency visits increased from 128.97 million in 2010 to 144.82 million in 2016 with the cumulative annual growth rate of 1.95% which is higher than population growth at the rate of 0.73% (Lane et al. 2020). These findings indicate the need for efficiency in both ambulatory and inpatient care.

2.1 Ambulatory Care

Demand for outpatient services is constantly growing. Ambulatory care visits nearly doubled in the past decade (Ackerman et al. 2014). More than a third of patients are referred to outpatient services every year (Mehrotra et al. 2011). Growing demand has negatively impacted the patient access to ambulatory services. Access issue is even more pronounced among underserved populations (Cook et al. 2007, Ferrer 2007, Mayer 2008, Weissman et al. 2003).

Research has shown that patients who encounter longer wait times for their outpatient services are more likely to have worse health outcomes (Pizer and Prentice 2011). For instance, Veterans with more than a month wait time for outpatient services are 21% more likely to die, compared with patients who waited less than a month (Prentice and Pizer 2007). Similarly, a 10-day increase in wait time for primary care services among veterans aged 70 or more resulted in 2% increase in the odds of mortality and 6% increase in the odds of experiencing a stroke (Pizer and Prentice 2011). Other studies also suggest associations between poor access and worse health outcomes (Landon et al. 2005, Wu et al. 2001).

Poor access negatively impacts patient satisfaction. Patient satisfaction mainly depends on the aspects that patients can judge, such as timeliness of services (Eilers 2004, Fogarty and Cronin 2008, Kenagy et al. 1999). Poor access also increases downstream costs and healthcare utilization by deferring appropriate diagnosis and treatments (Kenagy et al. 1999) such as for preventable diagnosis in patients with diabetes (Mayfiel et al. 1998). As such, it is crucial to identify effective strategies that improve patient access to ambulatory care.

A recent review of 152 studies, identified three major themes for improving access to outpatient clinics (Naiker et al. 2018). The themes included resource alignment strategies (e.g., limiting the number of referrals, wait list audits, discharging patients from specialty to primary care, and triaging patients), operational efficiencies (e.g., early start of clinics, improved scheduling, separating new and follow-up access measures, and matching supply to demand) and process improvements (e.g., improving efficiencies, reducing supply and demand variations, no-show modeling, guidelines to improve efficiency of care processes, referral management, telemedicine, and use of technologies such as text messaging, e-referrals, automated scheduling, and reminders).

In the following sub-sections, we discuss the most common access improvement strategies, one from each of the above themes. More precisely, we explain overbooking from the process improvement theme (Laganga and Lawrence 2007, 2012, Liu et al. 2010), reducing unnecessary follow-up visits from the resource alignment theme (Demeere et al. 2009), and increasing providers from the operational efficiencies theme (Ponis et al. 2013).

2.1.1 No-show management

Patient no-show is a common issue in outpatient clinics, which can vary from 3% to 80% (LaGanga and Lawrence 2012). Previous studies estimated patient no-show rates in different clinics and location. For instance, 55% in an outpatient clinic (Vikander et al. 1986), 13.6% up to 23.1% in an academic outpatient practice (Parikh et al. 2010), 18% in an Endoscopy clinic (Berg et al. 2013), 18% in primary care (Mehrotra et al. 2008), 15.8% in a Swiss university outpatient clinic (Lehmann et al. 2007), and 8.5% in an endocrinology clinic (Kim et al. 2018). Regardless of the significance, no-shows negatively impact provider productivity, clinic efficiency, healthcare costs, and patients access to care by reducing the effective capacity (Laganga and Lawrence 2007, Ratcliffe et al. 2012).

For instance, 25.4% no-show rate in a family medicine clinic resulted in 14% loss in its anticipated daily revenue (Moore et al. 2001). Similar study in an endoscopy clinic revealed 16.4% profit loss due to its 18% patient no-show rate (Berg et al. 2013).

As such, researchers began to investigate the no-show drivers (Tan et al. 2019, Yang et al. 2020, Zailinawati et al. 2006), intervene to reduce no-show rates using reminder calls (Parikh et al. 2010), and incorporate no-show behaviors into appointment scheduling models through overbooking.

In particular, El-Sharo et al. (El-Sharo et al. 2015) studied overbooking strategies to maximize profit in a multi-provider outpatient clinic. Similarly, Ratcliffe et al. formulated an optimization model for overbooking and capacity decisions in outpatient clinics with two classes of patients and no-shows (Ratcliffe et al. 2012). Overbooking also resulted in significant improvements in patient access and provider productivity in different studies (Ahmadi-Javid et al. 2017, Cayirli and Yang 2014, Laganga and Lawrence 2007, 2012, Liu et al. 2010).

Huang and Hanauer compared personalized no-show prediction with traditional evenly-distributed overbooking in a general pediatrics clinic and concluded that earlier resulted in 6-8% less average patient wait time and 24-29% less overtime (Huang and Hanauer 2014). Other studies also stated the superiority of including personalized no-show rates to fixed or randomized ones (Glowacka et al. 2009, Salzarulo et al. 2016). For instance, Reid et al. proposed a predictive overbooking that performed better than fixed overbooking (e.g., 19%, 29%, 38%) in minimizing underutilization and overutilization of a Veterans Administration healthcare network clinic (Reid et al. 2015). Similarly, Daggy et al. used logistic regression to predict patient no-shows, and incorporated them into simulation model to optimize patient wait time, clinic utilization, and overtime using three years data from Veterans Affairs medical center (Daggy et al. 2010).

Despite the abundance of overbooking models in monodisciplinary outpatient clinics (i.e., a single provider type provides care services), none of the scheduling models in multidisciplinary outpatient clinics (i.e., multiple provider types collaborate to deliver care services) studied overbooking rules (Leeftink et al. 2018). As such, this study contributes to the literature by incorporating overbooking levels into access improvement strategies for a multidisciplinary outpatient clinic. Moreover, it considers queue length, as well as patient wait time, provider utilization, and number of visits as key performance indicators.

2.1.2 Managing follow-up visits

Follow-up patients account for majority of outpatient clinic visits. As reported in several studies, follow-up visits account for about 75% of specialist visits in England (Reeve et al. 1997), and nearly 50% of overall outpatient visits in the United States (Ackerman et al. 2014). In specialty clinics, some of these follow up patients can be referred back to primary care, which is known as repatriation. National Ambulatory Medical Care Survey report in 2013 estimated repatriation for different specialties, such as 10% for cardiology, 8% for psychiatry, and 5.6% for otolaryngology (U.S. 2013). Other studies reported repatriation estimates across multiple specialties, such as 48% in medical clinics (Reeve et al. 1997), 41.3% (Hashim 2020), and 16% (Ackerman et al. 2014).

Considering the significance of these estimates, it is believed that repatriation can lower healthcare costs and improve the access to specialty clinics (Ackerman et al. 2014, Mehrotra et al. 2011, Naiker et al. 2018). As such, numerous studies investigated repatriation barriers such as social, legal, and financial barriers (Ackerman and Gleason 2018), communication, guilt and trust difficulties (Burkey et al. 1997, Foy et al. 2010, Reeve et al. 1997), and care coordination issues (Liss et al. 2011). Accordingly, strategies have been proposed to facilitate the repatriation process, such as implementing gatekeepers and referral guidelines (Kouroukis et al. 2017, Mehrotra et al. 2011). However, there is no study to measure the impact of repatriation on patient access. To support the implementation of effective repatriation levels, the current study measures the impact of different repatriations on patient access to a multidisciplinary outpatient clinic, considering the complex nature of follow-up patterns, within-clinic referrals between disciplines, and no-show behaviors.

2.1.3 Capacity planning

Extending provider shifts and increasing capacity can improve patient access if the clinic is performing near its maximal capacity (Kritchanchai and Hoeur 2018). In addition, measuring access (e.g., mean wait time, queue length and backlog, supply and demand volumes) over long period of time can indicate potential capacity strains (van Bussel et al. 2018, Deslauriers et al. 2017, Johannessen and Alexandersen 2018, Kortbeek et al. 2017, O'Neill et al. 2012).

Capacity planning based on a target access time for some percentile of new patients is a common technique in the literature. For instance, Elkhuizen et al. calculated short-term and permanent capacity needed for neurology and gynecology outpatient clinics in order to achieve two weeks access time for 95% of new patients (Elkhuizen et al. 2007). As such, they measured mean access over time and suggested to have 26 additional consultations per week over two months period to clear the neurology backlog, and to have 2 additional weekly consultations to retain the access within two weeks (Elkhuizen et al. 2007). Similarly, Nguyen et al. proposed a mixed-integer programming model to minimize the maximum required capacity in an urology outpatient clinic where 6 weeks access time for 95% of patients was one of the constraints (Nguyen et al. 2015).

Another common capacity planning technique in the literature is based on demand variations and matching it to supply. For instance, capacity planning in an outpatient physical therapy service considering different service types and demand variations was studied using a discrete event simulation model (Rau et al. 2013). Similarly, capacity planning by matching supply and demand in the presence of walk-in and no-show was studied (Jiang et al. 2017).

Unlike these studies that have been done in monodisciplinary clinics, the current study evaluates the effectiveness of different capacity levels on patient access by minimizing overall patient wait time and provider idle time in a multidisciplinary outpatient clinic.

2.2 Inpatient Care

Hospital capacity planning is the effort of assigning hospital resources into different areas in order to match supply to demand (Li and Benton 2003). Assignment of these resources mainly depend on planning horizon. While short-term and intermediate-term capacity plans (e.g., scheduling, admission and discharge planning, and staffing) focus on operational and tactical goals, long-term capacity plans (e.g., allocating beds to different hospital units) aim to achieve strategic goals (Hulshof 2013, Hulshof et al. 2012). Among these, bed allocation has always been one of the key focus areas for hospitals that strive for excellence in care delivery (L. V. Green 2006).

Improper allocation of beds results in ceaseless congestion in high traffic units such as Intensive Care Unit (ICU), stepdown (Armony et al. 2015) and general medical floor (Crilly et al. 2015, Hillier et al. 2006). Research has shown the association between capacity strain and adverse health outcomes such as readmission (Shi et al. 2018) and mortality (Eriksson et al. 2017). In a recent systematic review, mortality rates increased during times of capacity strain in 18 of 30 studies and in 9 of 12 studies in ICUs (Eriksson et al. 2017), further indicating the importance of balanced bed allocation.

2.2.1 Single-unit studies

Initial models studied bed allocation in different hospital units such as Emergency Department (ED), ICU, and surgical units separately.

Bed allocation and improving patient flow in ED is of special importance. ED is the main point of entrance to hospitals. In fact, majority of admitted patients to general medicine beds come through the ED (Shi et al. 2015). ED visits account for approximately 85% of the admitted patients to hospital beds (Hillier et al. 2006).

Bed allocation based on target occupancy rate of 85% has been a common practice for the past decades (L. Green 2006, Green and Nguyen 2001). Bed allocation based on average occupancy rate has several issues. Occupancy rate is based on certified number of beds which is typically higher than staffed beds. Also, occupancy rate is captured based on midnight census which is often the lowest level. Finally, occupancy rate is averaged throughout a year without considering seasonal and time varying demands (Saghafian et al. 2015). As such, it is crucial to incorporate demand variations over time into capacity plans. Higginson et al. studied bed allocation problem in ED by tracking demand variation over time within different segmentations (e.g., hours of day, weekdays, and seasonal changes) (Higginson et al. 2011). A review of similar studies to improve patient flow and bed allocation in ED is provided in (Saghafian et al. 2015).

In line with bed allocation efforts within the ED, several models have been developed to identify avoidable ED visits and estimate potential capacity gains (Brousseau et al. 2006, Hsia and Niedzwiecki 2017, Johnston et al. 2017). Among others, NYU algorithm, also known as Billings algorithm, is able to classify ED visits into four major categories of non-emergent (i.e., visits that didn’t require care within 12 hours), emergent but primary care treatable (i.e., visits that required care within 12 hours that could be treated in primary care), emergent but avoidable (i.e., visits that could have been avoided through better primary care management such as medication adherence) and non-preventable emergent visits (i.e., visits that required emergency care) (Billings et al. 2000b, a). NYU algorithm was also applied to 2-years Medicare claims data from 5 states (Dowd et al. 2014). In this study, about 35% of ED visits were appropriate (i.e., non-preventable emergent), about 50% could have been treated in primary care, and about 15% were deemed preventable (Dowd et al. 2014).

Bed allocation in ICU has also been studied widely. Cost of care in the ICU is considered expensive, and is expected to increase over the next decade (Angus 2000, Cohen et al. 2010, Halpern et al. 1994). ICU patients account for 5% of total hospital admissions, yet they account for 15-20% of hospital budgets (Marlene Gyldmark 1995).

Wild and Narath studied ICU bed distribution, including percent of total hospital beds and number of beds per 100,000 population in the United States, Germany, Austria, Spain, Japan, Italy, United Kingdom, and Australia (Wild and Narath 2005). Among others, United States owns the highest number of ICU beds (6.3% of all hospital beds, and 30.5 beds per 100,000 population) which indicate the need for capacity planning in the US hospitals (Wild and Narath 2005).

In most countries, ICU capacity is planned based on estimated need, defined as multiplication of annual admissions, average Length Of Stay (LOS), and ideal occupancy rate (Wild and Narath 2005). While the use of aggregated annual admission and average LOS ignores time varying fluctuations, determining the ideal occupancy rate is challenging by itself. In this regard, Tierney and Conroy (Tierney and Conroy 2014) reviewed ICU studies that recommended capacity planning based on occupancy rates. While the US guideline for ICU occupancy rate is around 80%-85%, which is deemed to be unrealistically high (Halpern et al. 2006), several studies suggested 75% or below as the optimal occupancy rate (Green 2002, Valentin and Ferdinande 2011). Despite these recommendations, capacity planning based on average occupancy rate has been criticized. As discussed in the literature (Chrusch et al. 2009), occupancy rate can vary over time and increase the chance of adverse outcomes. Moreover, there seems to be a correlation between hospital size and its occupancy rate. In fact, Halpern et al. (Halpern et al. 2006) showed that larger hospitals tend to perform in higher occupancy rates than smaller size hospitals. Alternative approaches in managing ICU capacity using Operations Research techniques have been reviewed in (Bai et al. 2018).

Upon completion of ICU stay, patients often being transferred to step-down units (SDU). SDU is designed to offer intermediate level of care for patients downgraded from ICU or surgery. Capacity planning in SDU is also critical due to its vital role on smoothing ICU flow (Armony et al. 2018b). As such, one can expect to face the same challenges of ICU bed planning (Armony et al. 2018b, Corwin et al. 2005, Fernando et al. 2019, Zimmerman et al. 1999). Rodrigues et al. and references therein discussed the potential benefits of SDU on ICU patient flow and cost reductions (Rodrigues et al. 2018).

Capacity planning in surgical units, or operating rooms (OR) is another challenging research area due to the involvement of different stakeholders (e.g., elective vs. non-elective patients) as well as uncertainty sources (e.g., no-show, surgery duration) (Van Riet and Demeulemeester 2015). It is also one of the major revenue generating units in hospitals (Bekes et al. 2004).

While majority of works in this area relate to scheduling operating rooms (Cardoen et al. 2010, Guerriero and Guido 2011, Zhu et al. 2019), bed allocation has often been studied with the aim of determining the tradeoff between elective and emergency patient volumes (Van Riet and Demeulemeester 2015). In this regard, Helm et al. proposed an admission model for elective patients by smoothing the overall occupancy of hospital (Helm et al. 2011). Other studies aimed to reduce patient wait time by optimizing the number of required beds for elective and non-elective populations (Ferrand et al. 2014, Vanberkel and Blake 2007).

After surgery, patients either being discharged or held in post-anesthesia care unit (PACU). As such, PACU plays a key role in smoothing patient flow in the OR. Hence, capacity planning models in PACU and evaluation of their impacts were mainly tied to OR metrics (Dexter et al. 2005, Khorasanian et al. 2018, Marcon et al. 2003).

Capacity planning for each hospital unit separately results in sub-optimal plans that require practitioners to use different strategies for smoothing real-time flow of patients. For instance, hospitals tend to overflow patients to a non-preferred unit when there is capacity strain in the preferred unit (i.e., off-service placement). One of the recent studies stated that more than 20% of ED admitted patients were overflowed to inpatient wards (Dai and Shi 2019). In another study, consequences of overflowing on health outcomes were measured (Song et al. 2019). In this study, overflowing resulted in adverse outcomes due to the mismatch in nursing skills and extended travelling distance for rounding physicians (Song et al. 2019).

Another real-time strategy for alleviating congestion is prematurely discharging patients from a congested unit, such as ICU, which is also associated with higher risk of mortality (Rodríguez-Carvajal et al. 2011). In fact, average Length Of Stay (LOS) in ICU decreases when its occupancy rate increases which then increases the likelihood of ICU readmission (i.e., bounce-back) (Singh and Terwiesch 2012).

2.2.2 Cross-unit studies

Studies on multi-unit capacity planning were motivated by findings of earlier works on patient flow and its impact on downstream units. For instance, McConnell showed that an increase of 20 beds in an ICU can reduce ambulance diversion hours and LOS in ED by 66%, and 10%

respectively (McConnell et al. 2005). Similar studies investigated the impact of ICU capacity on patient flow within ED and reported potential associations between them (Allon et al. 2013, Pham et al. 2006). Studies also repeatedly reported the association between OR and PACU flows (Corwin et al. 2005, Dexter et al. 2005, Khorasanian et al. 2018, Marcon et al. 2003). As such, researchers began to incorporate multiple units in their capacity planning models. These models were reviewed from uncertainty quantification and modeling perspectives (Bhattacharjee and Ray 2014).

Similarly, He et al. identified nearly 1,500 scholarly articles published between 2013-2017 and criticized their static approach toward the flow (He et al. 2019). In this line, Table 2.1 shows some of the most relevant studies that considered multiple hospital units within their bed allocation problems.

Although the systematic approach aims to combine multiple patient groups together, the use of this approach requires a method to group and prioritize patients based on their characteristics and clinical needs. Bed allocation models need to incorporate metrics that are beyond the operational outcomes. For instance, 5 hours reduction in average wait time has different significance for a readmitted 80-year patient that seeks an ICU bed, and a 30-year patient that seeks a floor bed. Despite the abundance of system-level studies for bed allocation, only one of them included risk factors into their surge capacity planning model (Kelen et al. 2006). As shown in Table 2.2, majority of these system-level studies included only operational outcomes and ignored characteristics, risk factors, and clinical needs of patients. Including such features may reform the existing patient clusters, as in the case of type 2 diabetes mellitus domain (Lismont et al. 2016).

System-level studies require a method to group and prioritize patients based on their overall similarities. These similarities can be studied using process analytics (Lismont et al. 2016). Process analytics (i.e., process mining) offers a wide variety of techniques to track the movements of individual patients between different hospital units and extract the full trajectory of their pathways (Hripcsak and Albers 2013, Lismont et al. 2016). These techniques include sequencing events, temporal abstraction, clustering, sequence clustering, social network discovery, and decision mining (Lismont et al. 2016, Mans et al. 2015).

Although a recent review of these models identified their potential benefits in healthcare resource allocation problems (Garcia et al. 2019), several major challenges exist in their application, including inadequate granularity of recorded data, high complexity of healthcare data, and clouding effect of overflowing activities (Lismont et al. 2016), which have limited their applications to small size practice.

Table 2.1. Recent cross-unit studies for bed allocation with included units.

	ED	Ward	ICU	PACU	Ob/Gyn	SDU	Surgery
(Burdett et al. 2017)	✓	✓	✓	✓	✓	✓	✓
(Burdett and Kozan 2016)	✓		✓	✓			✓
(Cochran and Bharti 2006)	✓	✓	✓	✓	✓	✓	✓
(Hick et al. 2010)		✓	✓	✓	✓		✓
(Li et al. 2009)	✓	✓	✓	✓	✓	✓	✓
(Cochran and Roche 2008)			✓		✓		✓
(Lee et al. 2019)	✓	✓	✓				
(Lee et al. 2016)	✓	✓	✓				
(Mathews and Long 2015a)			✓			✓	
(Helm et al. 2011)	✓	✓					✓
(Helm and Van Oyen 2014)	✓		✓				✓
(Schafermeyer and Asplin 2003)	✓	✓	✓				
(Martin Prodel et al. 2013)	✓	✓					
(Kortbeek et al. 2015)	✓						✓
(Best et al. 2015)		✓					✓
(Harper and Shahani 2002)	✓	✓					✓
(Shi et al. 2015)	✓	✓	✓				✓
(Armony et al. 2015)	✓	✓					
(Khanna et al. 2012)	✓	✓					

For instance, Lismont et al. applied process analytics to study pathways of type 2 diabetes mellitus patients in primary care setting, and identified ten clusters where each contained a unique pathway, except one containing all remained 562 traces (Lismont et al. 2016). Similarly, resource allocation rules were extracted from clustering patient traces in a radiology CT-scan facility (Huang et al. 2011). Trace or sequence clustering was also combined with text mining to identify standard and atypical association rules (De Weerdt et al. 2012).

Table 2.2. Classification of cross-unit studies for bed allocation based on outcome measures.

Operational Outcomes	(Akcali et al. 2006, Armony et al. 2015, Best et al. 2015, Burdett et al. 2017, Burdett and Kozan 2016, Cochran and Bharti 2006, Cochran and Roche 2008, Costa et al. 2003, Feng et al. 2017, Gorunescu et al. 2002, Gupta et al. 2007, Harper 2002, Harper and Shahani 2002, Helm et al. 2011, Helm and Van Oyen 2014, Howell et al. 2007, Khanna et al. 2012, Kortbeek et al. 2015, Lee et al. 2016, 2019, Li et al. 2009, Martin Prodel et al. 2013, Mathews and Long 2015a, Schafermeyer and Asplin 2003, Shao et al. 2013, Shi et al. 2015, Villa et al. 2009, Yang et al. 2016)
Financial Outcomes	(Barz and Rajaram 2015, Chapman and Carmel 1992, Gorunescu et al. 2002, Klassen and Rohleder 2001, Li et al. 2009, Li and Benton 2003)
Health Outcomes	(Kelen et al. 2006)

Clustering was also applied in an inpatient radiology unit to understand its workflow and detect variations such as cancellations, association between certain processes, and neglecting guidelines (Rebuge and Ferreira 2012). For instance, they were able to identify cases where instead of first requesting an exam, physicians scheduled and completed the exam, then requested the exam (Rebuge and Ferreira 2012). Similarly, Mans et al. applied process analytics to stroke pathways in two different hospitals and compared their practices, bottlenecks, and preadmission processes (Mans et al. 2008).

In addition, Najjar et al. applied clustering algorithms to hospital visits data for patients over 65 years old who had kidney and heart problems (Najjar et al. 2018). They also compared different clusters in terms of their most frequent diagnosis, specialists, age and sex, and length of stay information. Similarly, Antonelli et al. applied frequent diagnostic pathways for colon cancer and showed that existing diagnostic guidelines were rarely followed by practitioners (Antonelli et al. 2012b). They also identified exam frequency, and frequency of exam sequences in the clinic that can be used for allocating resources and identifying bottlenecks (Antonelli et al. 2012b).

Other applications of process analytics and clustering include mining discharge patterns of over 60,000 hospitalized patients (Pagnoni et al. 2001), anomaly detection in clinical practices of colon cancer and diabetes (Antonelli et al. 2013), redesigning cancer and neuroscience outpatient centers (Yoo et al. 2016), predicting revisit probability and revisit disease types in a public health center using classification and sequential pattern analysis (Choi et al. 2010), construction of clinical pathways based on nursing order sequences in a hospital (Iwata et al. 2014), extracting frequent pathways in a prenatal diagnostic testing clinic to evaluate patient adherence to existing medical guidelines (Antonelli et al. 2012a), identifying frequent clinical pathways to model progression of arterial hypertension and evaluate the effectiveness of visits on health outcomes (Balakhontceva et al. 2018), studying radiology workflow and care processes in a gynecologic oncology department using sequential pattern mining (Caron et al. 2014), understanding ED process flow (Delias et al. 2015), identifying most frequent clinical pathways for patients with acute coronary syndrome (Funkner et al. 2017), and defining chronic obstructive pulmonary disease (COPD) phenotypes using clustering algorithms (Weatherall et al. 2010). Finally, Rojas et al. reviewed process mining studies in different healthcare areas such as arthritis, breast examination, cardiology, chronic cough, clinical imaging, dentistry, diabetes, ear infection, emergency, ICU, oncology, ophthalmology, outpatient care, stroke patients, surgery, trauma, and urology (Rojas et al. 2016).

Despite the potentials of process analytics in clustering patients across all types, none of the studies considered more than one patient population. As such, this study aims to extend them to multiple patient types and inform system-level approach for bed allocation.

In a nutshell, we identified the following gaps from literature:

1. Despite the popularity of multidisciplinary outpatient models in practice, there is no study in literature to evaluate access improvement strategies regarding no-show and follow-up management among them.
2. Despite popularity of long-stay patients in medical literature, little is known about their impact on hospital flow and capacity.
3. Improving patient flow in hospitals and reducing the bed wait times require balanced distribution of beds among hospital units. While numerous cross-unit bed allocation models have been proposed to address this issue, none of them considered grouping patients based on their clinical needs, and individual characteristics. Separate body of research has shown that patient clustering can improve patient flow, increase productivity, reduce misdiagnosis, and improve health outcomes.

As such, in this study:

1. We aim to develop an empirical simulation-optimization model for a multidisciplinary memory clinic, including multiple patient flows, no-shows, and follow-up patterns. We

then evaluate the effectiveness of multiple access improvement strategies related to no-show, follow-up, and capacity management.

2. We quantify the impact of long-stay patients on patient flow and hospital capacity.
3. We develop a two-step clustering and classification based on patient data available at the time of admission.

3. EVALUATING THE EFFECTIVENESS OF ACCESS IMPROVEMENT STRATEGIES IN A MULTIDISCIPLINARY MEMORY CLINIC

Demand for treatment services related to neurocognitive disorders is growing due to the aging of our population, increased life expectancy, and the high prevalence of cognitive symptoms. Since these disorders require both acute intervention and long-term care plans from collaborative disciplines (e.g., neurologist, geriatrician, psychiatrist, neuropsychologist, social worker, speech therapist, physical therapist, care manager), demand for multidisciplinary memory clinics is increasing rapidly. In the studied multidisciplinary memory disorders clinic with three disciplines, average monthly demand and average wait time of patients to receive their first evaluation have increased by five folds and three folds between 2011 and 2017. Reducing this wait time and improving access require effective strategies that are tailored for multidisciplinary nature of these clinics. In this paper, we investigate the effectiveness of overbooking, reducing unnecessary follow-up visits, and increasing provider hours using a simulation-optimization model. Our results suggest that despite the increasing wait times in the multidisciplinary memory clinic, increasing provider slots is not always an effective strategy. In fact, overbooking and reducing unnecessary follow-up visits can result in more significant performance improvements.

3.1 Introduction

Demand for multidisciplinary memory disorder clinics is growing due to the chronic nature of neurocognitive disorders (Akushevich et al. 2018) and the advantages of multidisciplinary over monodisciplinary approach (Hodges et al. 2010). Early detection and treatment planning in the care of these disorders can result in better health outcomes and reduce downstream costs (Knopman et al. 2000, Lee et al. 2018, Leifer 2003). Despite these facts, our analysis shows that patients in our studied Multidisciplinary Memory Clinic (MMC) need to wait for 1-3 months to receive their first evaluation.

A recent review of 152 studies, identified three major themes for reducing patient wait time and improving access to monodisciplinary clinics (Naiker et al. 2018). The themes included process improvements (e.g., overbooking, improving efficiencies, reducing supply and demand variations, no-show modelling, guidelines to improve efficiency of care processes, referral management, telemedicine, and use of technologies such as text messaging, e-referrals, automated scheduling), resource alignment strategies (e.g., reducing unnecessary follow-up visits, wait list audits, and triaging patients), operational efficiencies (e.g., increasing provider hours, early start of clinics, improved scheduling, separating new and follow-up access measures, matching supply to demand). When these strategies are applied within multidisciplinary clinics, shared nature of resources and interaction of different patient flows can hinder their effectiveness. Due to the popularity of multidisciplinary practices (J. Morrice et al. 2019, Kortbeek et al. 2017, Leeftink et al. 2018, 2019, Mutlu et al. 2015), and in the lack of studies to inform the effectiveness of access improvement strategies within these practices, this study aims to evaluate the effectiveness of overbooking, reducing unnecessary follow-up visits, and increasing provider hours within a multidisciplinary memory clinic.

Overbooking is a common strategy to better utilize resources against patient no-show. Depending on the clinic type, no-show can vary from 3% to 80% (LaGanga and Lawrence 2012). For instance, 55% in an outpatient clinic (Vikander et al. 1986), 13.6% up to 23.1% in an academic outpatient practice (Parikh et al. 2010), 18% in an Endoscopy clinic (Berg et al. 2013), 18% in primary care (Mehrotra et al. 2008), 15.8% in a Swiss university outpatient clinic (Lehmann et al. 2007), and 8.5% in an endocrinology clinic (Kim et al. 2018). In the studied clinic, no-show varied between 17.4-34.8% which suggests the need for better scheduling systems (Bahalkeh 2015, Bahalkeh et al. 2015, Madraki et al. 2015) or overbooking in order to improve the access. In addition to the no-show issue, outpatient clinics serve great volume of follow-up patients. As reported in several studies, follow-up visits account for nearly 50% of overall outpatient visits in the United States (Ackerman et al. 2014). Since majority of follow-up specialty visits can be handled through primary care, referring these visits to primary care can free up the capacity in specialty care and improve the access (Ackerman et al. 2014, Mehrotra et al. 2011, Naiker et al. 2018). This proportion was estimated between 5.6% to 48% (Ackerman et al. 2014, Hashim 2020, Reeve et al. 1997, U.S. 2013). Finally, extending provider shifts and increasing capacity can improve patient access if the clinic is performing near its maximal capacity (Kritchanchai and Hoeur 2018).

This study contributes to the literature in several ways. First, we develop generic logic flowchart and simulation model for the MMC with multiple provider types. These models can be readily extended to other specialty clinics with similar structure. Second, we estimate actual arrivals of new patients as well as follow-up patterns using finite mixture distributions. These models can account for latent behaviors such as patient preferences in the scheduling system and disrupted patient pathways (Kim et al. 2015, 2018). Finally, through the literature, expert knowledge, and supporting evidence based on clinic visits data, we calibrate strategies to reduce patient wait time and provide idle time (i.e., overbooking, reducing unnecessary follow-ups, increasing provider hours) and quantify their effects using a simulation-optimization model. We also draw upon the rich literature on the application of discrete-event simulation in healthcare (Günal and Pidd 2010, Hasan et al. 2020, Shoaib et al. 2020, Zhang 2018).

3.2 Data and Background

The MMC is a comprehensive outpatient clinic for neurocognitive disorders. It offers consultative, diagnostic, and treatment services for six types of patients: memory new, memory revisit, neurology initial consultation, neurology follow-up, geriatric psychiatry initial consultation, and geriatric psychiatry follow-up. These patients meet with clinicians from three disciplines in a shared physical space, supported by a shared clinic staff (registrar, medical assistant). Moreover, the clinicians interact with each other through frequent discussion of practices and approaches as well as by referring their patients to each other.

The MMC operates five days a week, Monday-Friday, from 8:00 AM to 4:30 PM. In addition, a full time receptionist handles the check-in process, a full time medical assistant examines patients and schedules follow-up appointments, two social workers provide consult to the patients or clinicians as needed, a nurse (22 hours/week) sees memory follow-up patients, four geriatric specialist physicians (total 42 hours/week) see both memory new and memory revisit patients, a geriatric psychiatrist (8 hours/week) sees geriatric memory disorder patients with psychiatric complications. Finally, a neurologist (10 hour/week) sees both initial memory visits as well as neurology initial and revisits for memory patients with neurological symptoms or concerns beyond the expertise of the other clinicians. Details of appointment length and service distributions are shown in Table 3.2.

The patient intake process is performed over the phone and supplemented through responses to a mailed questionnaire. As shown in Figure 3.1, new appointment requests arrive as phone calls. These requests are scheduled for the earliest available time. The time interval between a phone call and the appointment is often referred as out-clinic wait time. On the other hand, in-clinic wait time is the time a patient spends in the clinic before seeing a provider. Since the in-clinic wait time is much shorter than the out-clinic wait time, we only consider the latter, and we refer to it as wait time for simplicity.

Ideally, wait time for new patients should be zero, but follow-up patients may need to wait for clinical reasons (e.g., effect of prescriptions on a patient). Therefore, we focus on the wait time for new patients only. For simplicity, we use “memory” for “memory new patients”, “geriatric psychiatry” for “geriatric psychiatry initial consultation”, and “neurology” for “neurology initial consultation” in the rest of the paper.

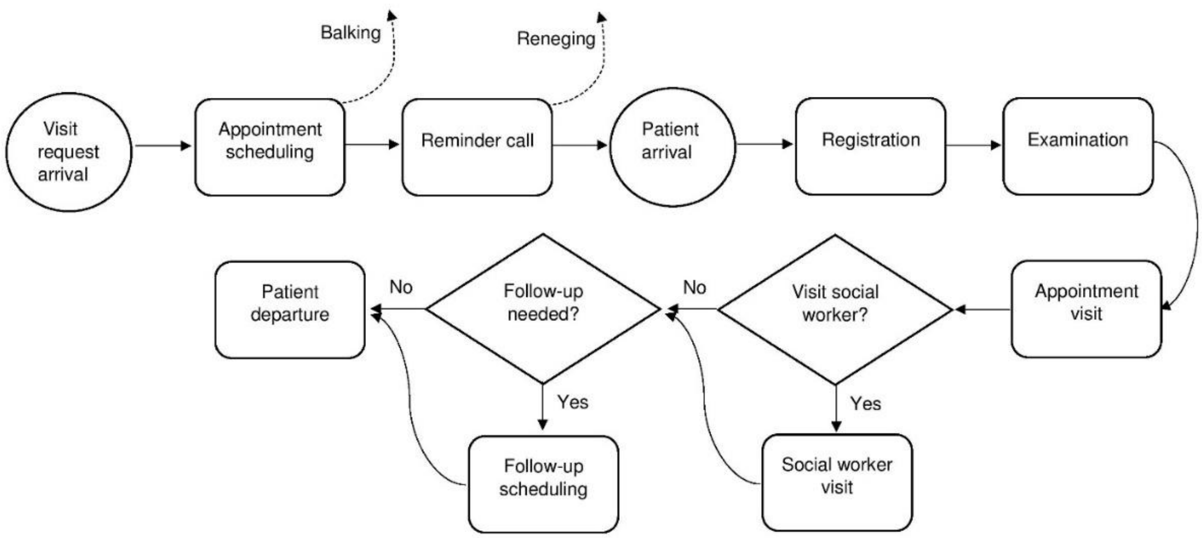

Figure 3.1. Patient flow in the multidisciplinary memory clinic.

The data for memory, geriatric psychiatry, and neurology patients cover 06/2011-08/2017, 11/2015-09/2017, 04/2016-06/2017, respectively. Table 3.1summarizes the average follow-up and no-show rates of new and initial consultation patients, estimated from retrospective visits data. Apart from the average number of follow-ups, some patients experience a few follow-ups, as low as one, within a six-month period or less, while others have as high as ten follow-ups within a several year window.

Table 3.1. Average follow-up and no-show rates.

	Cancel and no-show rate (%)	Follow-up visit rate (%)	Average number of follow-up visits
Memory	34.8	62	8
Geriatric psychiatry	17.5	73	7
Neurology	33.3	25	1

3.2.1 Supply and demand volumes

We examine the MMC supply and demand volumes by tracking the number of scheduled and the number of requested appointments each month, as shown in Figure 3.2. Both supply and demand graphs have upward trends. The sudden drop toward the end is due to incompleteness of recorded data. Also, the narrow gap between supply and demand curves indicates clinic's ability to respond to demand changes.

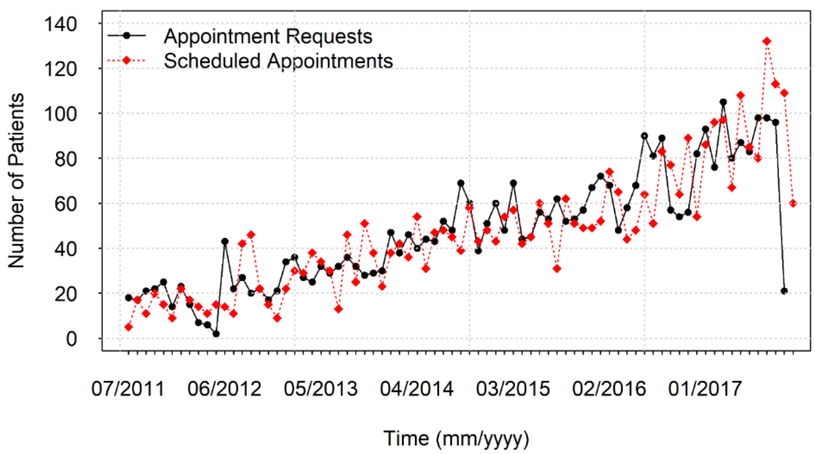

Figure 3.2. Supply and demand volumes for memory patients.

3.2.2 Average wait time

The average wait time in a particular month was calculated as the arithmetic mean of the wait time of the patients who had any number of appointments in that month. Figure 3.3 represents the average wait time (dashed line) and demand (bar graph) over time. As shown in Figure 3.3, despite the constant growth of demand volumes, wait time fluctuates for memory patients, which could be caused by many mechanisms over time (e.g., staff changes, backlog in the queue).

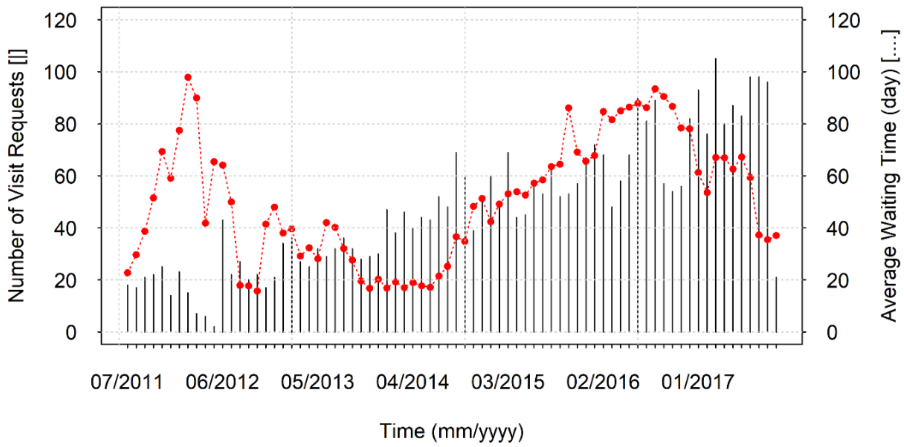

Figure 3.3. Number of visit requests and average wait time per month for memory patients.

3.2.3 Queue length

Queue length is another facet of the access which indicates the overall busyness of a system. At a given time t, queue length is defined as the total number of appointment requests that have arrived before t and have been scheduled for any time after t. In our analysis, t is a continuous variable, updated every day. Figure 3.4 represents a constantly growing queue length for memory revisit patients. In addition, queue for memory patients represent an increasing pattern followed by a slight drop. This analysis shows that there is a build-up of memory and revisit patients from past years, further indicating the need to provide improved access to providers for these patients.

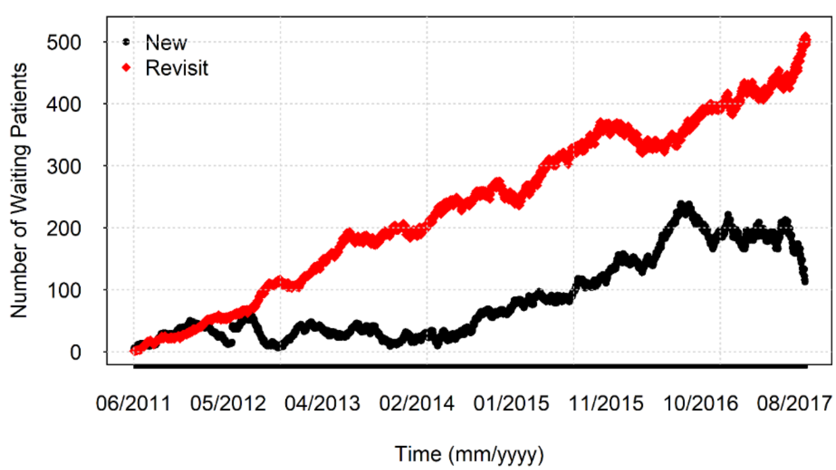

Figure 3.4. Queue length for memory patients.

3.3 Methodology

The studied clinic was interested to evaluate the effectiveness of overbooking, reducing unnecessary follow-up visit and increasing provider hours on the providers' idle time as well as wait time of new patients. Revisit and follow-up patients were excluded from this objective because often they need to wait for prespecified amount of time for monitoring prescription effects. As such, our goal is to determine the optimal level of overbooking, capacity expansion, and follow-up reduction so that the weighted sum of expected patient wait time and expected provider idle time is minimized. To account for differences in scale, we normalized these two objectives according to their base (without any intervention) values. A general form of the model can be written as

$$\min \sum_k (c_k^{WT} \sum_i E[\widehat{WT_{ik}}(\boldsymbol{x})] + c_k^{IT} \sum_j E[\widehat{IT_{jk}}(\boldsymbol{x})]) \tag{3.1}$$

$$s.t. \boldsymbol{x} \in \boldsymbol{X} \tag{3.2}$$

where

$$i = patient\ index$$

$$j = provider\ index$$

$$k = patient/provider\ type$$

$$c_k^{WT} = cost\ coefficient\ of\ waiting\ time\ for\ patient\ of\ type\ k$$

$$c_k^{IT} = cost\ coefficient\ of\ idle\ time\ for\ provider\ of\ type\ k$$

$$\boldsymbol{x} = solution\ vector$$

$$E[\widehat{WT_{ik}}(\boldsymbol{x})] = expected\ normalized\ wait\ time\ of\ patient\ i\ of\ type\ k, given\ \boldsymbol{x}$$

$$E[\widehat{IT_{jk}}(\boldsymbol{x})] = expected\ normalized\ idle\ time\ of\ provider\ j\ of\ type\ k, given\ \boldsymbol{x}$$

$$\boldsymbol{X} = feasible\ space\ (capacity\ and\ process\ configuartions)$$

The costs of patient *wait time* and provider idle time can be balanced by defining $c_k^{WT} + c_k^{IT} = 1$ where $c_k^{WT} > 0$ and $c_k^{IT} > 0$. Each clinic can specify these weights based on its own operational goals and financial constraints. For instance, a high-volume, low-acuity clinics may prefer to minimize patient wait times ($c_k^{WT} \gg c_k^{IT}$) or a for-profit imaging clinic wants to maximize its utilization ($c_k^{WT} \ll c_k^{IT}$) as discussed in (Froehle and Magazine 2013).

To determine the optimal level of overbooking for each patient type, the optimization model needs to be evaluated for each feasible combination of overbooking levels across patient types. To speed up this process, we developed a discrete-event simulation model in Arena and used the OptQuest to search for the optimal solution. The OptQuest is a combination of several heuristic methods such as scatter search, Tabu search, and neural network guides a given stochastic optimization problem (Klassen and Yoogalingam 2009).

We developed the simulation model, and incorporated the OptQuest search method based on the following details:

1. To account for differences in date ranges of available data across patient populations, we set 01/2017 as simulation start time and initialized the simulation model with the snapshot of the clinic on 01/2017. Thus, we set the warm-up period to zero.
2. The independent effects of each simulation scenario were simulated in Arena by modifying the cost coefficients in (3.1), and constraints in (3.2).
3. For each of the scenarios, we ran the OptQuest for 1,000 iterations. In each iteration, a randomly selected feasible solution is evaluated. Each iteration consisted of three replications. Each replication ran for a two-year period.
4. The simulation-optimization algorithms would stop after either reaching the error (i.e., difference between two consecutive objective function values) of smaller than 0.0001, or completing 1,000 iterations.
5. To refine the solutions upon termination, top 25 solutions were selected, and an additional 100 replications were run on each of them. Then, the final solution was selected from the updated ranking of the solution set.

3.3.1 Logic flow

For each patient type, a new visit request arrives according to a specified interarrival distribution. If the patient does not show-up, scheduled resources (e.g., provider, nurse) will remain idle. Otherwise, the patient checks in and completes the visit. If the patient does not require a follow-up visit, the patient leaves the clinic. Otherwise, returns to the clinic after a random follow-up interval that is drawn from a specified distribution. Upon arrival as a follow-up patient, the loop repeats until the patient completes the random number of required follow-up visits. Figure 3.5 shows the flowchart of the described logic.

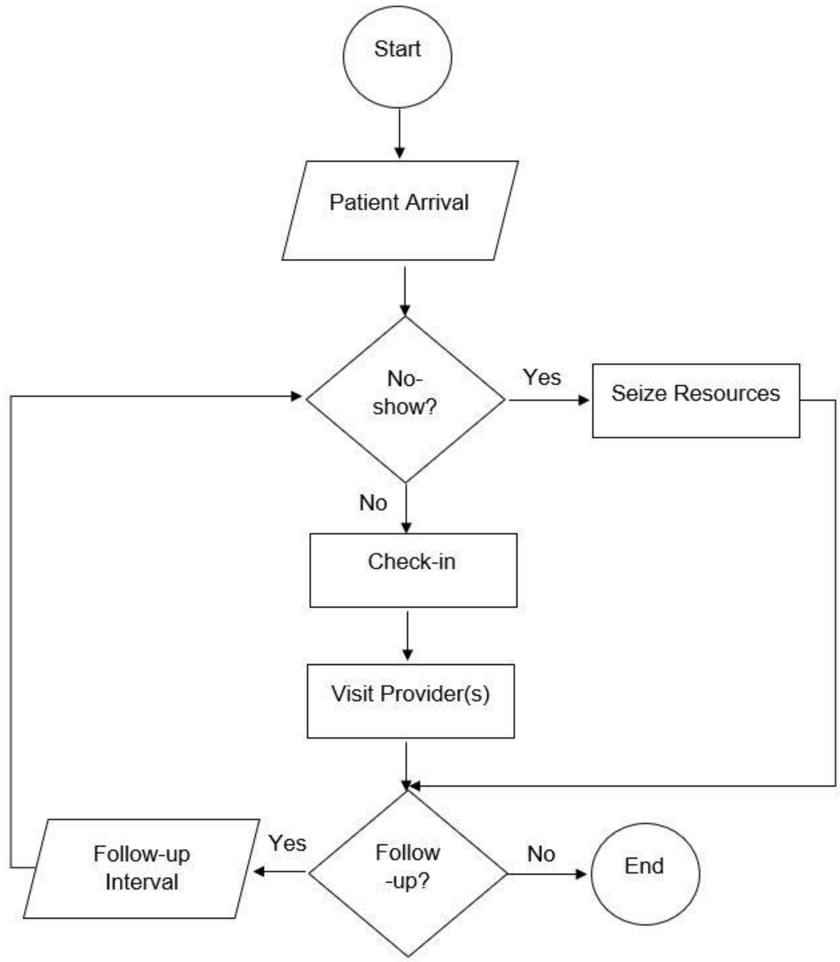

Figure 3.5. Logic flowchart of patient visits.

Figure 3.6 and Figure 3.7 illustrate the implementation of no-show, visit, and follow-up logic flows for one of the patient types in Arena.

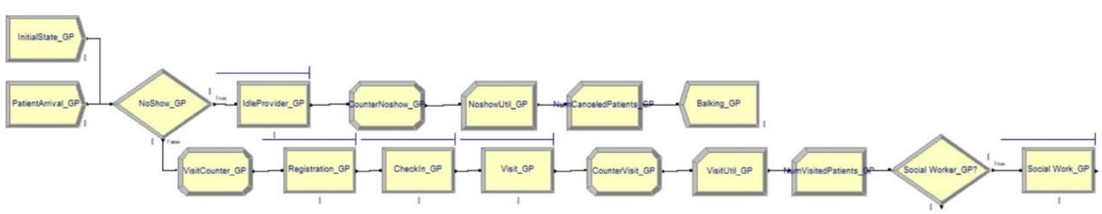

Figure 3.6. No-show and visit logic flows in Arena for Geriatric Psychiatry patients.

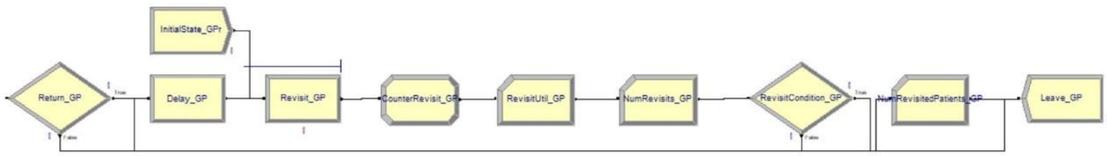

Figure 3.7. Follow-up logic flow in Arena for Geriatric Psychiatry patients.

3.3.2 Service time distributions

Patients utilize multiple services during their clinic visits. Table 3.2 summarizes these services and their estimated durations.

Table 3.2. Description of service types and service time distributions.

Definition	Duration (min/patient)	Capacity (hour/week)
Check-in	Triang (2,4,6)	40
Examination	Triang (2,4,6)	40
Follow-up scheduling	Triang (2,4,6)	
Social worker consult	Triang (24, 30, 36)	80
Memory new visit	75	64
Memory revisit	45	
Geriatric psychiatry initial consultation	60	8
Geriatric psychiatry follow-up	30	
Neurology initial consultation	60	10
Neurology follow-up	30	

3.3.3 Interarrival distributions

We examine time-dependency of patient arrivals using retrospective visits data. Among all, only memory patients represent such dependency. We model the interarrival of memory patients as $1.8479\exp(-0.022T)+\epsilon$ where $\epsilon \sim N(0,1\ hour)$ and T is the arrival month. Figure 3.8 represents the time varying interarrival rates and fitted decaying function ($R^2 = 83\%$). Irregular patterns at the beginning are due to data limitations (only 7, 6, and 0 datapoints on 3/2012, 4/2012, and 5/2012 respectively).

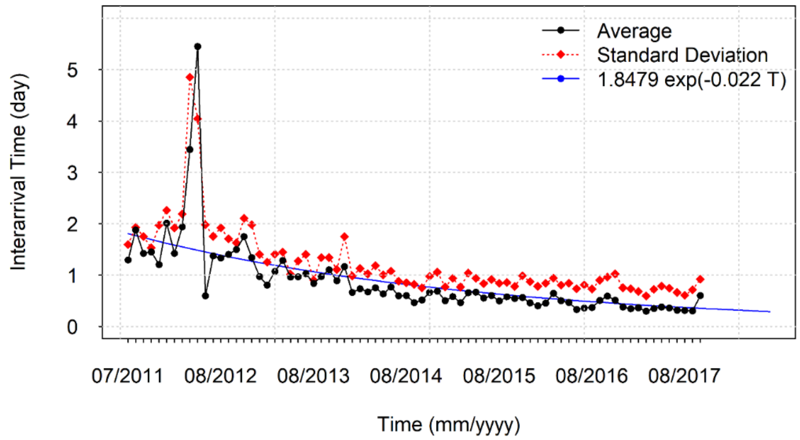

Figure 3.8. Empirical interarrival time and fitted function for memory patients.

Interarrival of other patient types do not represent time-varying patterns. In addition, they do not satisfy the assumption of equal mean and variance of the Poisson distribution (Kim et al. 2015, 2018). As such, we used bootstrapping with a confidence level of 95% to estimate the interarrival distribution of other patients with Gaussian mixture models. A Gaussian mixture model is a linearly weighted sum of multiple Gaussian distributions with known mean and variance. More precisely, a Gaussian mixture with C components can be written as $\sum_{i=1}^{C} \lambda_i N(\mu_i, \sigma_i^2)$ in which $\sum_{i=1}^{C} \lambda_i = 1$. Table 3.3 summarizes the estimated Gaussian mixtures.

Figure 3.9 represents the empirical probability mass function, estimated Kernel density function, and fitted Gaussian mixture model for interarrival of memory revisit patients, and Figure 3.10 visualizes its goodness of fit (Cosma Shalizi 2013).

Table 3.3. Gaussian mixture distributions for interarrival times.

	Interarrival distribution (day)	p-value
Memory revisit	0.07 N(5.72, 17.64) + 0.22 N(40.98, 317.55) + 0.26 N(99.85, 272.58) + 0.45 N(145.37, 3970.26)	0.42
Geriatric psychiatry	0.17 N(2.26,0.75) + 0.46 N(0.48, 0.2) + 0.31 N(4.8, 2.99) + 0.06 N(8.52, 9.06)	0.32
Geriatric psychiatry follow-up	0.56 N(20.88, 151.78) + 0.34 N(74.43, 522.58) + 0.08 N(183.32, 282.59) + 0.02 N(365.14, 46.38)	0.32
Neurology	0.31 N(0.62, 0.26) + 0.69 N(8.91, 37.95)	0.17
Neurology follow-up	0.88 N(53.49, 1000.46) + 0.12 N(181.48, 32.04)	0.32

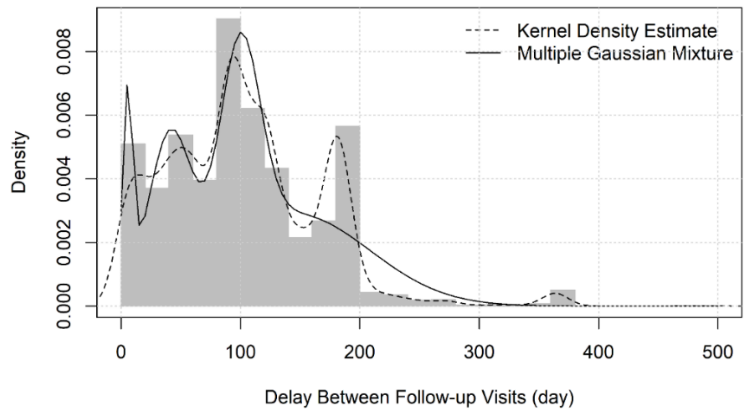

Figure 3.9. Empirical and fitted interarrival distributions for memory revisit patients.

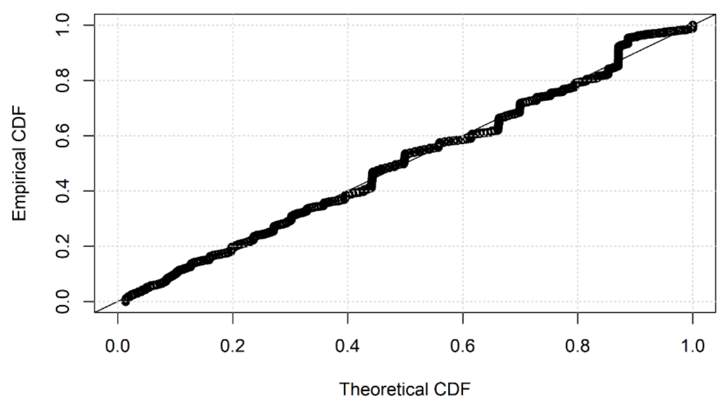

Figure 3.10. Goodness of fit for the Gaussian mixtures in memory revisit patients.

3.3.4 Model validation

We compared the base simulation model with clinic's data as shown in Table 3.4. Despite changes in the clinic's staffing and operations throughout the years, our simulation is able to mimic the actual behavior of the system for memory and geriatric psychiatry populations. Major differences in queue performance measures for neurology population can be explained by its low utilization in practice, which is 9%. Increasing this utilization in practice can potentially reduce both average wait time and average queue length in practice as estimated in our simulation. Due to these differences, simulated results for the neurology population should only be compared with those in the simulated base model.

Table 3.4. Comparison of queue performance measures from simulation and data.

Patient Type	Performance Measures	Simulation	Data
Memory	Average wait time (day)	67.6	68.2
	Average queue length	224.1	212.6
Geriatric psychiatry	Average wait time (day)	14.2	18.8
	Average queue length	5.5	5.7
Neurology	Average wait time (day)	1.5	44.8
	Average queue length	0.2	3

3.4 Results

3.4.1 Overbooking

For each patient population, the maximum level of overbooking is set to be slightly less than no-show rates, estimated from the data. In particular, we set 30% as the overbooking upper-bound for memory and neurology patients who had total no-show rates of 34.8% and 33.3%, respectively. This upper-bound for geriatric psychiatry patients who had a no-show rate of 17.5% was set to 15%.

Table 3.5 represents the impact of overbooking on performance measures under different C^{WT} where $C^{WT}+C^{IT}=1$. The first column represents the base simulation results without any intervention.

For memory population, when $C^{WT} = 0.25$, overbooking to 29.37% level is the optimal action. This can increase the provider utilization from 74% to 87% and increase the average *wait time* by 1 day. Average queue length is also increased significantly. These results are due to the low value for cost coefficient of the *wait time*, $C^{WT} = 0.25$. For that, at $C^{WT}= 0.5$ and $C^{WT} = 0.75$, optimal overbooking levels are only 0.54% and 0.98% respectively.

For geriatric psychiatry population, optimal overbooking levels are 14.98%, 15%, and 14.44% under $C^{WT} = 0.25$, $C^{WT} = 0.5$ and $C^{WT} = 0.75$ respectively. Opposed to memory population, this population needs to be overbooked by almost 15% regardless of C^{WT}.

For neurology population, optimal overbooking levels are 28.25%, 19.32%, and 15.68% under $C^{WT} = 0.25$, $C^{WT} = 0.5$ and $C^{WT} = 0.75$ respectively. Unlike two other populations, optimal overbooking drops constantly as C^{WT} is increased.

Table 3.5. Performance measures under optimal overbooking per patient type and C^{WT}.

Patient Type	Performance Measures	Base Model	$C^{WT} = 0.25$	$C^{WT} = 0.5$	$C^{WT} = 0.75$
Memory	Average wait time (day)	90.8	91.21	87.92	87.9
	Average queue length	327.2	537.57	323.33	330.38
	Number of visits	926.2	1151	913.33	925.67
	Provider utilization (%)	74	87	74	75
Geriatric psychiatry	Average wait time (day)	23.2	27.55	26.72	27.83
	Average queue length	9.3	14.30	14.62	14.88
	Number of visits	153.5	166.33	162.33	161.67
	Provider utilization (%)	92	97	96	95
Neurology	Average wait time (day)	1.4	1.44	1.40	1.31
	Average queue length	0.2	0.23	0.21	0.18
	Number of visits	49.5	77.33	71.67	65.67
	Provider utilization (%)	6	10	9	8

3.4.2 Reducing unnecessary follow-up visits

We tested the effectiveness of reducing unnecessary follow-up visits under three levels of 25%, 50%, and 75%. To make these levels comparable, we made sure that scenarios produce exactly the same number of patients by relaxing the two-year simulation length. As such, we ran the simulation model alone, without considering the optimization model. As shown in Table 3.6, this intervention does not benefit the memory population unless it's done at 75%, reducing the number of follow-ups from 8 to 2. On the other hand, it benefits geriatric psychiatry population significantly. Reducing the average number of follow-ups from 7 to 5.25 results in about 60% reduction in both average *wait time* and queue length. These patterns continue with slower rates as the average number of follow-ups decreases more. This change can be explained by the greater saturation of available hours. Since the neurology population has only one follow-up per patient on average, this intervention has a negligible effect on their average *wait time* and queue length.

3.4.3 Increasing provider hours

We relaxed the capacity constraint by a reasonably large amount to explore total provider hours needed for each scenario. As such, we allowed capacity expansion up to three times, even if it might be unrealistic in reality. Table 3.7 summarizes the results for different values of C^{WT}. As shown, current capacities are optimal for neurology and geriatric psychiatry populations under all scenarios. However, the memory population requires more capacity when C^{WT}=0.95. For this case, increasing provider hours from 64 hours/week to 108 hours/week is the optimal level that reduces the average *wait time* from 90.8 days to 86.8 days. It also reduces the providers' utilization from 74% to 37%.

Table 3.6. Percent reduction in average wait time and queue length for different follow-up reduction levels compared to the base scenario.

		Number of follow-up reduction (% base)		
		25%	50%	75%
Memory	Average wait time	≅ 0	2%	53%
	Average queue length	≅ 0	8%	65%
Geriatric psychiatry	Average wait time	59%	68%	70%
	Average queue length	57%	67%	69%
Neurology	Average wait time	≅ 0	≅ 0	≅ 0
	Average queue length	≅ 0	≅ 0	≅ 0

Table 3.7. Performance measures under optimal capacity per patient type and C^{WT}.

Patient Type	Performance Measures	Base Model	C^{WT} = 0.25, 0.5, 0.75	C^{WT} = 0.95
Memory	Average wait time (day)	90.8	90.8	**86.8**
	Average queue length	327.2	327.2	**316**
	Number of visits	926.2	926.2	**926.2**
	Provider utilization (%)	74	74	**37**
Geriatric psychiatry	Average wait time (day)	23.2	23.2	23.2
	Average queue length	9.3	9.3	9.3
	Number of visits	153.5	153.5	153.5
	Provider utilization (%)	92	92	92
Neurology	Average wait time (day)	1.4	1.4	1.4
	Average queue length	0.2	0.2	0.2
	Number of visits	49.5	49.5	49.5
	Provider utilization (%)	6	6	6

3.5 Discussion and Conclusions

We studied the effectiveness of overbooking, reducing unnecessary follow-up visits, and increasing provider hours on reducing patient wait time and provider idle time in a multidisciplinary memory clinic that provides care to six different patient types. We developed generic logic flowchart for patient visits, and simulated it using a discrete-event simulation model in Arena. Combining retrospective data analysis on queue performance measures and simulation-optimization results suggests the following:

1. For the memory population which had the highest demand volume, queue length, wait time, no-show rate and follow-up visits, extensive reduction in the number of follow-ups improved the performance measures. Under extreme values of C^{WT}, overbooking or expanding capacity can be effective as well.
2. For the geriatric psychiatry population that had medium demand volume, queue length, wait time, no-show rates and follow-up visits, reducing the number of follow-ups by any amount improved the performance indicators significantly. In addition, overbooking to the fullest (15%) can improve the overall performance.
3. For the neurology population that had the lowest demand, wait time, queue length, and follow-up visits with high rates of no-show, overbooking can improve the provider's productivity without a significant impact on patient wait time. However, as discussed above, due to the nature of neurology practice that is not able to be captured in the simulation model, the conclusion above is only true when compared to the base case of the model. The base case assumes that patients are scheduled on a first-come, first served basis instead of by patient preferences, and providers' schedules are to be made available for seeing patients instead of other duties.

Despite the long wait times across all patient populations, expanding capacity was not an effective strategy for improving access. Instead, reducing no-show or unnecessary follow-up visits can result in better improvements in performance measures. These findings are consistent with similar access improvement strategies in monodisciplinary clinics that include similar patient flow (Naiker et al. 2018).

Our study has several limitations. First, we tested the impact of reducing unnecessary follow-up visits numerically. However, a more realistic approach is to perform chart reviews or to conduct a prospective study to capture a more accurate estimation on percent of patients seen in the multidisciplinary clinic who should have been repatriated to primary care. Estimating this proportion can also provide a more accurate range than that of the literatures which is anywhere between 5.6%-48% (Ackerman et al. 2014, Hashim 2020, Reeve et al. 1997, U.S. 2013).

Reducing unnecessary follow-up visits is challenging in practice. Apart from difficulties in defining unnecessary follow-up visits in terms of clinical attributes, repatriating them should address the concerns discussed in the literature. These concerns include communication difficulties, uncertainties about primary care's ability to provide care, specialists' perceptions of their responsibilities, specialists' unease and guilt about discharging patients, organization of follow-up care in primary care, resources needed within primary care, flow of information from the clinic to primary care, among others (Ackerman et al. 2014, Burkey et al. 1997, Reeve et al. 1997). As an alternative, opening a geriatric psychiatry follow-up clinic in Behavioral Health can help the MMC to achieve the same goal without jeopardizing the continuity of care.

Overbooking is also challenging in practice. When all patients show up, the MMC needs to whether a) send overbooked patients home unseen, or b) keep overbooked patients waiting in the clinic, or c) reduce appointment length of other patients. To avoid overtime issue, we included overbooking thresholds based on the estimated no-show rates. As a future work, one could develop predictive models to estimate no-show probability of individual patients and incorporate those into the overbooking strategy.

Another limitation of this study relates to the use of past data (that are reflective of past decisions) to model future decisions which can induce inherent heterogeneity issues. Future studies can attempt to address this issue. In addition, future studies can extend our work in several ways. First, including additional performance measures such as cost components, and patient outcomes. Second, performing sensitivity analysis on our results and obtain more robust conclusions. Finally, future research can quantify the economic trade-off between providers idle time and patient wait times, taking into consideration societal costs incurred due to patient wait times, and provide better interpretations for C^{WT} and C^{IT}.

4. IMPACT OF LONG-STAY PATIENTS ON HOSPITAL FLOW AND CAPACITY

Patients with discharge barriers stay in medical units for non-medical reasons (e.g., homelessness and guardianship issues) and contribute to flow and capacity issues within and beyond medical units. Using patient-level data at two academic hospitals within the same healthcare system, we estimate the impact of long-stay patients on length of stay and 30-day readmission of other patients in medical units, as well as wait time for patients transitioning from both intensive care unit (ICU) and step-down unit (SDU) to medical unit (MU). Inspired by prior studies on patient flow between ICU and MU, we include occupancy of origin (i.e., ICU, SDU) and destination (i.e., MU) units. We find that larger proportion of long-stay patients in the MU is correlated with shorter LOS for other patients in the MU, and longer wait time for patients leaving the ICU to MU. Also, proportion of long-stay patients is associated with neither 30-day readmission, nor wait time for patients leaving the SDU. For both the ICU and the SDU, we find that patients experience shorter wait time leaving these units to the MU as the unit gets busier. Finally, busier MU is correlated with longer wait time for patients leaving the SDU.

4.1 Introduction

Small number of patients with complex social needs use relatively large amount of hospital resources (Lantz 2020). This population is referred as long-stay patients due to their prolonged stay in the hospital for non-medical reasons such as lack of social support, lack of economic resources, and behavioral issues, among others (Gigantesco et al. 2009). Due to these discharge barriers, long-stay patients spend majority of their stay in non-critical Medical Units (MU) (Heincelman et al. 2016).

Changes on proportion of long-stay patients within a medical unit can have several implications on the flow of the rest of patients in that unit. From operations perspective, servers employ different strategies when they encounter customers with long service times (e.g., long-stay patients) such as multitasking (Freeman et al. 2017, Jaeker and Tucker 2017), task reduction (Alizamir et al. 2013, Kuntz et al. 2015, Singh and Terwiesch 2012), rushing (Kc and Terwiesch 2009, Staats and Gino 2012, Tan and Netessine 2012), and early task initiation (Batt and Terwiesch

2017). Studies suggest that multi-tasking and early task initiation strategies are common within Emergency Departments (ED) where physicians can order tests and lab works before seeing patients (Batt and Terwiesch 2017, Freeman et al. 2017, Jaeker and Tucker 2017). In addition, several studies indicate that providers tend to discharge patients earlier than expected when medical units (Long and Mathews 2018) and cardiothoracic Intensive Care Unit (ICU) (Singh and Terwiesch 2012) operate in busy periods. While long-stay patients occupy beds in a medical unit for a long period of time, other patients in that unit are more likely to be discharged in order to board waiting patients into that unit. As such, we investigate the hypothesis that regular patients in medical units will have shorter length of stay (LOS) if proportion of long-stay patients increase in that unit.

Although clinical studies suggest that policies that incentivize short LOS may lead to worse patient outcomes (Southern and Arnsten 2015), relationship between shortened LOS due to operational behaviors and patient outcomes is challenging to measure. While early discharge from ICU due to ICU busyness is likely to result in ICU bounce-back (Singh and Terwiesch 2012), such incidents are not correlated with readmission and mortality (Long and Mathews 2018). As such, this study investigates the impact of long-stay patients in medical units on 30-day readmission of regular patients in that unit.

Long-stay patients residing in medical units can impact not only regular patients in those units, but also patients in upstream units such as ICU and stepdown unit (SDU), especially during their busy periods. In particular, ICU patients experience longer wait time for medical beds when medical units operate in higher occupancy rates (Long and Mathews 2018, Singh and Terwiesch 2012). Since long-stay patients occupy medical beds for a long period of time, accumulation of these patients in a medical unit can congest that unit and exacerbate the wait time for ICU patients. As such, we investigate the impact of long-stay patients on the wait time of ICU patients prior their transfer to medical units.

Despite the critical role of SDU in alleviating ICU flow (Mathews and Long 2015a), little attention has been paid to investigate patient flow between SDU and medical units. SDU provides intermediate level of care to patients who are in transition between ICU and medical units (Armony et al. 2018a). Our study is the first attempt to investigate patient flow between SDU and medical units. We investigate the impact of long-stay patients in medical units on the wait time of patients exiting SDU to medical units.

Our study is motivated by our observation from impacts of long-stay patients on hospital flow at two academic hospitals within the same healthcare system. Our study is the first attempt to estimate the impact of long-stay patients in medical units on LOS and readmission of other patients in those units. In addition, we estimate the impact of long-stay patients on the wait time of ICU, and SDU patients being transferred to medical units.

4.2 Literature Review

Past studies have mainly focused on identifying long-stay patients through predicting their cost (Heincelman et al. 2016, Ng et al. 2019), LOS (Polito et al. 2019), prolonged discharge boarding (Shaikh et al. 2018), discharge barriers (Afilalo et al. 2017, Gigantesco et al. 2009, Oseran et al. 2019), expert knowledge through survey analysis (Woodger et al. 2018) and methodological review of past studies (Grafe et al. 2020). Despite extensive research on identifying long-stay patients, there is no study to quantify their impact on hospital flow and patient outcomes, which is an important issue from Operations perspective in order to design case mixes (Vitikainen et al. 2009).

Since long-stay patients occupy medical beds for a long period of time, those beds can be viewed as closed beds which then will exacerbate occupancy rates. Congested hospital can experience higher in-hospital mortality (Schilling et al. 2010, Yu et al. 2020). In fact, mortality rates increase when hospitals operate beyond a tipping point of 92.5% (Kuntz et al. 2015). Higher occupancy is also correlated with several other issues such as higher rates of overflowing patients to less desired units (Song et al. 2020), higher incidence of hospital-acquired infections (Kaier et al. 2012), worse patient care (Diwas Singh et al. 2020), and less likelihood of admitting new patients (Kim et al. 2020)**.** As such, we study the impact of total occupancy rate, as well as proportion of long-stay patients on LOS and 30-day readmission rate of other patients in medical units.

Total occupancy rate of medical units, along with proportion of long-stay patients within those medical units can also impact ICU patients that are being transferred to those medical units. Numerous studies in the literature pointed out the impact of medical and surgical occupancy rates on ICU flow. For example, ICU patients experience longer wait time when downstream medical units are busy (Long and Mathews 2018)**.** As a result of higher wait time, ICU can experience higher occupancy. Similar to medical units, higher ICU occupancy rate is associated with a lower likelihood of ICU admission (Kim et al. 2016). As such, delayed ICU admission can result in negative outcomes. One observational study finds that timely ICU admission reduces 28-day mortality by 30% (Edbrooke et al. 2011). Other studies demonstrate that delaying ICU admission can prolong ICU length of stay (Chalfin et al. 2007) and increase the risk of death (Cardoso et al. 2011). In addition, congested ICU can negatively impact ED boarding time and ambulance diversions (Chan et al. 2017, McConnell et al. 2005). Despite these insights from the literature, there is no study that investigates the impact of a particular patient population (e.g., long-stay patients) on ICU flow. To further investigate the flow between ICU and medical units, we focus on patient transfers from ICU to medical units, and evaluate the impact of both total occupancy rate of medical units and proportion of long-stay patients in medical units on transfer wait times.

In addition to medical and ICU units that are designed to provide care for low and high acuity levels respectively, some hospitals include Stepdown Unit (SDU) that provides medium level of care. Nurse to patient ratio in SDU is lower than ICU, but higher than medical units (Mathews and Long 2015a). SDU can provide a higher level of care for patients deteriorating on a ward ("step-up"), a lower level of care for patients transitioning out of intensive care ("stepdown") or a lateral transfer of care from a recovery room for postoperative patients (Prin and Wunsch 2014). As such, SDU play a vital role in improving flow and costs within the hospital. Studies suggest that SDU can improve cost per patient-day, and total cost per year (Rodrigues et al. 2018), ICU throughput (Gershengorn et al. 2020), as well as bed occupancy and wait time for ICU admission (Mathews and Long 2015a). Magnitude of these effects can vary between patient types. For example, ICU patients are likely to benefit more, compared to ED patients (Chan et al. 2019). Majority of studies in literature focused on either effectiveness of SDU on patient outcomes (Chan et al. 2019, Gershengorn et al. 2020, Prin and Wunsch 2014) or determining the optimal SDU size (Armony et al. 2018a, Mathews and Long 2015a, Rodrigues et al. 2018). As such, this study investigates the impact of overall occupancy rate of medical unit as well as proportion of long-stay patients in medical units on wait time of SDU patients that are going to be transferred to medical units.

4.3 Study Setting and Hypotheses

Small portion of patients in medical units, known as long-stay patients, experience longer LOS than medically needed due to discharge barriers and other non-medical reasons. Accumulation of these patients in a medical unit can have several consequences on patient flow.

Since long-stay patients have discharge barriers, they will reside in medical units for a long period of time. Therefore, beds that are occupied by long-stay patients can be regarded as closed or unavailable beds. Therefore, remaining beds in the medical unit will be the only candidate beds to accept new patients. As demand for medical beds exceeds the number of available medical beds, providers and bed assigners may keep patients waiting until beds become available or decide to transfer some of the existing patients off the unit and place new patients in those beds. For the first scenario, we consider patient flow between ICU to medical units, as well as SDU to medical units, and assess the wait time of patients being transferred to medical units with respect to overall occupancy rates, and proportion of long-stay patients in the medical unit. For the second scenario, we investigate the LOS and 30-day readmission rate of patients in the medical unit with respect to overall occupancy and proportion of long-stay patients in the medical unit.

4.3.1 ICU to MU flow

Cost of care in the ICU is considered expensive, and is expected to increase over the next decade (Angus 2000, Cohen et al. 2010, Halpern et al. 1994). ICU patients account for 5% of total hospital admissions, yet they account for 15-20% of hospital budgets (Marlene Gyldmark 1995). As such, numerous studies looked into the flow between the ICU and the ED (Kolker 2009), the ICU and the SDU (Mathews and Long 2015b), and the ICU and the medical unit (Long and Mathews 2018). Among these, Long and Mathews (Long and Mathews 2018) concluded that the wait time is likely to increase if either the medical unit gets busier or the ICU gets less busy. They measured occupancy rates of the ICU and the medical unit at transfer times (Long and Mathews 2018). Since patient transfers occur more within certain shifts (Luyt et al. 2007), capturing occupancy rate in a specific timestamp can introduce biases into the model. To resolve this issue, we use average occupancy rate over the entire wait time interval. In addition, we measure the average proportion of long-stay patients in the medical unit over the entire wait time interval and investigate its impact on the wait time. As such, we have the following hypotheses.

Hypothesis 1A: Higher ICU occupancy is correlated with a shorter wait time.

Hypothesis 1B: Higher medical unit occupancy is correlated with a longer wait time.

Hypothesis 1C: Higher proportion of long-stay patients is correlated with a longer wait time.

4.3.2 SDU to MU flow

SDU provides intermediate level of care to patients coming mainly from the ICU and PACU. Majority of these patients will then transition to the medical unit. Despite the importance of SDU in alleviating the ICU and the medical unit flow, there is no empirical research to understand its flow patterns and behaviors. This is the first study to investigate the impact of overall occupancy of the medical unit and proportion of long-stay patients in the medical unit on the wait time of patients transitioning from the SDU to the medical unit. Similar to the ICU, we have the following hypothesis.

Hypothesis 2A: Higher SDU occupancy is correlated with a shorter wait time.

Hypothesis 2B: Higher medical unit occupancy is correlated with a longer wait time.

Hypothesis 2C: Higher proportion of long-stay patients is correlated with a longer wait time.

4.3.3 MU flow

Since long-stay patients reside in the medical unit, and have discharge issues, they are more likely to stay in the unit even when the unit is congested. As such, other patients in the unit are more likely to be transitioned prematurely. Premature discharge from a unit due to capacity strain is a common practice (Rodríguez-Carvajal et al. 2011). Studies show that premature ICU discharge can result in more readmissions (Chan et al. 2012). As such, we investigate the impact of long-stay patients on premature discharge as well as 30-day readmission likelihood with the following hypotheses.

Hypothesis 3A: Higher proportion of long-stay patients is correlated with a shorter LOS for regular patients.

Hypothesis 3B: Higher proportion of long-stay patients is correlated with a higher likelihood of 30-day readmission for regular patients.

4.4 Data

We use patient visits data from Christiana hospital and Wilmington hospital within the same health system, ChristianaCare, between 1/1/2018 and 10/31/2019. These hospitals are non-sectarian, not for profit, urban and suburban, academic and community hospitals. The Christiana hospital with 906 beds, includes Delaware's only Level I trauma center, and the Wilmington hospital consists of 321 beds.

Visit data excludes patients under age 18, patients who expired within the hospital visit, visits to women and children service line (e.g., newborns, obstetrics and gynecology), and all encounters with missing values. The dataset includes unit codes, bed requested time (day vs. evening shift, day of week, month of year), unit occupancy as ratio of occupied beds to total number of beds, ratio of long-stay patients in a medical unit, severity of illness at the time of admission, risk of mortality at the time of admission, complications during hospitalization, 30-day readmission, number of ICU days during the hospitalization, comorbidity score as a total number of chronic conditions identified in the hospitalization, diagnosis related groups (DRG) codes, and patient data such as ethnicity, age, sex, and race. Depending on independent variables used for estimation and their missing records, our dataset included 1239-1513 records for ICU to MU transfers, 2716-3409 records for SDU to MU transfers, and 7123-9375 records for transfers out of MU.

4.4.1 Long-stay patients

Unlike other studies that identified long-stay patients based on thresholds on LOS such as 95-percentile (Woodger 2017), our dataset uses the result of a prior project to identify long-stay patients in the health system. In that project, long-stay patients were identified in a two-step process. In the first step, a team of case managers proactively searched through the EHR to identify potential long-stay patients based on LOS and clinical conditions. In the second step, case managers reached out to their care teams to verify if patients qualify as long-stay patients. Within our study period, total number of 682 unique long-stay patients were identified in both Christiana and Wilmington hospitals. Distribution of these patients over specialty is shown in Table 4.1.

Table 4.1- Total number of long-stay patients in each specialty area.

Specialty	Total	Specialty	Total	Specialty	Total
General Medicine	212	Pulmonary	22	Thoracic Surgery	4
General Surgery	80	Psychiatry	21	Urology	4
Neurology	68	Oncology	20	Spinal Surgery	3
Trauma	33	Complications of Prior Care	12	Ophthalmology	2
Orthopedics	30	Neurosurgery	12	Aftercare and Other Factors	1
Vascular Surgery	24	HIV	10	Burns	1
Cardiology	22	Cardiac Surgery	4	Dermatology	1

Majority of long-stay patients stay in the hospital for less than 100 days, but occasionally it extends to over a year as shown in Figure 4.1.

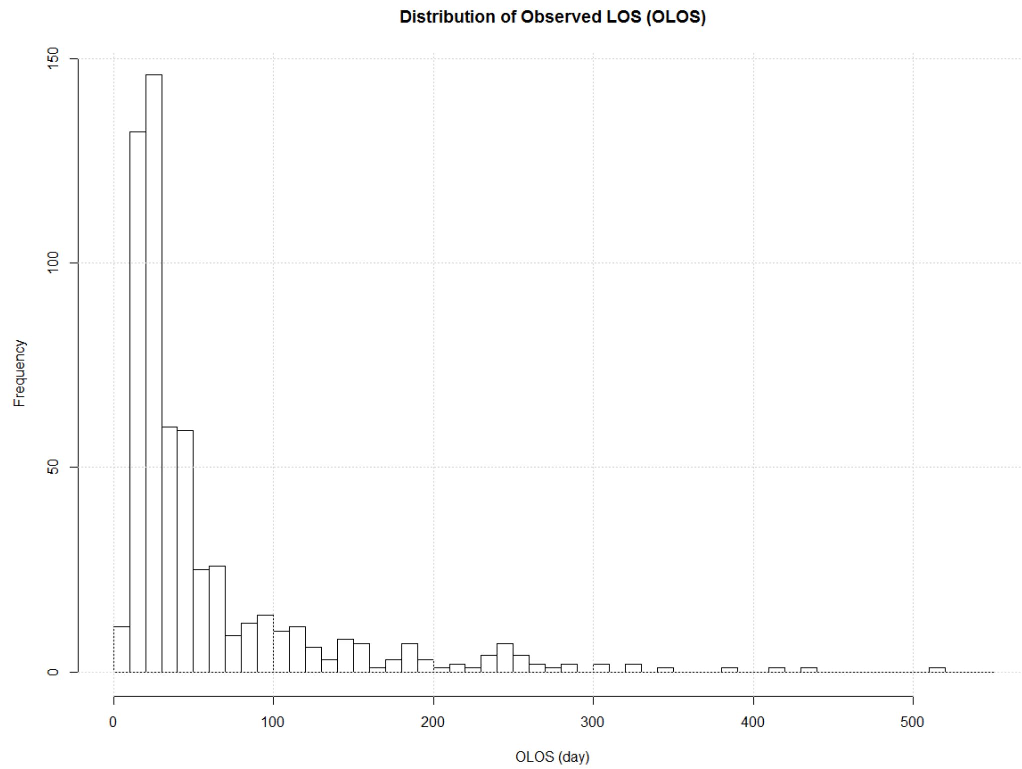

Figure 4.1. LOS histogram for long-stay patients.

4.4.2 Occupancy levels

We define occupancy as a ratio of occupied beds to total number of beds in that unit. In order to investigate the impact of long-stay patients on the flow of regular patients, we divide the occupancy into two mutual exclusive components, occupancy of long-stay (i.e., exceptional) patients and occupancy of regular patients, and update them every hour. Figure 4.2 represents an example of these occupancies in one of the MU. We then convert the occupancy of long-stay patients to a ratio and define it as proportion of long-stay patients.

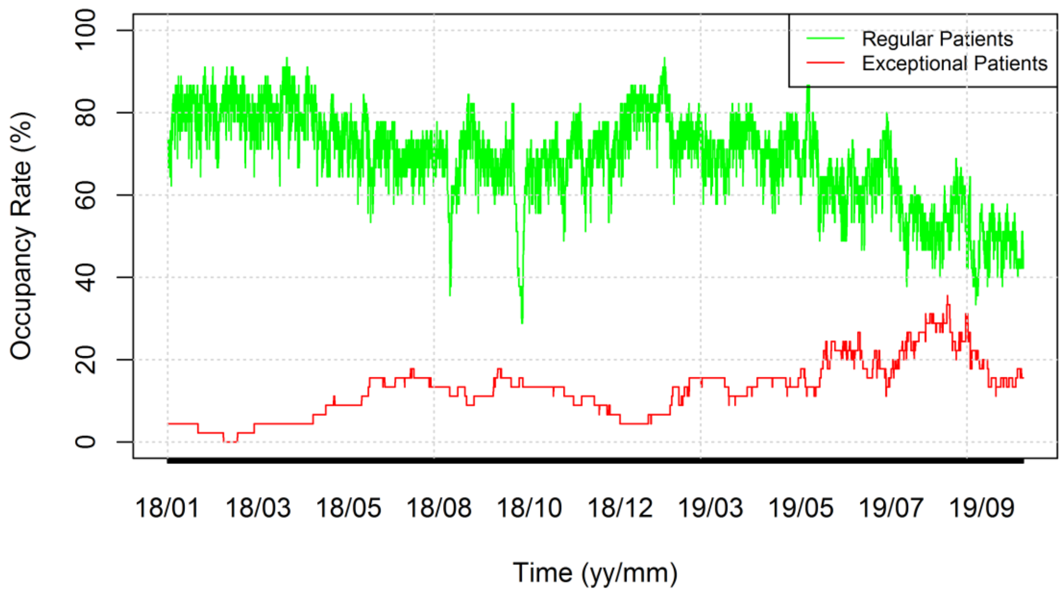

Figure 4.2. Occupancy of regular and long-stay patients in an MU.

4.5 Empirical Specification

4.5.1 ICU to MU flow

Our first model considers ICU wait time ($WaitTimeICU_i$) as the dependent variable and examines its relationship with ICU ($OccupancyICU_i$) and medical ($OccupancyMED_i$) occupancy levels, and proportion of long-stay patients ($LongStayMED_i$), controlling for unit codes, bed requested time (day vs. evening shift, day of week, month of year), severity of illness at the time of admission, risk of mortality at the time of admission, complications during hospitalization, 30-day readmission, number of ICU days during the hospitalization, comorbidity score as a total number of chronic conditions identified in the hospitalization, DRG codes, and patient characteristics such as ethnicity, age, sex, and race ($\boldsymbol{X_i}$). To capture non-linear effect, we break ICU and medical occupancies, and proportion of long-stay patients to four quartiles.

Because $WaitTimeICU_i$ is positive and skewed, we use the natural logarithm and obtain the following empirical specification to test Hypotheses 1A, 1B, and 1C.

$$\ln(WaitTimeICU_i) = \alpha_0 + \alpha_1 OccupancyICU_i + \alpha_2 OccupancyMED_i + \alpha_3 LongStayMED_i + \boldsymbol{\gamma X_i} + \varepsilon_i \quad (4.1)$$

We used ordinary least square (OLS) method to estimate (4.1), and present nested models with base results that include only the control variables. In addition, we include two interaction terms. First, for simultaneously high occupancy in the ICU and medical unit where both in the highest quartile of occupancies. Second, for $OccupancyMED_i$ and $LongStayMED_i$, where both in the highest quartile of occupancies.

4.5.2 SDU to MU flow

Similar to ICU wait time, our second model considers SDU wait time ($WaitTimeSDU_i$) as the dependent variable and examines its relationship with SDU ($OccupancySDU_i$) and medical ($OccupancyMED_i$) occupancy levels, and proportion of long-stay patients ($LongStayMED_i$), controlling for same control variables in equation (1) ($\boldsymbol{X_i}$). To capture non-linear effect, we break SDU and medical occupancies, and proportion of long-stay patients to four quartiles.

Because $WaitTimeSDU_i$ is positive and skewed, we use the natural logarithm and obtain the following empirical specification to test Hypotheses 2A, 2B, and 2C.

$$\ln(WaitTimeSDU_i) = \beta_0 + \beta_1 OccupancySDU_i + \beta_2 OccupancyMED_i + \beta_3 LongStayMED_i + \boldsymbol{\gamma X_i} + \varepsilon_i \quad (4.\ 2)$$

We used ordinary least square (OLS) method to estimate (4.2), and present nested models with base results that include only the control variables. In addition, we include two interaction terms. First, for simultaneously high occupancy in the SDU and medical unit where both in the highest quartile of occupancies. Second, for $OccupancyMED_i$ and $LongStayMED_i$, where both in the highest quartile of occupancies.

4.5.3 MU flow

Our third model considers LOS in the medical unit ($losMED_i$) as the dependent variable and examines its relationship with medical occupancy level ($OccupancyMED_i$) and proportion of long-stay patients ($LongStayMED_i$), controlling for unit codes, severity of illness at the time of admission, risk of mortality at the time of admission, complications during hospitalization, 30-day readmission, number of ICU days during the hospitalization, comorbidity score as a total number of chronic conditions identified in the hospitalization, DRG codes, and patient characteristics such as ethnicity, age, sex, and race ($\boldsymbol{X_i}$). Because $losMED_i$ is positive and skewed, we use the natural logarithm and obtain the following empirical specification to test Hypotheses 3A.

$$\ln(losMED_i) = \delta_0 + \delta_1 OccupancyMED_i + \delta_2 LongStayMED_i + \boldsymbol{\gamma X_i} + \varepsilon_i \qquad (4.3)$$

With the same control variables in equation (4.3), our fourth model considers probability of readmission to the hospital within 30 days of discharge ($Readmission_i$) as the dependent variable and examines its relationship with medical occupancy level ($OccupancyMED_i$) and proportion of long-stay patients ($LongStayMED_i$). We obtain the following empirical specification to test Hypotheses 3B.

$$\ln\left(\frac{P(Readmission_i)}{1-P(Readmission_i)}\right) = \rho_0 + \rho_1 OccupancyMED_i + \rho_2 LongStayMED_i + \boldsymbol{\gamma X_i} + \varepsilon_i \quad (4.4)$$

In both models (4.3) and (4.4), we break medical occupancy level and proportion of long-stay patients to four quartiles in order to capture non-linear effect. We also present nested models with base results that include only the control variables. In addition, we include an interaction term for $OccupancyMED_i$ and $LongStayMED_i$, where both in the highest quartile of occupancies. Finally, we use OLS to estimate (4.3), and binomial logistic regression to estimate (4.4).

4.6 Results

4.6.1 ICU to MU flow

We find that higher ICU occupancy is associated with shorter ICU wait time. In particular, ICU wait time in the second quartile of ICU occupancy is 17% (1- exp(-0.186)= 1- 0.8303) shorter than the first quartile of ICU occupancy. Similarly, ICU wait time in third and fourth quartiles are 24% and 36% shorter than the first quartile, respectively, as shown in Table 4.2 model (2). These findings are consistent with similar studies in other ICU units (Long and Mathews 2018, Singh and Terwiesch 2012), and support our Hypothesis 1A, in which higher ICU occupancy is correlated with a shorter ICU wait time. We also find that ICU wait time in the third quartile of medical unit occupancy is 28% longer than the first quartile of medical unit occupancy ($p<0.05$). In addition, second and fourth quartiles of medical unit occupancy is not correlated with significantly longer ICU wait time than the first quartile. After including proportion of long-stay patients and interaction terms, we found that medical unit occupancy is no longer associated with

ICU wait time, which does not support our Hypothesis 1B (models (3) and (4) in Table 4.2). Unlike prior studies that suggest higher medical unit occupancy is associated with longer ICU wait time (Long and Mathews 2018), our results show that this association is not significant when we include proportion of long-stay patients and interaction terms within the model.

Similar to other studies (Long and Mathews 2018), we defined binary interaction variables to differentiate surge periods from normal periods. In particular, we included $OccupancyICU_i(74.4,96] * OccupancyMED_i(86.2,98]$ and $OccupancyMED_i(86.2,98] * LongStayMED_i(16.3,48.6]$ in model (4), Table 4.2 that all occupancies indicate fourth quartiles.

Our results suggest that higher proportion of long-stay patients in medical unit is associated with longer ICU wait time, which support our Hypothesis 1C. In particular, ICU wait time in second, third and fourth quartiles of proportion of long-stay patients variable are 30%, 34% and 42% longer than the first quartile, respectively.

We find that ICU wait time is associated with timing of transfer requests. Transfer requests on Sunday and Tuesday are correlated with 30-47% and 32-33% longer ICU wait time than those of Friday, respectively. Longer ICU wait time on Sunday is likely due to limited access to hospital resources (Black 2016). Due to high volume of admissions from ED on Monday, our studied hospitals tend to schedule most of elective surgeries on Tuesday. As such, longer ICU wait time on Tuesday is likely due to higher volume of surgeries. In addition, ICU wait time is associated with transfer requested month, January being the first month and resulting in the longest ICU wait time. Finally, we find that ICU wait time is not associated with transfer requested shift.

Our results also suggest positive correlations between ICU wait time and age, as well as number of days spent in the ICU. Older patients, and patients with longer ICU days are likely to have complex issues that need longer time to coordinate their care transfer, resulting in longer ICU wait times (Guest 2017, Schoen et al. 2011).

Table 4.2. Estimated results for ICU wait time.

	ln(*WaitTimeICU*)			
	1	2	3	4
OccupancyICU(61.8,69.2]		-0.186* (-0.375, 0.003)	-0.196* (-0.404, 0.013)	-0.189* (-0.398, 0.019)

Table 4.2 continued

OccupancyICU(69.2,74.4]		-0.274*** (-0.475, -0.073)	-0.288** (-0.512, -0.064)	-0.274** (-0.498, -0.051)
OccupancyICU(74.4,96]		-0.443*** (-0.652, -0.235)	-0.468*** (-0.702, -0.233)	-0.450*** (-0.705, -0.196)
OccupancyMED(68.6,81.2]		0.028 (-0.190, 0.246)	-0.049 (-0.329, 0.230)	-0.037 (-0.316, 0.243)
OccupancyMED(81.2,86.2]		0.249** (0.016, 0.482)	0.173 (-0.125, 0.471)	0.194 (-0.104, 0.493)
OccupancyMED(86.2,98]		0.168 (-0.066, 0.403)	0.070 (-0.230, 0.371)	0.214 (-0.118, 0.546)
LongStayMED(4.97,11]			0.268* (-0.021, 0.557)	0.266* (-0.023, 0.555)
LongStayMED(11,16.3]			0.294* (-0.006, 0.593)	0.291* (-0.008, 0.590)
LongStayMED(16.3,48.6]			0.240 (-0.074, 0.553)	0.349** (0.022, 0.677)
OccupancyICU(74.4,96]* OccupancyMED(86.2,98]				-0.037 (-0.394, 0.320)
LongStayMED(16.3,48.6]* OccupancyMED(86.2,98]				-0.401** (-0.753, -0.049)
NextBedRequestedShift[15-23)	-0.053 (-0.208, 0.102)	-0.057 (-0.211, 0.097)	-0.047 (-0.216, 0.122)	-0.054 (-0.223, 0.115)
NextBedRequestedShift[23-07)	-0.021 (-0.256, 0.214)	0.007 (-0.228, 0.241)	0.041 (-0.224, 0.305)	0.041 (-0.223, 0.306)
NextBedRequestedDayMonday	0.156 (-0.083, 0.396)	0.156 (-0.083, 0.395)	0.155 (-0.105, 0.416)	0.169 (-0.091, 0.430)
NextBedRequestedDaySaturday	0.116 (-0.126, 0.357)	0.094 (-0.147, 0.336)	0.108 (-0.160, 0.376)	0.133 (-0.136, 0.401)
NextBedRequestedDaySunday	0.264** (0.026, 0.503)	0.253** (0.016, 0.491)	0.368*** (0.110, 0.627)	0.386*** (0.127, 0.645)
NextBedRequestedDayThursday	0.032 (-0.205, 0.269)	0.011 (-0.225, 0.248)	0.080 (-0.178, 0.338)	0.091 (-0.167, 0.349)
NextBedRequestedDayTuesday	0.289** (0.055, 0.523)	0.280** (0.047, 0.512)	0.275** (0.021, 0.529)	0.288** (0.034, 0.542)
NextBedRequestedDayWednesday	0.096 (-0.140, 0.331)	0.097 (-0.138, 0.331)	0.034 (-0.225, 0.292)	0.039 (-0.219, 0.297)
NextBedRequestedMonth2	-0.155 (-0.409, 0.098)	-0.106 (-0.360, 0.148)	-0.283* (-0.575, 0.009)	-0.261* (-0.554, 0.031)
NextBedRequestedMonth3	-0.324** (-0.579, -0.070)	-0.269** (-0.525, -0.013)	-0.447*** (-0.741, -0.153)	-0.449*** (-0.742, -0.155)
NextBedRequestedMonth4	0.074 (-0.182, 0.330)	0.092 (-0.164, 0.348)	0.068 (-0.218, 0.355)	0.075 (-0.212, 0.362)

Table 4.2 continued

NextBedRequestedMonth5	-0.124 (-0.384, 0.135)	-0.219 (-0.487, 0.049)	-0.364** (-0.672, -0.056)	-0.364** (-0.672, -0.057)
NextBedRequestedMonth6	-0.217 (-0.483, 0.050)	-0.307** (-0.582, -0.032)	-0.446*** (-0.759, -0.133)	-0.457*** (-0.769, -0.144)
NextBedRequestedMonth7	0.036 (-0.285, 0.356)	-0.135 (-0.476, 0.207)	-0.180 (-0.550, 0.190)	-0.165 (-0.535, 0.205)
NextBedRequestedMonth8	-0.059 (-0.405, 0.286)	-0.091 (-0.443, 0.261)	-0.216 (-0.615, 0.183)	-0.203 (-0.602, 0.196)
NextBedRequestedMonth9	-0.135 (-0.489, 0.220)	-0.289 (-0.656, 0.077)	-0.483** (-0.880, -0.087)	-0.485** (-0.881, -0.089)
NextBedRequestedMonth10	-0.400** (-0.728, -0.073)	-0.385** (-0.722, -0.048)	-0.521*** (-0.901, -0.141)	-0.487** (-0.867, -0.106)
NextBedRequestedMonth11	-0.087 (-0.432, 0.258)	-0.096 (-0.443, 0.250)	-0.123 (-0.504, 0.258)	-0.108 (-0.489, 0.273)
NextBedRequestedMonth12	-0.052 (-0.401, 0.296)	-0.102 (-0.454, 0.250)	-0.023 (-0.446, 0.400)	-0.026 (-0.448, 0.396)
CampusW	-0.155 (-0.476, 0.165)	-0.411** (-0.774, -0.047)	-0.226 (-0.673, 0.222)	-0.265 (-0.713, 0.183)
UnitCode	Included	Included	Included	Included
Readmission_30d	0.097 (-0.094, 0.289)	0.098 (-0.093, 0.289)	0.054 (-0.158, 0.266)	0.059 (-0.153, 0.271)
ICU.Days.Obs.from.ICU.File	0.073*** (0.051, 0.096)	0.069*** (0.047, 0.091)	0.074*** (0.050, 0.098)	0.075*** (0.051, 0.099)
ComorbidityScore	-0.014 (-0.094, 0.066)	-0.012 (-0.092, 0.067)	-0.039 (-0.125, 0.048)	-0.035 (-0.122, 0.052)
Admit.Severity.of.Illness	Included	Included	Included	Included
Admit.Risk.of.Mortality	Included	Included	Included	Included
Complication	Included	Included	Included	Included
DRG	Included	Included	Included	Included
Age	0.005** (0.0002, 0.009)	0.005** (0.001, 0.009)	0.005** (0.001, 0.010)	0.005** (0.001, 0.010)
SexMale	-0.005 (-0.135, 0.126)	-0.009 (-0.139, 0.121)	0.048 (-0.097, 0.194)	0.057 (-0.089, 0.203)
Ethnicity	Included	Included	Included	Included
Race	Included	Included	Included	Included

Table 4.2 continued

Constant	4.609*** (2.360, 6.857)	4.756*** (2.520, 6.991)	4.117*** (1.809, 6.425)	4.196*** (1.890, 6.502)
Observations	1,513	1,511	1,239	1,239
R^2	0.095	0.111	0.14	0.144
Adjusted R^2	0.043	0.056	0.072	0.075

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.6.2 SDU to MU flow

We find that SDU wait time is not associated with SDU occupancy, unless we include proportion of long-stay patients and interactions terms within the model. We added interaction terms in model (4) shown in Table 4.3 by defining binary variables that distinguish surge periods from regular periods (Long and Mathews 2018). Specifically, we included $\mathrm{OccupancySDU}(82.9{,}97.3] * \mathrm{OccupancyMED}(86.7{,}97.4]$ and $\mathrm{LongStayMED}(15.3{,}44.7] * \mathrm{OccupancyMED}(86.7{,}97.4]$ where occupancy intervals represent fourth quartile occupancies. We find that SDU wait time in second and third quartiles of SDU occupancy are not significantly shorter than its first quartile. When SDU occupancy increases from its first quartile to fourth quartile, associated SDU wait time reduces by 20% which is consistent with our Hypothesis 2A.

Similarly, we find that only fourth quartile of medical unit occupancy is correlated with a significantly different SDU wait time. As such, when medical unit occupancy changes from its first quartile to fourth quartile, SDU wait time extends 21-37%, which supports our Hypothesis 2B. In addition, we find no significant association between SDU wait time and proportion of long-stay patients in medical unit and reject our Hypothesis 2C.

We find that SDU wait time is associated with timing of transfer requests. Transfers within the evening shift (i.e., 3:00-11:00pm) have 23-25% shorter SDU wait time than the morning shift (i.e., 7:00am-3:00pm). In addition, transfers on Thursday result in 17-21% shorter SDU wait time than Friday. Finally, SDU wait time during July and August are longer than that of January.

Comorbidity score is also positively correlated with SDU wait time which can be explained by complexity of care transition processes (Guest 2017, Schoen et al. 2011). In addition, SDU wait time in the Christiana campus is almost five times longer than that of the Wilmington campus.

Table 4.3. Estimated results for SDU wait time.

	ln(*WaitTimeSDU*)			
	1	2	3	4
OccupancySDU(73.2,78.7]		0.011 (-0.140, 0.162)	-0.035 (-0.214, 0.143)	-0.033 (-0.212, 0.145)
OccupancySDU(78.7,82.9]		0.014 (-0.172, 0.200)	-0.089 (-0.302, 0.124)	-0.088 (-0.301, 0.125)
OccupancySDU(82.9,97.3]		-0.069 (-0.265, 0.126)	-0.170 (-0.391, 0.052)	-0.220* (-0.453, 0.014)
OccupancyMED(69.2,82.1]		-0.045 (-0.215, 0.125)	0.025 (-0.210, 0.260)	0.028 (-0.207, 0.264)
OccupancyMED(82.1,86.7]		0.132 (-0.051, 0.315)	0.190 (-0.058, 0.437)	0.205 (-0.043, 0.453)
OccupancyMED(86.7,97.4]		0.195** (0.010, 0.381)	0.261** (0.011, 0.511)	0.313** (0.038, 0.589)
LongStayMED(3.39,9.95]			-0.187 (-0.450, 0.076)	-0.193 (-0.456, 0.070)
LongStayMED(9.95,15.3]			-0.079 (-0.343, 0.184)	-0.091 (-0.355, 0.172)
LongStayMED(15.3,44.7]			-0.081 (-0.354, 0.192)	-0.009 (-0.290, 0.272)
OccupancySDU(82.9,97.3]* OccupancyMED(86.7,97.4]				0.174 (-0.101, 0.449)
LongStayMED(15.3,44.7]* OccupancyMED(86.7,97.4]				-0.333** (-0.617, -0.049)
NextBedRequestedShift[15-23)	-0.266*** (-0.411, -0.121)	-0.262*** (-0.408, -0.117)	-0.283*** (-0.449, -0.117)	-0.289*** (-0.455, -0.123)
NextBedRequestedShift[23-07)	0.159 (-0.082, 0.400)	0.152 (-0.089, 0.393)	0.129 (-0.147, 0.405)	0.141 (-0.135, 0.416)
NextBedRequestedDayMonday	0.026 (-0.150, 0.202)	0.022 (-0.155, 0.199)	0.028 (-0.169, 0.225)	0.025 (-0.172, 0.222)
NextBedRequestedDaySaturday	-0.090 (-0.281, 0.100)	-0.083 (-0.274, 0.108)	-0.047 (-0.259, 0.165)	-0.053 (-0.265, 0.159)
NextBedRequestedDaySunday	-0.010 (-0.195, 0.175)	0.0004 (-0.185, 0.185)	0.006 (-0.201, 0.213)	0.010 (-0.197, 0.217)
NextBedRequestedDayThursday	-0.182** (-0.359, -0.005)	-0.186** (-0.364, -0.009)	-0.235** (-0.432, -0.037)	-0.241** (-0.438, -0.043)
NextBedRequestedDayTuesday	-0.065 (-0.242, 0.112)	-0.071 (-0.249, 0.107)	-0.065 (-0.265, 0.135)	-0.063 (-0.263, 0.136)
NextBedRequestedDayWednesday	0.014 (-0.163, 0.191)	0.007 (-0.170, 0.185)	0.089 (-0.108, 0.287)	0.091 (-0.107, 0.289)

Table 4.3 continued

NextBedRequestedMonth2	-0.104 (-0.299, 0.091)	-0.084 (-0.280, 0.113)	-0.048 (-0.273, 0.178)	-0.043 (-0.268, 0.182)
NextBedRequestedMonth3	-0.112 (-0.304, 0.079)	-0.081 (-0.274, 0.112)	-0.025 (-0.248, 0.198)	-0.037 (-0.260, 0.187)
NextBedRequestedMonth4	-0.110 (-0.314, 0.094)	-0.073 (-0.279, 0.133)	0.009 (-0.222, 0.239)	0.005 (-0.225, 0.236)
NextBedRequestedMonth5	-0.050 (-0.255, 0.156)	-0.024 (-0.232, 0.184)	0.140 (-0.102, 0.382)	0.146 (-0.096, 0.388)
NextBedRequestedMonth6	-0.054 (-0.268, 0.159)	-0.017 (-0.234, 0.200)	0.040 (-0.211, 0.290)	0.018 (-0.233, 0.269)
NextBedRequestedMonth7	0.302** (0.034, 0.571)	0.330** (0.057, 0.604)	0.416*** (0.116, 0.716)	0.396*** (0.095, 0.696)
NextBedRequestedMonth8	0.197 (-0.081, 0.474)	0.248* (-0.038, 0.533)	0.450*** (0.114, 0.786)	0.450*** (0.114, 0.785)
NextBedRequestedMonth9	0.116 (-0.167, 0.398)	0.140 (-0.146, 0.427)	0.245 (-0.073, 0.563)	0.227 (-0.092, 0.546)
NextBedRequestedMonth10	-0.289** (-0.547, -0.031)	-0.236* (-0.504, 0.032)	-0.113 (-0.415, 0.188)	-0.113 (-0.414, 0.189)
NextBedRequestedMonth11	-0.231* (-0.481, 0.019)	-0.202 (-0.457, 0.054)	-0.156 (-0.440, 0.127)	-0.160 (-0.443, 0.123)
NextBedRequestedMonth12	-0.074 (-0.304, 0.156)	-0.053 (-0.285, 0.179)	0.044 (-0.232, 0.321)	0.052 (-0.225, 0.329)
CampusW	-1.489*** (-2.191, -0.787)	-1.621*** (-2.336, -0.907)	-1.594*** (-2.346, -0.841)	-1.625*** (-2.378, -0.872)
UnitCode	Included	Included	Included	Included
Readmission_30d	-0.052 (-0.189, 0.084)	-0.055 (-0.191, 0.081)	-0.039 (-0.191, 0.114)	-0.038 (-0.191, 0.114)
ICU.Days.Obs.from.ICU.File	0.017 (-0.003, 0.037)	0.016 (-0.004, 0.037)	0.014 (-0.008, 0.036)	0.013 (-0.009, 0.035)
ComorbidityScore	0.053 (-0.013, 0.118)	0.050 (-0.016, 0.115)	0.073** (0.0004, 0.145)	0.075** (0.003, 0.147)
Admit.Severity.of.Illness	Included	Included	Included	Included
Admit.Risk.of.Mortality	Included	Included	Included	Included
Complication	Included	Included	Included	Included
DRG	Included	Included	Included	Included

Table 4.3 continued

Age	0.004** (0.00003, 0.007)	0.004** (0.00000, 0.007)	0.003 (-0.002, 0.007)	0.003 (-0.002, 0.007)
SexMale	-0.085* (-0.185, 0.014)	-0.087* (-0.187, 0.013)	-0.088 (-0.199, 0.023)	-0.087 (-0.198, 0.024)
Ethnicity	Included	Included	Included	Included
Race	Included	Included	Included	Included
Constant	7.747*** (4.703, 10.792)	7.734*** (4.690, 10.778)	7.709*** (4.656, 10.762)	7.709*** (4.658, 10.759)
Observations	3,409	3,407	2,716	2,716
R^2	0.091	0.094	0.105	0.107
Adjusted R^2	0.063	0.065	0.067	0.069

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.6.3 MU flow

We find that higher proportion of long-stay patients in a medical unit is correlated with significantly shorter unit LOS for other patients in that unit which supports our Hypothesis 3A. As shown in Table 4.4, presence of long-stay patients in a medical unit shortens the unit LOS of other patients in that unit by 74.31%-76.92%. This pattern is consistent across different quartiles of LongStayMED variable. The Wilmington hospital is smaller than the Christiana hospital, and provides care for less acute patients. As such, patients in the Wilmington hospital experience 46.85-74% shorter stay than patents in the Christiana hospital.

In addition, we find that patients experience longer stay when the unit is busier. Unit LOS extends by 39.65-57.78% when unit occupancy increases from its first quartile to fourth quartile. Moreover, patients with longer ICU stay or higher comorbidity score experience slightly longer stay (i.e., 2-5%) due to their acuter conditions. Readmitted patients within 30-day of discharge are associated with 18.78% shorter unit LOS. Finally, older patients are likely to experience slightly shorter unit LOS in medical units.

Table 4.4. Estimated results for LOS of MU.

	ln(*losMED*)			
	1	2	3	4
OccupancyMED(68.7,81.1]		-0.075 (-0.195, 0.045)	-0.101 (-0.261, 0.059)	-0.102 (-0.262, 0.058)
OccupancyMED(81.1,86.1]		0.334^{***} (0.208, 0.461)	0.366^{***} (0.201, 0.532)	0.362^{***} (0.197, 0.528)
OccupancyMED(86.1,100]		0.398^{***} (0.271, 0.526)	0.456^{***} (0.291, 0.622)	0.420^{***} (0.239, 0.601)
LongStayMED(1.94,8.05]			-1.423^{***} (-1.821, -1.025)	-1.420^{***} (-1.819, -1.022)
LongStayMED(8.05,14.6]			-1.359^{***} (-1.755, -0.962)	-1.359^{***} (-1.756, -0.962)
LongStayMED(14.6,54.5]			-1.437^{***} (-1.835, -1.040)	-1.466^{***} (-1.867, -1.065)
LongStayMED(14.6,54.5]* OccupancyMED(86.1,100]				0.106 (-0.107, 0.320)
CampusW	-0.301^{***} (-0.504, -0.098)	-0.632^{***} (-0.853, -0.411)	-0.553^{***} (-0.834, -0.273)	-0.538^{***} (-0.820, -0.256)
UnitCode	Included	Included	Included	Included
Readmission_30d	-0.209^{***} (-0.327, -0.091)	-0.208^{***} (-0.326, -0.091)	-0.208^{***} (-0.345, -0.071)	-0.208^{***} (-0.345, -0.070)
ICU.Days.Obs.from.ICU.File	0.020^{**} (0.005, 0.036)	0.019^{**} (0.004, 0.035)	0.018^{**} (0.001, 0.036)	0.018^{**} (0.001, 0.036)
ComorbidityScore	0.038 (-0.012, 0.088)	0.039 (-0.012, 0.089)	0.049^{*} (-0.007, 0.105)	0.049^{*} (-0.007, 0.105)
Admit.Severity.of.Illness	Included	Included	Included	Included
Admit.Risk.of.Mortality	Included	Included	Included	Included
Complication	Included	Included	Included	Included
DRG	Included	Included	Included	Included
Age	-0.004^{**} (-0.007, -0.001)	-0.004^{***} (-0.007, -0.001)	-0.005^{***} (-0.009, -0.002)	-0.005^{***} (-0.009, -0.002)
SexMale	0.097^{**} (0.018, 0.175)	0.090^{**} (0.012, 0.168)	0.070 (-0.020, 0.159)	0.069 (-0.020, 0.159)
Ethnicity	Included	Included	Included	Included

Table 4.4 continued

Race	Included	Included	Included	Included
Constant	4.146^{***} (2.517, 5.775)	4.319^{***} (2.697, 5.941)	5.866^{***} (4.030, 7.703)	5.868^{***} (4.031, 7.705)
Observations	9,375	9,374	7,123	7,123
R^2	0.068	0.077	0.097	0.097
Adjusted R^2	0.059	0.068	0.085	0.085

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

As shown in Table 4.5, and in-line with other similar studies (Long and Mathews 2018), we find no significant association between proportion of long-stay patients and 30-day readmission; hence, reject our Hypothesis 3B. In addition, we find no association between medical unit occupancy and 30-day readmission.

Table 4.5. Estimated results for 30-day readmission probability in MU.

	P(Readmission)			
	-1	-2	-3	-4
OccupancyMED(68.6,80.8]		-0.035 (-0.263, 0.192)	-0.054 (-0.360, 0.252)	-0.054 (-0.360, 0.252)
OccupancyMED(80.8,85.9]		0.009 (-0.236, 0.254)	0.053 (-0.263, 0.369)	0.053 (-0.263, 0.370)
OccupancyMED(85.9,99.3]		-0.085 (-0.332, 0.161)	-0.100 (-0.416, 0.216)	-0.097 (-0.440, 0.246)
LongStayMED(3.34,10.2]			0.213 (-0.143, 0.569)	0.213 (-0.143, 0.569)
LongStayMED(10.2,15.6]			0.004 (-0.357, 0.364)	0.004 (-0.357, 0.364)
LongStayMED(15.6,48.3]			-0.002 (-0.362, 0.358)	0.0002 (-0.377, 0.378)
LongStayMED(15.6,48.3]* OccupancyMED(85.9,99.3]				-0.009 (-0.427, 0.409)

Table 4.5 continued

UnitCode	Included	Included	Included	Included
ICU.Days.Obs.from.ICU.File	-0.109*** (-0.162, -0.057)	-0.110*** (-0.162, -0.057)	-0.105*** (-0.161, -0.048)	-0.105*** (-0.161, -0.048)
ComorbidityScore	-0.103** (-0.204, -0.001)	-0.102** (-0.204, -0.001)	-0.117** (-0.229, -0.005)	-0.117** (-0.229, -0.005)
Admit.Severity.of.Illness	Included	Included	Included	Included
Admit.Risk.of.Mortality	Included	Included	Included	Included
Complication	Included	Included	Included	Included
DRG	Included	Included	Included	Included
Age	-0.009*** (-0.015, -0.004)	-0.009*** (-0.015, -0.004)	-0.010*** (-0.016, -0.004)	-0.010*** (-0.016, -0.003)
SexMale	0.074 (-0.075, 0.224)	0.074 (-0.076, 0.224)	0.063 (-0.108, 0.233)	0.063 (-0.108, 0.233)
Ethnicity	Included	Included	Included	Included
Race	Included	Included	Included	Included
Constant	-16.835 (-1,532.886, 1,499.217)	-16.795 (-1,544.152, 1,510.563)	-16.220 (-1,709.604, 1,677.164)	-16.221 (-1,709.600, 1,677.157)
Observations	7,096	7,095	5,748	5,748
Akaike Inf. Crit.	5,122.00	5,126.87	4,045.81	4,047.81

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.7 Discussion and Conclusions

Our study examined patient flow in different level of care transitions, ICU to medical unit, SDU to medical unit, and exiting medical units.

We re-examined prior studies on ICU to medical unit flow and investigated the impact of both ICU and medical unit occupancy on ICU wait time. In addition, we included proportion of long-stay patients in medical unit which is believed to negatively impact the flow (Gigantesco et al. 2009, Polito et al. 2019). In-line with other studies (Long and Mathews 2018, Singh and

Terwiesch 2012), we found that patients likely to spend significantly shorter time to exist the ICU when the ICU gets busier. We also found that patients exiting the ICU experience longer wait time when the downstream medical unit gets busier; however, this association was insignificant when we modified our model by including the proportion of long-stay patients in medical unit. As we hypothesized, patients exiting the ICU experience longer wait time when there are more long-stay patients in the downstream medical unit. Our empirical results offer support for hospital-wide initiatives to identify long-stay patients in advance, and to better distribute these patients across hospital units. One extreme approach is to assign long-stay patients into a separate hospital unit. By grouping these patients, providers can deliver a focused care, and improve the ICU wait time simultaneously (Englander et al. 2017). Alternatively, hospitals can assign long-stay patients across different medical units based on a threshold-based rule, and redefine their case mix in unit-level operations (Vitikainen et al. 2009). In addition, improving ICU admission and discharge policies such as increasing the discharge window and balancing the ratio of different patient types known to improve the ICU flow and wait time (Hasan et al. 2020).

Our study is the first attempt to examine SDU wait time. As more and more hospitals begin to include SDU (Gershengorn et al. 2020, Prin and Wunsch 2014), this study sheds light on the importance of taking system-wide approach in order to achieve smooth flow between SDU and medical units. We found that drivers of SDU wait time is different from those of ICU wait time. As downstream medical unit gets busier, patients exiting the SDU experience longer wait time. Also, this wait time is not associated with the proportion of long-stay patients in the medical unit. Different effects of medical occupancy and proportion of long-stay patients in medical unit on SDU and ICU wait time provides opportunities to improve both SDU and ICU wait time by balancing the overall occupancy of medical unit and proportion of long-stay patients in them.

Concentration of long-stay patients within a medical unit is associated with significantly shorter LOS of other patients in that unit. In addition, proportion of long-stay patients is not correlated with the probability of 30-day readmission in the medical unit. Discretionary nature of patient transfers between hospital units, and lack of information on transfer reasons within the EHR limited our study to further investigate this phenomenon. As such, future study can build upon our finding and investigate transfer reasons that result in significant differences in LOS. Possibly, units occupied by long-stay patients are used as overflow for regular patients, resulting in premature transfers off those units.

Our study has several limitations. First, our analysis is for only two academic hospitals within the same health system where institution-specific bed capacity constraints and policies likely exist. Second, our dataset lacks transfer reasons and notes. Although shorter LOS in medical unit due to the presence of long-stay patients is intuitive but cannot be explained empirically due to the data limitations. Moreover, we do not observe other key variables such as physician experience, staff ratio, and team dynamics that are known to affect providers' cognitive load and clinical decision making (Kuntz et al. 2015).

Our study investigated the correlation of long-stay patient occupancy levels with wait time, LOS, and 30-day readmission. Future studies can extend our work and examine causality between long-stay patient occupancy levels with wait time, LOS, and 30-day readmission variations using randomized control trials. In addition, future studies can incorporate cost components to the model and perform cost effectiveness analysis on different occupancy levels of long-stay patients.

5. REDEFINING PATIENT GROUPS IN THE HOSPITAL

Hospital beds are often assigned among several major groups called service lines, each of which is aimed to provide care for patients with similar medical needs such as cancer, musculoskeletal disorders, vascular, surgical, medical, and women and children, among others. Despite benefits of service lines, this division can cause imbalanced capacity allocation, and flow issues. In addition, patients with multiple conditions might need interdisciplinary care from multiple service lines. Using entire patient records within two academic hospitals under the same health system, we propose a two-step clustering-classification approach to identify new patient clusters and shed light on existing service line grouping. Unlike existing 8 patient clusters (i.e., service lines), our results identified 11 patient clusters in Wilmington hospital and 15 patient clusters in Christiana hospital, indicating the need to further splitting some of the existing service lines such as internal medicine, general surgery, and neurological disorders.

5.1 Introduction

Hospital capacity planning is the effort of assigning hospital resources into different areas in order to match supply to demand (Li and Benton 2003). A gap between supply and demand for hospital beds results in ceaseless congestion in high traffic units such as Intensive Care Unit (ICU), stepdown (Armony et al. 2015) and general medical floor (Crilly et al. 2015, Hillier et al. 2006). Research has shown the association between capacity strain and adverse health outcomes such as readmission (Shi et al. 2018) and mortality (Eriksson et al. 2017). In a recent systematic review, mortality rates increased during times of capacity strain in 18 of 30 studies and in 9 of 12 studies in ICUs (Eriksson et al. 2017). As such, matching supply to demand among hospital units has always been one of the key focus areas for hospitals to strive for excellence in care delivery (L. V. Green 2006).

Matching supply to demand in hospital units can be challenging because of the way they are designed to cater certain patient conditions. Patients may present multiple comorbidity conditions (e.g., a medicine patient who is diagnosed with cancer) that require resources from multiple different units, and specialties. With the current design, patients will need to transition between hospital units or overflowed to non-preferred units, which both negatively impact safety (M.F. et al. 2020) and health outcomes (Song et al. 2019). In addition, patients with common conditions could be scattered over different hospital units. Alternatively, grouping these patients into a specialized unit and providing specialized care can improve their outcomes, and hospital flow (Englander et al. 2017).

Instead of dividing hospital beds into rigid units and assigning patients among them, hospitals need to restructure themselves around patient needs. Focusing on patient needs also promotes patient-centered care (de Boer et al. 2013), where patients can receive customized care plans and medications (NEJM Catalyst 2017). As such, moving toward patient-centered care requires grouping patients based on their similarities. These similarities can be studied using process analytics (Lismont et al. 2016).

Process analytics (i.e., process mining) offers a wide variety of techniques to extract patient similarities (Hripcsak and Albers 2013, Lismont et al. 2016). These techniques include clustering, sequencing events, temporal abstraction, sequence clustering, social network discovery, and decision mining (Lismont et al. 2016, Mans et al. 2015). Despite potentials of these techniques to identify similar patients (Garcia et al. 2019), application of process analytics in healthcare resource allocation has been limited to single-populations such as type-2 diabetes (Lismont et al. 2016), radiology patients (Rebuge and Ferreira 2012), stroke patients (Mans et al. 2008), and kidney and heart problems (Najjar et al. 2018). Extending these techniques to multiple patient populations across the hospital requires addressing several major challenges such as inadequate granularity of recorded data, high complexity of healthcare data, and clouding effect of overflowing activities (Lismont et al. 2016).

This study is the first attempt to cluster entire inpatient populations based on their similarities. In this study, we include patient level data that are available at the time of admission at two hospitals within the same healthcare system and apply latent class analysis to identify patient clusters and membership labels. In addition, we apply interpretable classification models to explain determining factors for each cluster membership.

5.2 Literature Review

The idea of grouping patients with similar needs started as a solution to the historical method of reimbursement problem, per diems, that were based on length of stay regardless of the illness of the patients (Goldfield 2010). As such, invention of Diagnosis-related Groups (DRG) by researchers at the Yale School of Public Health was the first attempt to define case types, each of which could be expected to receive similar outputs or services from a hospital (Fetter et al. 1980).

As US hospitals battered by competition, they have begun to pursue product line management techniques using DRG systems (Fetter and Freeman 1986). DRGs were used to create broader groups of patients, called service lines (Studnicki 1991). Then, service lines were used for allocating hospital resources such as beds, nurses, and equipment (Baghai et al. 2008, Studnicki 1991).

Although dividing hospital beds into a few service lines can help hospitals provide a focused care and reap tremendous fiscal benefits while enhancing their ability to serve their communities (Baghai et al. 2008), use of DRG alone to form the service lines can result in several issues. Because different DRG systems use different classification variables including treatment characteristics, patient characteristics, and provider/setting characteristics, DRGs can result in inconsistent patient groups (Pettengill and Vertrees 1982, Quentin et al. 2012, Vitikainen et al. 2009). In addition, patients within the same DRG can have quite different intensity of medical needs (Vitikainen et al. 2009). Moreover, patients can have multiple co-existing comorbidities that a single DRG fails to capture patient complexities. As such, patients can experience frequent transfers between service lines (Survey 2014).

Alternatively, process analytics can evaluate patient similarities using a more comprehensive list of variables including operational constraints, patient characteristics, and their complex clinical conditions. In particular, Latent Class Analysis (LCA) is a powerful statistical method for grouping data into classes of an unobserved (latent) variable. LCA is a common method in medical field since researchers often interested in phenomena that cannot be directly observed such as eating disorder, socialization, and temperament (Porcu and Giambona 2017). LCA applications include identifying subgroups of self-injurers among young adults (Klonsky and Olino 2008), analysis of cancer risk behaviors among U.S. college students (Kang et al. 2014), identifying clusters of alcohol and drug use and health-risk behaviors (Assanangkornchai et al. 2018), understanding health lifestyles and suicidal behaviors among US adolescents (Xiao et al. 2019), investigating cancer treatments and geriatric interventions (Ferrat et al. 2016), and distinguishing patients with low back pain diagnosis (Fop et al. 2017) among others. In addition, LCA can provide insights on resource utilization of different patient groups. Hastings et al. applied LCA to understand health service use of older adults in emergency department and identified five cluster of patients with distinct patterns of health service use (Hastings et al. 2014). Similarly, Young-Wolff et al. used LCA to investigate patterns of resource utilization among women exposed to victimization (Young-Wolff et al. 2013). Despite popularity of LCA in healthcare, its application has been limited to single patient populations. Our study is the first attempt to apply LCA among entire inpatient populations to identify latent patient clusters and their characteristics. These clusters can then improve existing service lines for resource allocation purposes.

Similar to clustering algorithms, LCA is not interpretable and does not provide interpretable rules on how the clusters form. To overcome this issue, we combine LCA with decision tree classifiers. The classification decision tree is a non-parametric supervised learning method used for classification of a target variable (e.g., cluster index from LCA output) by learning simple decision rules inferred from the data features. Because of its interpretability, classification decision tree is widely used in healthcare field including predicting the survivability of breast cancer patients (Khan et al. 2008), characterizing skin diseases (Chang and Chen 2009), and monitoring diabetes patients (Kelarev et al. 2012), among others.

5.3 Data

We use patient visits data from Christiana hospital and Wilmington hospital within the same health system, ChristianaCare, between 1/1/2018 and 12/31/2019. These hospitals are non-sectarian, not for profit, urban and suburban, academic and community hospitals. The Christiana hospital with 906 beds, includes Delaware's only Level I trauma center, and the Wilmington hospital consists of 321 beds.

To implement our findings in practice, we use the data that are available at the time of patient admission such as admission information, and care complexity. Our dataset contains 20,674 unique patient visits in the Wilmington hospital, and 61,289 unique patient visits in the Christiana hospital. In addition, our datasets include data related to geographic location of patients such as admitting unit code and admitting medical section.

5.3.1 Admission information

The dataset includes admission source, admission category, and admitting diagnosis code. Admission source refers to the source of admitted patients which can be either of born in hospital, born outside hospital, court, emergency room (ER), physician referral, transferred from other hospital, transfer from other hospital within same health system. Admission category refers to the type of admission which can be either of elective, emergency, newborn, trauma center, urgent.

Admitting diagnosis code is an ICD-10 code that is assigned to each admitted patient at the time of admission. This diagnosis code is different from primary diagnosis code and DRG codes that are determined after discharge. We grouped admitting diagnosis codes based on their initial alphabetic letters and defined a new variable which includes letters from A to Z, each of which reflect a certain illness category.

5.3.2 Care complexity

The dataset includes several variables to capture complexity of required medical needs such as triage severity of illness, level of care, age, and age adjusted Charlson comorbidity index. Triage severity of illness is available for patients admitted from ED and contains five levels, 1 being the most urgent patients, and 5 is the least urgent patients. Levels of care indicates the type of envisioned care such as nursing, ICU, and SDU. Age adjusted Charlson comorbidity index is introduced to account for comorbidity condition of patients by assigning score to each comorbidity condition (Charlson et al. 1987, Tian et al. 2017). In our dataset, age adjusted Charlson comorbidity index is only available for patients who have been in the hospital before, otherwise, it will be a missing index. Average (standard deviation) age adjusted Charlson comorbidity index in the Wilmington and Christiana campuses are 7.8 (4.16) and 7.9 (4.39).

5.4 Methodology

Since our goal is to implement our findings in practice, interpretability of results is the main deciding factor between different methods. As such, we design a two-step clustering, then classification approach.

In the first step, we use Latent Class Analysis (LCA) to form clusters and attach a cluster label to each datapoint. Unlike distance-based clustering methods that measure the distance between datapoints and assign them into different clusters, LCA is a model-based approach in which fits a finite mixture model to the underlying data (Andersen et al. 2003, Melnykov and Maitra 2010). To determine the optimal number of latent classes (i.e., clusters) in LCA, we fit 30 different models by varying the number of latent classes from 1 to 30 and select the one with the lowest Bayesian Information Criterion (BIC). BIC is a penalty-based method to overcome the overfitting issue (Schwarz 1978).

In the second step, we use classification tree models to predict the latent class labels that we created in the first step. Among other classification algorithms, classification trees are the most interpretable which will enable us to implement our results in practice (Steorts 2009).

5.4.1 LCA

LCA is a common method for clustering multivariate categorical data (Drew A. Linzer and Jefrey B. Lewis 2011, Fop et al. 2017, Fop and Murphy 2018). In this study, we use “LCAVarsel” package in R which is developed by Fop et al. (Fop et al. 2017). We convert numerical variables to categorical format. For age, category 1 represent age less than or equal to 10, category 2 represents age between 10 and 20, etc. Table 5.1 summarizes the distribution of patients in both hospitals across age categories. We converted age adjusted Chalrson comorbidity index to categorical format directly.

Table 5.1. Distribution of patients across age categories and hospitals.

Age Category	1	2	3	4	5	6	7	8	9	10	11
Christiana	43	493	3257	4276	4935	9924	13745	13679	8795	2110	32
Wilmington	0	72	607	1154	1848	4008	4628	4345	3016	980	16

To determine the number of clusters for each hospital, we fit different number of clusters and calculate Bayesian information criterion (BIC)(G 1978) for each scenario, and select the lowest BIC. Figure 5.1 demonstrates BIC values for number of clusters between 1 and 30 in Wilmington hospital. We find that 10 and 15 clusters yield minimum BIC in the Wilmington and Christiana hospitals, respectively.

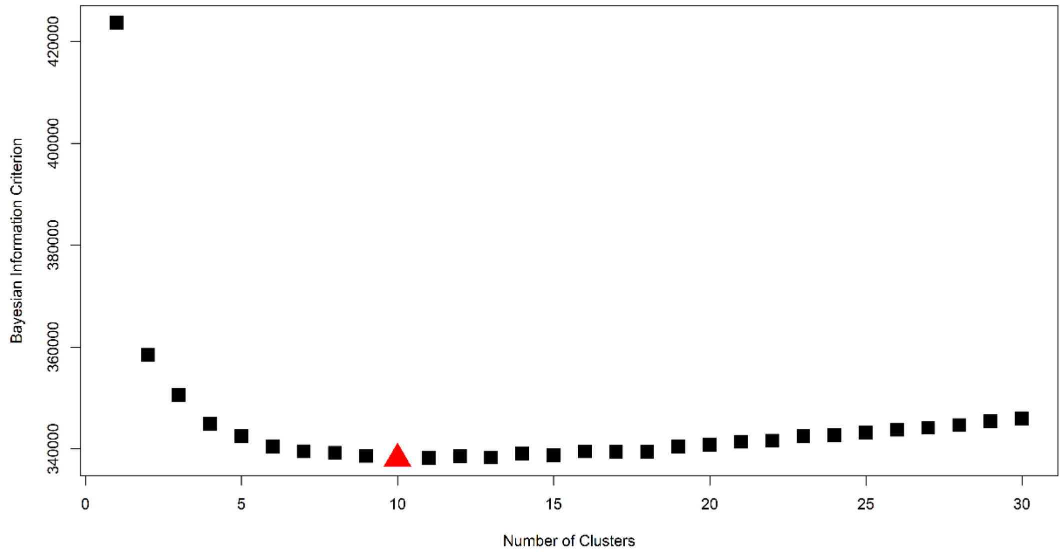

Figure 5.1. Bayesian information criterion for different number of clusters at the Wilmington hospital

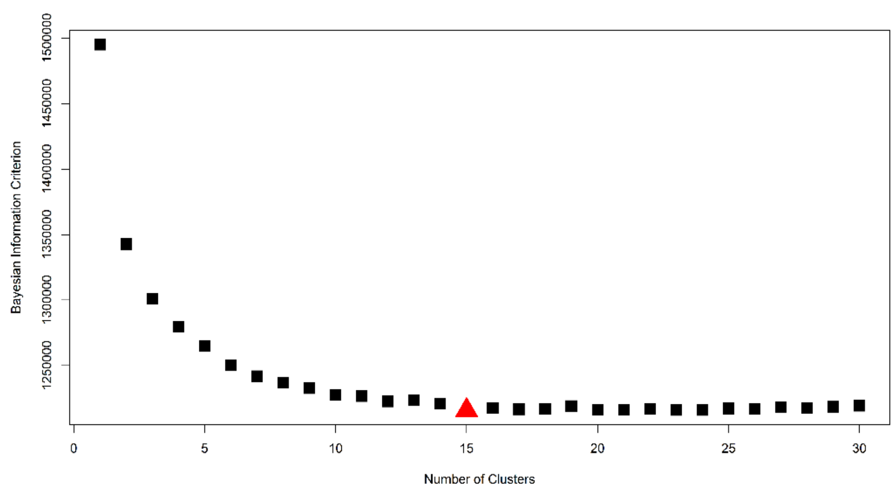

Figure 5.2. Bayesian information criterion for different number of clusters at the Christiana hospital.

5.4.2 Classification tree

Once we form clusters and label each visit within one of the clusters, we construct a classification tree for each hospital using “rpart” package in R. To obtain interpretable decision trees, we control for tree parameters as shown in Table 5.2.

Table 5.2. Classification tree parameters and setting.

Decision Tree Parameter	Definition	Value
Minimum split	The minimum number of observations that must exist in a node in order for a split to be attempted.	50
Maximum depth	Maximum number of child leaves, root node being depth 0	10
Cross validation	Number of cross validation folds	10
Complexity parameter (cp)	If the cost of adding another variable to the decision tree from the current node is above the value of cp, then tree building does not continue	0.01
Training dataset	Percentage of data used for training the algorithm	80

5.5 Results

5.5.1 Wilmington hospital

We used LCA to form 10 clusters in the Wilmington hospital, and constructed a classification tree with specified parameters in Table 5.2. We then used 20% testing dataset to test the performance of our classification tree. The accuracy of the classification tree was 88.04%, as shown in Table 5.3.

Table 5.3. Confusion matrix of classifier for the Wilmington hospital.

Row=actual Col= prediction	1	2	3	4	5	6	7	8	9	10
1	447	41	0	0	0	0	0	18	19	0
2	11	1396	0	0	0	0	0	31	12	0
3	47	1	327	0	0	0	0	41	0	0
4	0	0	0	714	26	28	1	0	0	0
5	0	0	0	7	297	9	0	0	0	0
6	0	0	0	5	25	131	4	0	0	12
7	0	0	0	1	8	64	284	0	0	5
8	12	105	0	0	0	0	0	520	6	0
9	9	29	0	0	0	0	0	0	331	0
10	0	0	0	0	28	0	13	0	0	104

First rule in splitting the nodes is based on the triage severity of illness. Clear separation between patients admitted from ED and non-emergency patients indicates their significant differences. Due to the large number of clusters, and classification tree size, we present the constructed classification tree as two separate figures, provided as Figure 5.3 which refers to patients admitted from the ED, and Figure 5.4 for all other patients. First observation from these two groups relates to their number of leaf nodes. Patients admitted from the ED include 11 leaves, while non-emergency admitted patients have only 6 leaves. Apart from natural differences between emergency and non-emergency patients, the difference in number of leaves can be explained by the number of admitted patients from the ED units (13,778) and non-ED units (6,896) where the number of ED admissions is almost twice the size of non-emergency admissions.

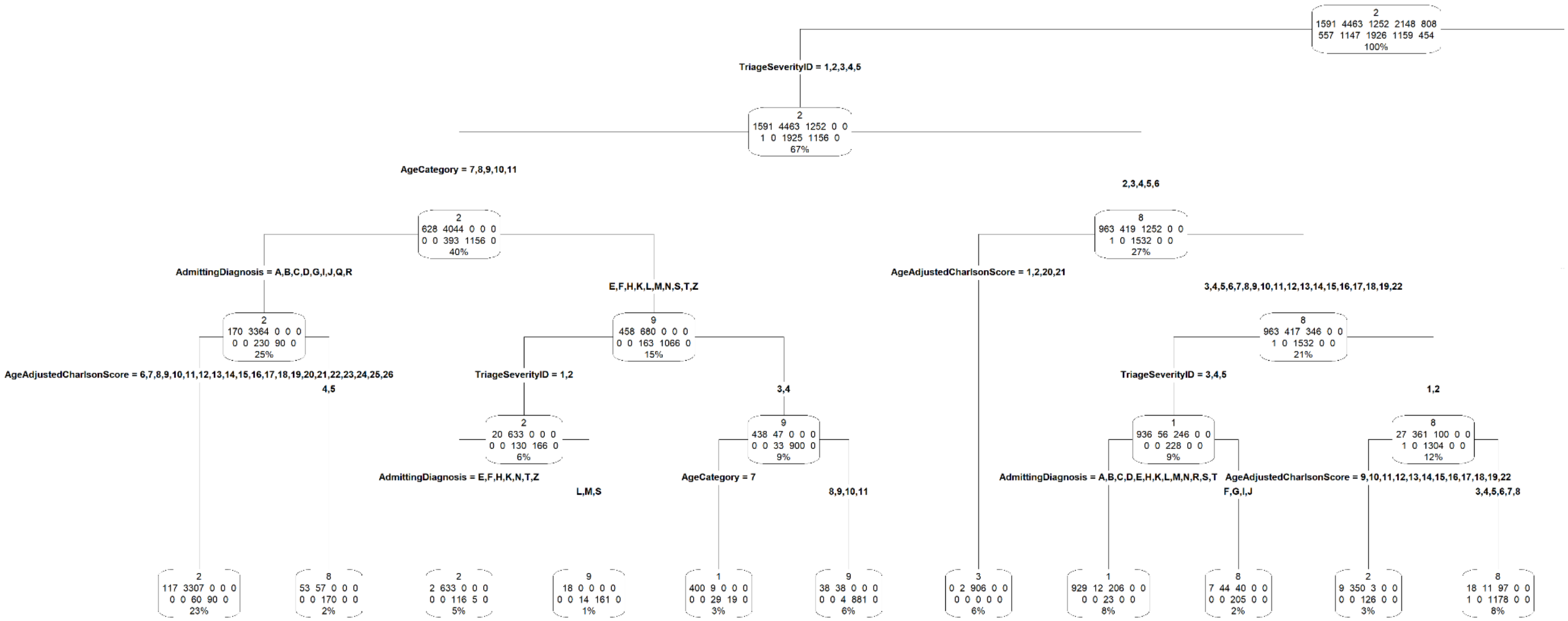

Figure 5.3. Decision tree for the Wilmington hospital (Part 1/2).

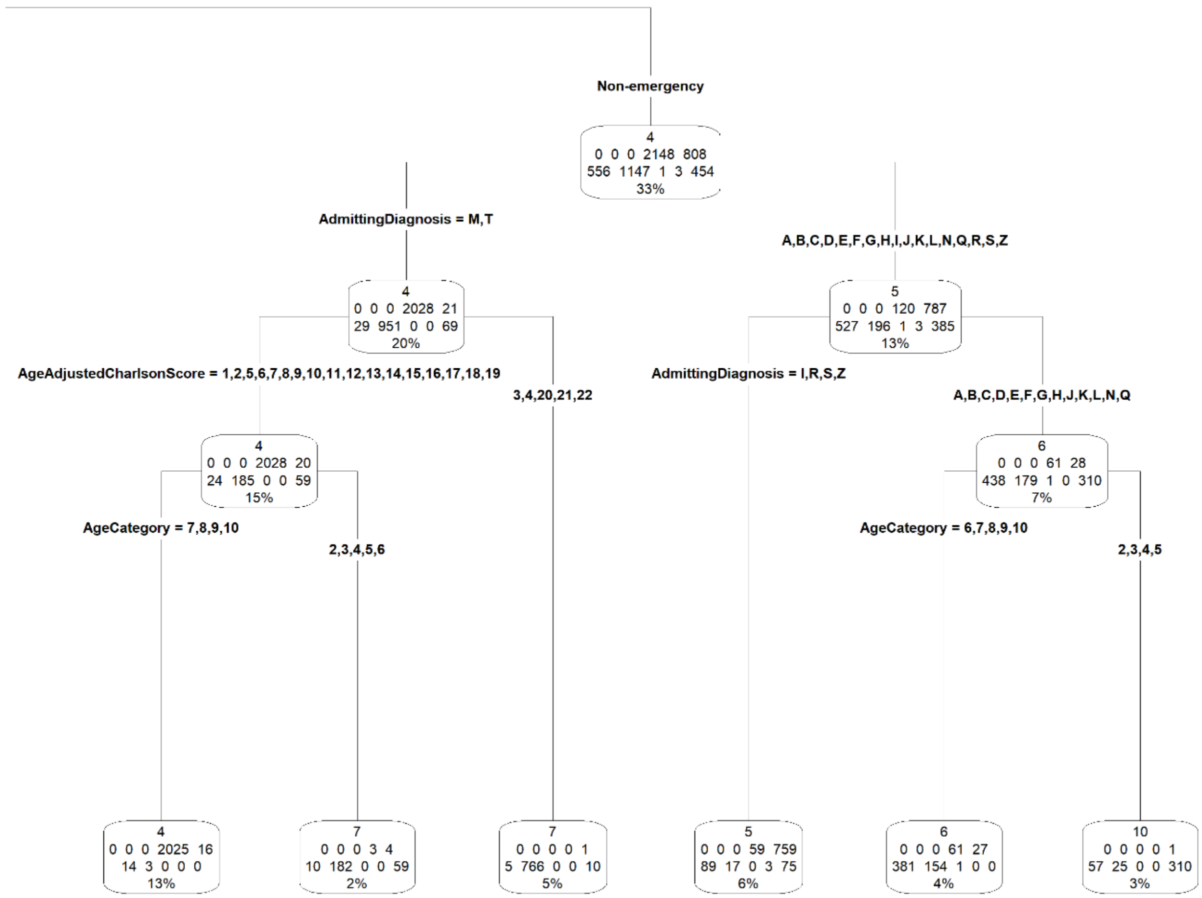

Figure 5.4. Decision tree for the Wilmington hospital (Part 2/2).

As shown in Figure 5.3, patients admitted from the ED are split based on their age. Patients older than 60 are assigned to either of the clusters 1, 2, 8, and 9, whereas patients younger than 60 are assigned to either of clusters 1, 2, 3, and 8. While clusters 1, 2, and 8 are common between this separation, clusters 1 and 9 are completely separated. The age difference between clusters 1 and 9 can be seen in Figure 5.5. Comparison of clusters 1,2, and 8 indicate that cluster 2 includes larger volume of patients with higher severity as shown in Figure 5.6. In addition, majority of cardiology patients are assigned to clusters 2 and 8 as listed in Table 5.4.

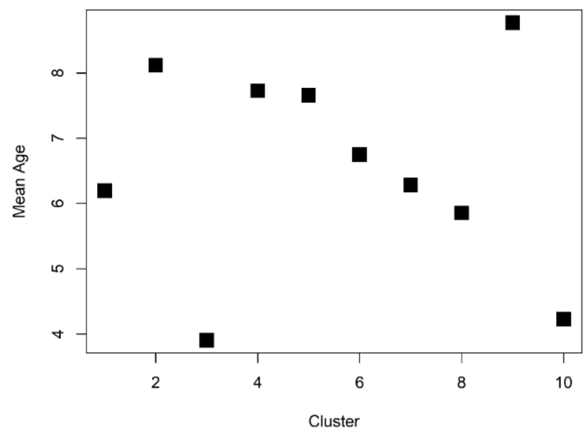

Figure 5.5. Average age between clusters in the Wilmington hospital.

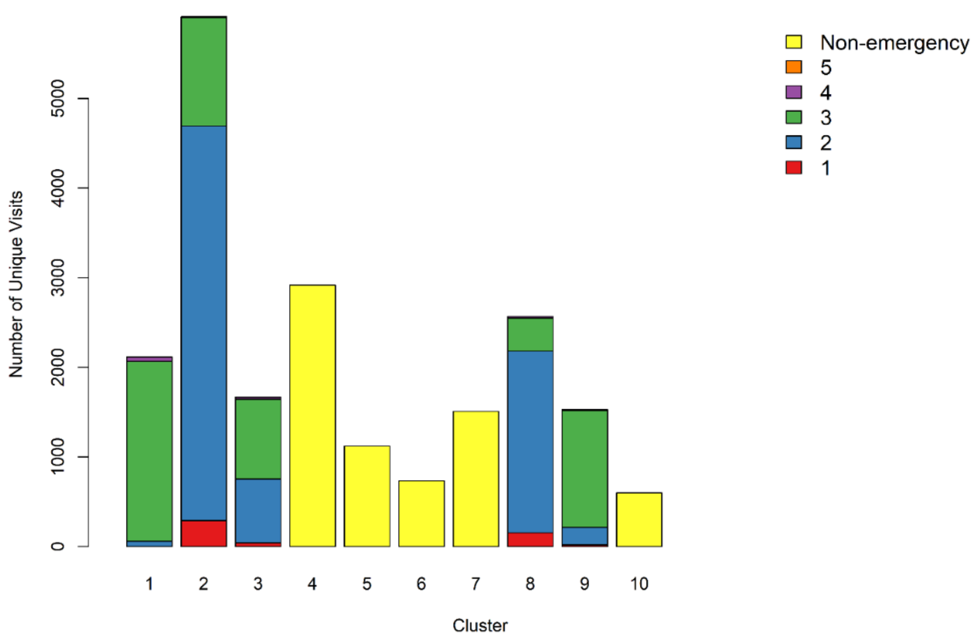

Figure 5.6. Triage severity of illness in the Wilmington hospital.

Table 5.4. Distribution of patients across admitting medical sections and clusters in the Wilmington hospital.

Admitting Medical Section	1	2	3	4	5	6	7	8	9	10
DENTISTRY/ORAL SURGERY	0	0	0	2	2	5	2	0	0	4
MEDICINE/ CARDIOLOGY	4	299	11	2	0	7	0	85	1	0
MEDICINE/GASTROENTEROLOGY	0	0	1	0	0	0	0	0	0	0
MEDICINE/ INFECTIOUS DISEASE	0	0	1	0	0	0	0	0	0	0
MEDICINE/ INTERNAL MEDICINE	819	2379	535	14	11	55	2	872	559	9
MEDICINE/ NEUROLOGY	0	2	0	0	0	0	0	0	0	0
MEDICINE/ PHYSICAL MEDICINE	0	1	0	30	913	31	5	0	3	80
MEDICINE/ PULMONARY	6	19	7	0	0	1	0	7	1	1
SURGERY/ GENERAL SURGERY	150	49	65	39	0	147	135	30	144	176
SURGERY/NEUROLOGIC	0	0	0	0	0	0	1	0	0	0
SURGERY/ORTHOPEDIC	6	1	0	2759	13	25	1239	0	8	72
SURGERY/ OTOLARYNGOLOGIC	0	1	0	13	4	57	2	1	0	4
SURGERY/ PLASTIC SURGERY	1	0	1	15	2	51	3	0	0	9
SURGERY/ THORACIC SURGERY	0	0	1	0	0	0	0	0	0	0
SURGERY/ TRAUMA SURGERY	14	3	3	1	0	1	0	5	27	0
SURGERY/ UROLOGIC SURGERY	0	0	0	3	0	3	5	0	0	0

Figure 5.4 shows that clusters 4, 5, 6, 7, and 10 fall under non-emergency admissions. As shown in Figure 5.7, these patients mainly came from physician referral and hospital transfers. Among these, clusters 4 and 7 include the same type of patients (i.e., admitting diagnosis letter codes M, and T that are admitted to orthopedic surgery section), in which cluster 4 contains patients older than 60, and cluster 7 contains remaining patients. Comparison of average age within these two clusters is shown in Figure 5.5. In addition, cluster 5 includes patients with admitting diagnosis letter code I, R, S, and Z. Majority of these patients are admitted in physical medicine as shown in Table 5.4. Finally, clusters 6, and 10 include all other patients that are separated based on age, in which cluster 10 includes patients younger than 60, and cluster 6 includes patients older than 60.

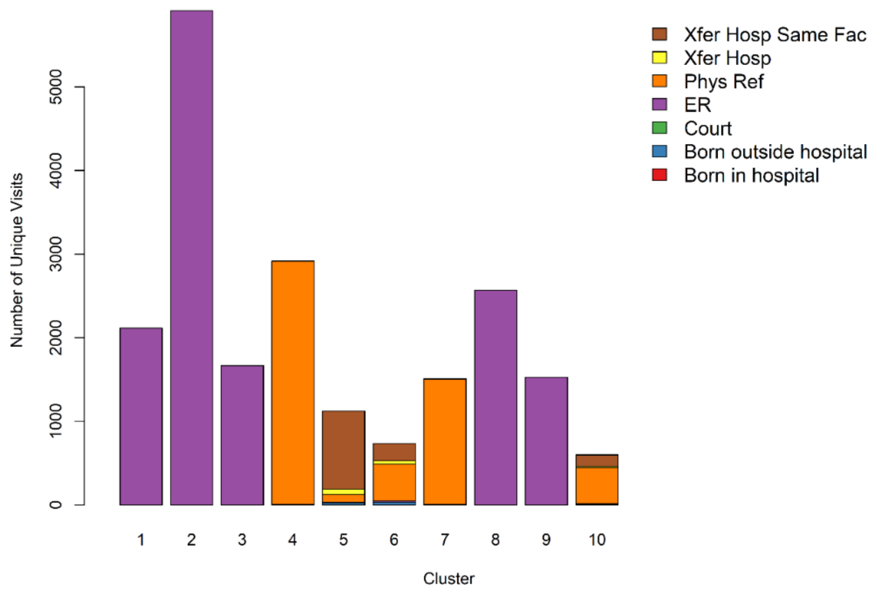

Figure 5.7. Admission source for patients visited the Wilmington hospital.

5.5.2 Christiana hospital

We used LCA to form 15 clusters in the Christiana hospital, and constructed a classification tree with specified parameters in Table 5.2. We then used 20% testing dataset to test the performance of our classification tree. The accuracy of the classification tree was 78.22%. Due to the large number of clusters, and classification tree size, we present the constructed classification tree as three figures, provided in Figure 5.8, Figure 5.9, and Figure 5.10.

Figure 5.8 includes clusters 1, 2, 5, 6, 8, and 14. These clusters are completely separated from the rest of the clusters based on their triage severity of either 5 or non-emergency patient visits. Clusters 2, and 14 include patients with admitting diagnosis letter code of "O" which refers to pregnancy, childbirth and the puerperium, as listed in Table 5.5. Clusters 5 and 6 include similar patients, but different in age adjusted Charlson score as shown in Figure 5.11. In addition, clusters 1 and 8 are separated based on the admission source.

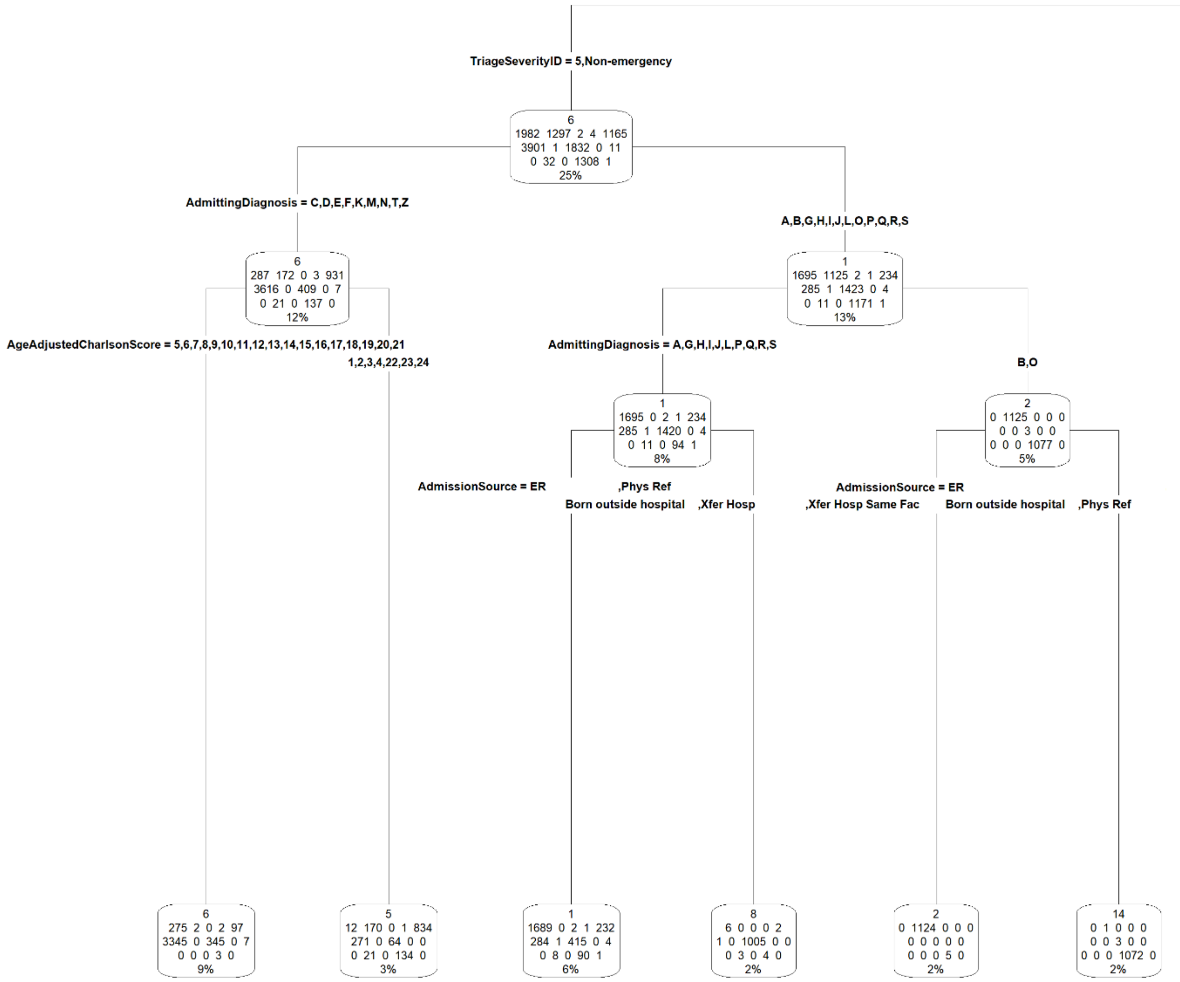

Figure 5.8. Decision tree for the Christiana hospital (Part 1/3).

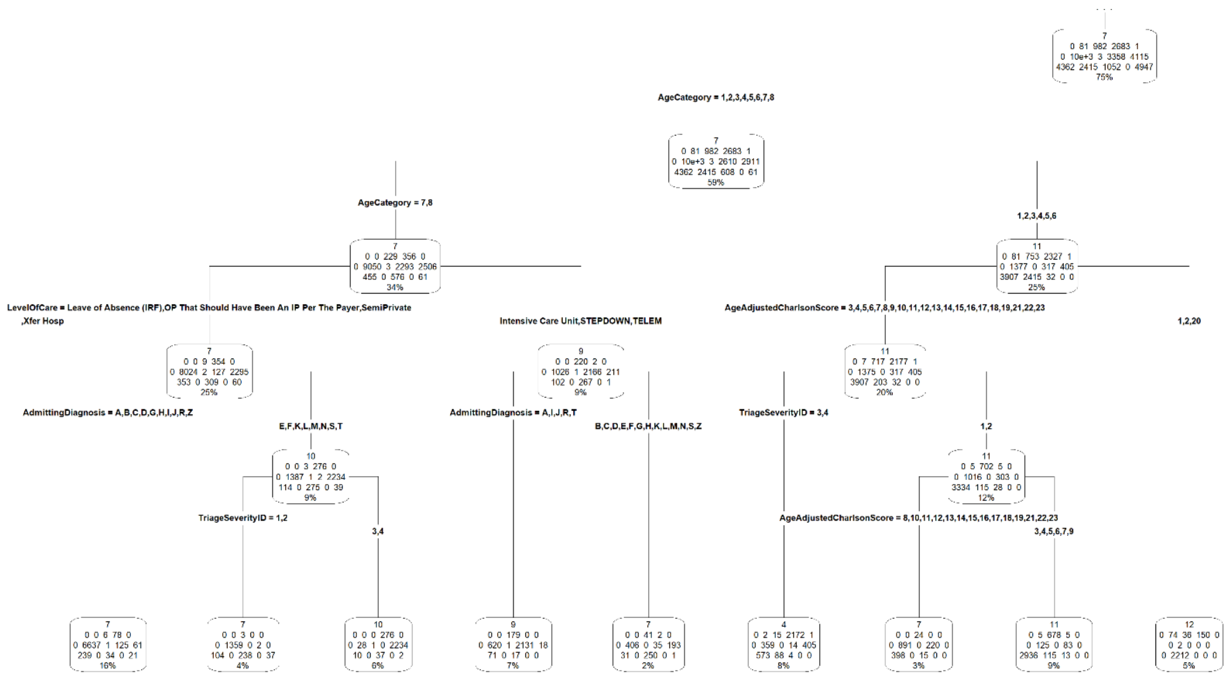

Figure 5.9. Decision tree for the Christiana hospital (Part 2/3).

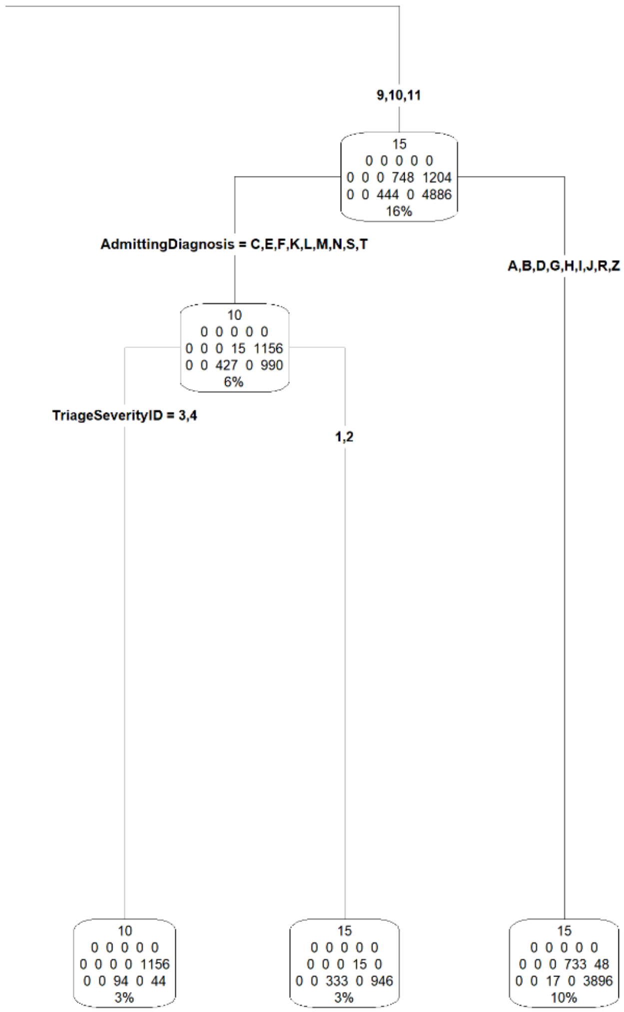

Figure 5.10. Decision tree for the Christiana hospital (Part 3/3).

Table 5.5. Admitting diagnosis codes across clusters in the Christiana hospital.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
A	0	0	42	53	0	0	261	31	216	51	46	38	0	1	109
B	0	0	0	19	0	1	35	3	0	4	10	3	0	4	5
C	168	0	0	0	76	1067	276	75	4	38	14	7	0	0	27
D	48	0	2	61	122	168	361	36	0	6	77	107	1	20	128
E	17	0	0	296	19	74	485	24	0	305	238	188	0	2	132
F	0	0	0	59	0	1	25	1	0	21	193	112	3	0	6
G	53	0	20	75	102	54	400	105	2	1	173	98	16	49	165
H	0	0	0	11	0	1	83	6	0	0	71	17	0	0	36
I	2155	0	840	0	91	0	1616	758	2635	0	879	207	0	7	904
J	9	0	30	0	10	21	2105	118	467	0	1011	342	0	2	958
K	65	2	0	927	160	453	1024	175	57	1368	431	330	0	23	508
L	3	0	0	373	0	9	125	69	0	517	23	121	1	0	29
M	2	0	2	361	568	2155	212	79	0	877	90	145	64	54	74
N	6	0	0	345	81	343	619	47	0	1134	158	114	10	7	357
O	0	1574	0	0	0	0	0	0	0	0	0	7	0	1428	0
P	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0
Q	8	0	0	0	14	6	0	7	0	1	0	3	0	5	1
R	58	0	95	802	91	181	6147	651	1127	71	1994	890	80	37	2865
S	2	0	221	92	11	92	0	149	0	802	200	311	1236	18	184
T	62	0	62	121	79	213	142	102	57	246	178	151	8	17	42
Z	20	238	0	2	152	366	14	9	0	0	0	21	3	65	26

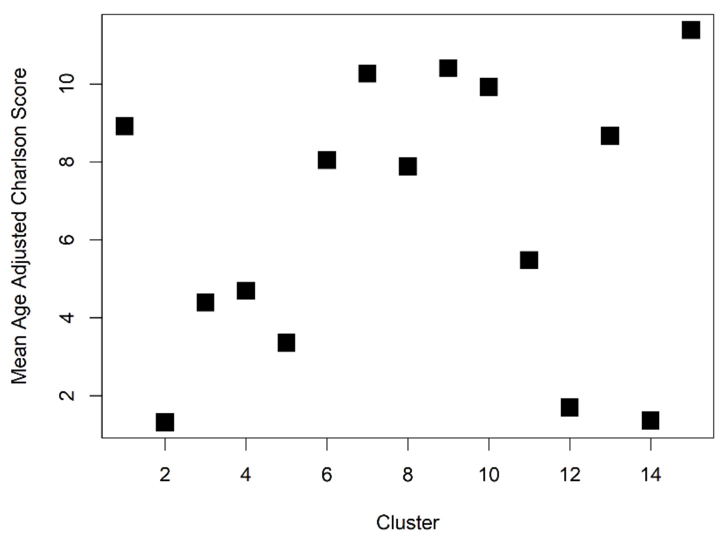

Figure 5.11. Average age adjusted Charlson score across clusters in the Christiana hospital.

Figure 5.9 includes clusters 4, 7, 9, 10, and 11. These clusters include patients with triage severity of less than 5 and younger than 90. Majority of patients in cluster 9 fall under stepdown or ICU level of care, as shown in Figure 5.12.

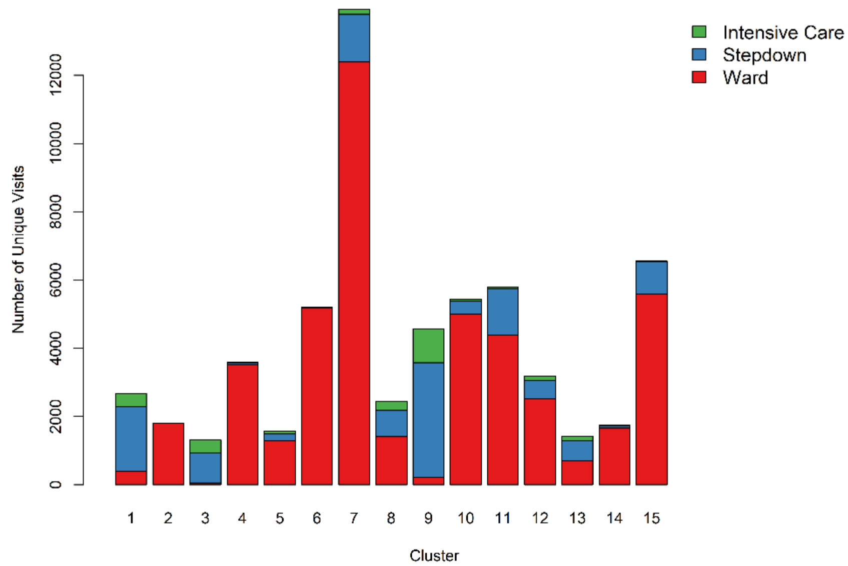

Figure 5.12. Level of care for the Christiana hospital.

Finally, Figure 5.10 includes clusters 10, and 15. These clusters include patients with triage severity of less than 5 and older than 90.

5.6 Discussion and Conclusions

In this study, we investigated existing patient grouping in two academic hospitals within the same health system using a two-step clustering, then classification approach. To facilitate implementation of our results in practice, we used available data at the time of patient admission and used interpretable classification tree models. Using patient admission data and our interpretable results from the classification trees, hospital admins can readily determine cluster membership of admitted patients. Currently, there are 8 patient groups (i.e., service lines) within these hospitals. Using patient records within a two-year period, and information available at the time of patient admission, we applied latent class analysis and BIC criterion to identify new patient groups. We identified 10 and 15 patient groups in the Wilmington and Christiana hospitals, respectively. We then constructed a classification tree for each hospital (accuracy of 88.04% in the Wilmington hospital, and 78.22% in the Christiana hospital) and analyzed distribution of patient types across clusters. High accuracies achieved in our classification trees indicate that available information at the time of admission, despite being limited, can provide significant insights to form patient groups. We found that existing 8 service lines can be further split into 10 and 15 groups in the Wilmington and Christiana hospitals, respectively. Most splits occur between surgery and medicine service lines. More specifically, internal medicine, neurological disorders, and general surgery patients spread across multiple clusters.

Comparing patient distribution across clusters with rules extracted from classification trees, we can identify some of the clusters that include unique patient populations such as orthopedic surgery, cardiology, and physical medicine in the Wilmington hospital, and pregnancy, childbirth and the puerperium in the Christiana hospital.

Our findings also shed light on the usefulness of triage severity index, age adjusted Charlson comorbidity score, and age in determining patient condition and required care complexity. In particular, we found that using all these information can provide a more robust picture of patient conditions. In addition, our classification trees repeatedly split nodes based on age threshold of 60, suggesting potential differences among patients younger than 60 and older than 60.

In the existing design, hospital units are specialized in different levels of care such as ICU, stepdown, and ward. Literature suggests that separating ICU and stepdown can exacerbate flow issues within the hospital by increasing number of patient transfers (Edbrooke et al. 2011, Hasan et al. 2020, Long and Mathews 2018, Singh and Terwiesch 2012). Ideally, a hospital unit should be equipped with skilled staff and facilities, and able to provide any needed level of care. As such, each unit should be able to provide ICU, stepdown, and ward level of care without being specialized in one of these levels. Our findings also support this idea. As shown in Figure 5.12, clusters (e.g., 1, 7, 9) include patients from different levels of care.

Top 3 most common ZIP codes of visited patients from the Wilmington hospital, and their racial distribution according to the census data is shown in Table 5.6. While majority of these ZIP code residents are black or African American, our records show that black or African American make up much smaller number of visits from the Wilmington hospital. Figure 5.13 represents the distribution of race across clusters in the Wilmington hospital. Although top three ZIP codes are mainly black or African American residents, majority of hospital visits belong to white race, indicating potential issues related to access.

Table 5.6. Top 3 ZIP codes in the Wilmington hospital and their racial distribution.

ZIP Code	Name	Number of Visits	% Black/African American	% White
19802	Wilmington, DE	2491	76.1	18.5
19805	Wilmington, DE	1990	56	32.7
19801	Wilmington, DE	1752	74.5	19.5

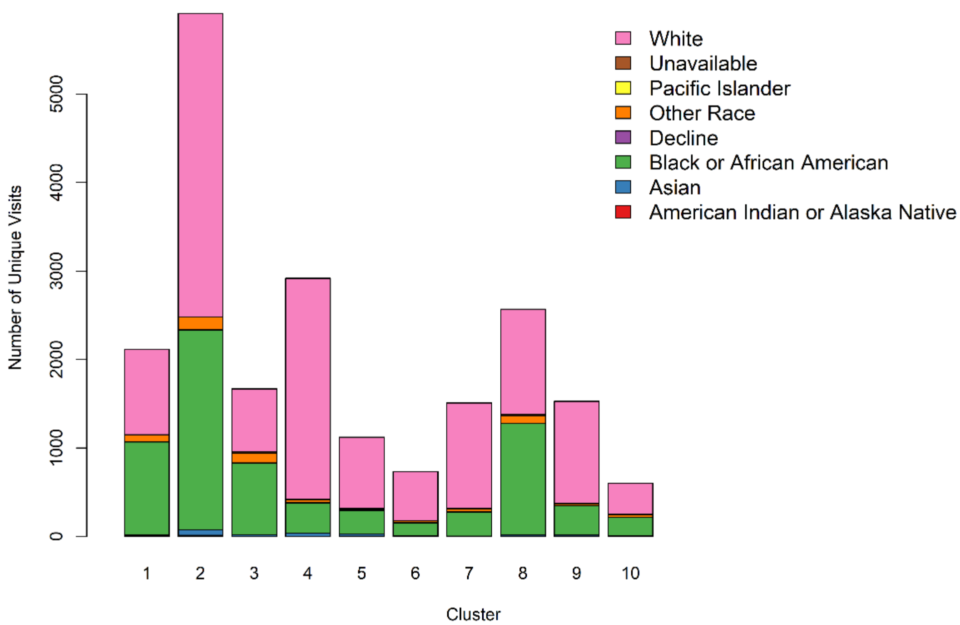

Figure 5.13. Distribution of race across clusters in the Wilmington hospital.

Although we designed our study to facilitate the implementation phase, there are several challenges and barriers to implement our results in practice. Future studies can extend our work and attempt to identify these challenges. In addition, future studies can incorporate patient outcomes and compare the effectiveness of formed clusters in practice. In this direction, counterfactual analysis using simulation models can inform the impacts of these clusters on patient flow and capacity within the hospitals.

6. FUTURE WORK

In this dissertation, we investigated some of the issues related to patient flow and capacity management in two major components of health services, namely ambulatory care and inpatient care. Using administrative data and quantitative methods, we explored access issue in the ambulatory care, as well as flow and capacity challenges in the inpatient care. While our study shed light on the effectiveness of current policies regarding access and flow within these settings, further studies needed to address some of the limitations of our work.

As healthcare delivery is shifting from volume-based to value-based, integration is becoming more essential than ever. As such, future studies should investigate access and flow issues within ambulatory (e.g., primary care, specialty care, nursing home) and inpatient care simultaneously. Identifying vulnerable patient cohorts and investigating their access and flow barriers across the entire healthcare system can provide opportunities to improve both system performance and patient outcomes. These studies can also inform health organizations about the importance and advantages of implementing integrated information systems across the board.

To facilitate the Triple aims introduced by the Institute for Healthcare Improvement (IHI), flow and capacity policies should be evaluated holistically. As such, future studies should evaluate the impact of flow and capacity policies on population health, costs, and quality of care. Multidisciplinary nature of these studies can introduce new challenges and opportunities for collaboration.

To bridge the gap between theoretical development and practical implementation, future studies should focus on addressing challenges of incorporating algorithms at the provider site and aid clinicians in decision making. These efforts can investigate the dynamics between leadership support, incentives, training opportunities, global vs. local perception of employees, technology infrastructure, user friendliness of products, and efficiency of developed algorithms.

Amidst the global pandemic, we experienced that health systems were able to adopt rapid strategies to restructure their inpatient groups, and facilitated patient access to ambulatory care through telemedicine (Bashshur et al. 2020, Patterson et al. 2020). While it is not the end of the pandemic, it is definitely the beginning for flow and capacity management in health services.

REFERENCES

Ackerman SL, Gleason N (2018) Transitioning patients from specialty care to primary care what we know and what we can do. *J. Ambul. Care Manage.* 41(4):314–322.

Ackerman SL, Gleason N, Monacelli J, Collado D, Wang M, Ho C, Catschegn-Pfab S, Gonzales R (2014) When to repatriate? Clinicians' perspectives on the transfer of patient management from specialty to primary care. *J. Gen. Intern. Med.* 29(10):1355–1361.

Afilalo M, Xue X, Soucy N, Colacone A, Jourdenais E, Boivin JF (2017) Patient Needs, Required Level of Care, and Reasons Delaying Hospital Discharge for Nonacute Patients Occupying Acute Hospital Beds. *J. Healthc. Qual.* 39(4):200–210.

Ahmadi-Javid A, Jalali Z, Klassen KJ (2017) Outpatient appointment systems in healthcare: A review of optimization studies. *Eur. J. Oper. Res.* 258(1):3–34.

Akcali E, Côté MJ, Lin C (2006) A network flow approach to optimizing hospital bed capacity decisions. *Health Care Manag. Sci.* 9(4):391–404.

Akushevich I, Yashkin AP, Kravchenko J, Ukraintseva S, Stallard E, Yashin AI (2018) Time Trends in the Prevalence of Neurocognitive Disorders and Cognitive Impairment in the United States: The Effects of Disease Severity and Improved Ascertainment. *J. Alzheimer's Dis.* 64(1):137–148.

Alizamir S, De Véricourt F, Sun P (2013) Diagnostic accuracy under congestion. *Manage. Sci.* 59(1):157–171.

Allon G, Deo S, Lin W (2013) The impact of size and occupancy of hospital on the extent of ambulance diversion: Theory and evidence. *Oper. Res.* 61(3):544–562.

Andersen R, Hagenaars JA, McCutcheon AL (2003) Applied Latent Class Analysis. *Can. J. Sociol. / Cah. Can. Sociol.* 28(4):584.

Angus DC (2000) Current and Projected Workforce Requirements for Care of the Critically Ill and Patients With Pulmonary Disease:Can We Meet the Requirements of an Aging Population. *JAMA* 284(21):2762–2770.

Antonelli D, Baralis E, Bruno G, Chiusano S, Mahoto NA, Petrigni C (2012a) Extraction of medical pathways from electronic patient records. *Med. Appl. Intell. Data Anal. Res. Adv.* 273–289.

Antonelli D, Baralis E, Bruno G, Chiusano S, Mahoto NA, Petrigni C (2012b) Analysis of diagnostic pathways for colon cancer. *Flex. Serv. Manuf. J.* 24(4):379–399.

Antonelli D, Bruno G, Chiusano S (2013) Anomaly detection in medical treatment to discover unusual patient management. *IIE Trans. Healthc. Syst. Eng.* 3(2):69–77.

Armony M, Chan CW, Zhu B (2018a) Critical Care Capacity Management: Understanding the Role of a Step Down Unit. *Prod. Oper. Manag.* 27(5):859–883.

Armony M, Chan CW, Zhu B (2018b) Critical Care Capacity Management: Understanding the Role of a Step Down Unit. *Prod. Oper. Manag.* 27(5):859–883.

Armony M, Israelit S, Mandelbaum A, Marmor YN, Tseytlin Y, Yom-Tov GB (2015) On Patient Flow in Hospitals: A Data-Based Queueing-Science Perspective. *Stoch. Syst.* 5(1):146–194.

Assanangkornchai S, Li J, McNeil E, Saingam D (2018) Clusters of alcohol and drug use and other health-risk behaviors among Thai secondary school students: A latent class analysis. *BMC Public Health* 18(1).

Baghai R, Levine E, Sutaria S (2008) Service-line strategies for US hospitals. *McKinsey Q.* (july):1–9.

Bahalkeh E (2015) *Efficient Algorithms for Calculating the System Matrix and the Kleene Star Operator for Systems Defined by Directed Acyclic Graphs over Dioids*. (Ohio University).

Bahalkeh E, Madraki G, Judd R (2015) Efficient system matrix calculation for manufacturing systems. *IIE Annu. Conf. Expo 2015*. (Institute of Industrial and Systems Engineers (IISE)), 1943–1950.

Bai J, Fügener A, Schoenfelder J, Brunner JO (2018) Operations research in intensive care unit management: a literature review. *Health Care Manag. Sci.* 21(1):1–24.

Balakhontceva MA, Funkner AA, Semakova AA, Metsker OG, Zvartau NE, Yakovlev AN, Lutsenko AE, Kovalchuk S V. (2018) Holistic modeling of chronic diseases for recommendation elaboration and decision making. *Procedia Comput. Sci.* 138:228–237.

Barz C, Rajaram K (2015) Elective Patient Admission and Scheduling under Multiple Resource Constraints. *Prod. Oper. Manag.* 24(12):1907–1930.

Bashshur RL, Doarn CR, Frenk JM, Kvedar JC, Shannon GW, Woolliscroft JO (2020) Beyond the COVID Pandemic, Telemedicine, and Health Care. *Telemed. e-Health* 26(11):1310–1313.

Batt RJ, Terwiesch C (2017) Early task initiation and other load-Adaptive mechanisms in the Emergency Department. *Manage. Sci.* 63(11):3531–3551.

Bech-Azeddine R, Waldemar G, Knudsen GM, Høgh P, Bruhn P, Wildschiødtz G, Gjerris F, Paulson OB, Juhler M (2001) Idiopathic normal-pressure hydrocephalus: Evaluation and findings in a multidisciplinary memory clinic. *Eur. J. Neurol.* 8(6):601–611.

Bekes CE, Dellinger RP, Brooks D, Edmondson R, Olivia CT, Parrillo JE (2004) Critical care medicine as a distinct product line with substantial financial profitability: The role of business planning. *Crit. Care Med.* 32(5):1207–1214.

Berg BP, Murr M, Chermak D, Woodall J, Pignone M, Sandler RS, Denton BT (2013) Estimating the cost of no-shows and evaluating the effects of mitigation strategies. *Med. Decis. Mak.* 33(8):976–985.

Best TJ, Sandıkçı B, Eisenstein DD, Meltzer DO (2015) Managing Hospital Inpatient Bed Capacity Through Partitioning Care into Focused Wings. *Manuf. Serv. Oper. Manag.* 17(2):157–176.

Bettenhausen JL, Colvin JD, Berry JG, Puls HT, Markham JL, Plencner LM, Krager MK, et al. (2017) Association of income inequality with pediatric hospitalizations for ambulatory care-sensitive conditions. *JAMA Pediatr.* 171(6).

Bhattacharjee P, Ray PK (2014) *Patient flow modelling and performance analysis of healthcare delivery processes in hospitals: A review and reflections* (Elsevier Ltd).

Billings J, Parikh N, Mijanovich T (2000a) Emergency department use: the New York Story. *Issue Brief (Commonw. Fund)* (434):1–12.

Billings J, Parikh N, Mijanovich T (2000b) Emergency department use in New York City: a substitute for primary care? *Issue Brief (Commonw. Fund)* (433):1–5.

Black N (2016) Is hospital mortality higher at weekends? If so, why? *Lancet* 388(10040):108–111.

de Boer D, Delnoij D, Rademakers J (2013) The importance of patient-centered care for various patient groups. *Patient Educ. Couns.* 90(3):405–410.

Brousseau DC, Mistry RD, Alessandrini EA (2006) Methods of Categorizing Emergency Department Visit Urgency. *Pediatr. Emerg. Care* 22(9):635–639.

Burdett R, Kozan E (2016) A multi-criteria approach for hospital capacity analysis. *Eur. J. Oper. Res.* 255(2):505–521.

Burdett RL, Kozan E, Sinnott M, Cook D, Tian YC (2017) A mixed integer linear programing approach to perform hospital capacity assessments. *Expert Syst. Appl.* 77:170–188.

Burkey Y, Black M, Reeve H, Roland M (1997) Long-term follow-up in outpatient clinics. 2: The view from the specialist clinic. *Fam. Pract.* 14(1):29–33.

van Bussel EM, van der Voort MBVR, Wessel RN, van Merode GG (2018) Demand, capacity, and access of the outpatient clinic: A framework for analysis and improvement. *J. Eval. Clin. Pract.* 24(3):561–569.

Cardoen B, Demeulemeester E, Beliën J (2010) Operating room planning and scheduling: A literature review. *Eur. J. Oper. Res.* 201(3):921–932.

Cardoso LTQ, Grion CMC, Matsuo T, Anami EHT, Kauss IAM, Seko L, Bonametti AM (2011) Impact of delayed admission to intensive care units on mortality of critically ill patients: A cohort study. *Crit. Care* 15(1).

Caron F, Vanthienen J, Vanhaecht K, Limbergen E Van, De Weerdt J, Baesens B (2014) Monitoring care processes in the gynecologic oncology department. *Comput. Biol. Med.* 44(1):88–96.

Cayirli T, Yang KK (2014) A Universal Appointment Rule with Patient Classification for Service Times, No-Shows, and Walk-Ins. *Serv. Sci.* 6(4):274–295.

Chalfin DB, Trzeciak S, Likourezos A, Baumann BM, Dellinger RP (2007) Impact of delayed transfer of critically ill patients from the emergency department to the intensive care unit*. *Crit. Care Med.* 35(6):1477–1483.

Chan CW, Farias VF, Bambos N, Escobar GJ (2012) Optimizing intensive care unit discharge decisions with patient readmissions. *Oper. Res.* 60(6):1323–1341.

Chan CW, Farias VF, Escobar GJ (2017) The impact of delays on service times in the intensive care unit. *Manage. Sci.* 63(7):2049–2072.

Chan CW, Green L V., Lekwijit S, Lu L, Escobar G (2019) Assessing the impact of service level when customer needs are uncertain: An empirical investigation of hospital step-down units. *Manage. Sci.* 65(2):751–775.

Chang CL, Chen CH (2009) Applying decision tree and neural network to increase quality of dermatologic diagnosis. *Expert Syst. Appl.* 36(2 PART 2):4035–4041.

Chapman SN, Carmel JI (1992) Demand/capacity management in health care: an application of yield management. *Health Care Manage. Rev.* 17(4):45–54. http://www.ncbi.nlm.nih.gov/pubmed/1428858.

Charlson ME, Pompei P, Ales KL, MacKenzie CR (1987) A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. *J. Chronic Dis.* 40(5):373–383.

Choi K, Chung S, Rhee H, Suh Y (2010) Classification and sequential pattern analysis for improving managerial efficiency and providing better medical service in public healthcare centers. *Healthc. Inform. Res.* 16(2):67–76.

Chrusch CA, Olafson KP, McMillan PM, Roberts DE, Gray PR (2009) High occupancy increases the risk of early death or readmission after transfer from intensive care *. *Crit. Care Med.* 37(10):2753–2758.

Cochran JK, Bharti A (2006) A multi-stage stochastic methodology for whole hospital bed planning under peak loading. *Int. J. Ind. Syst. Eng.* 1(1/2):8.

Cochran JK, Roche K (2008) A queuing-based decision support methodology to estimate hospital inpatient bed demand. *J. Oper. Res. Soc.* 59(11):1471–1482.

Cohen ER, Feinglass J, Barsuk JH, Barnard C, O'Donnell A, McGaghie WC, Wayne DB (2010) Cost Savings From Reduced Catheter-Related Bloodstream Infection After Simulation-Based Education for Residents in a Medical Intensive Care Unit. *Simul. Healthc. J. Soc. Simul. Healthc.* 5(2):98–102.

Cook NL, Hicks LS, O'Malley AJ, Keegan T, Guadagnoli E, Landon BE (2007) Access to specialty care and medical services in community health centers. *Health Aff.* 26(5):1459–1468.

Corwin HL, Surgenor SD, Morgan R, Reeves SA (2005) Impact of Icu and Step-Down Unit Organization on Utilization of Critical Care Resources. *Crit. Care Med.* 33:A25.

Cosma Shalizi (2013) *Advanced data analysis from an elementary point of view* (Citeseer).

Costa AX, Ridley SA, Shahani AK, Harper PR, De Senna V, Nielsen MS (2003) Mathematical modelling and simulation for planning critical care capacity. *Anaesthesia* 58(4):320–327.

Crilly JL, Boyle J, Jessup M, Wallis M, Lind J, Green D, FitzGerald G (2015) The implementation and evaluation of the patient admission prediction tool: Assessing its impact on decision-making strategies and patient flow outcomes in 2 australian hospitals. *Qual. Manag. Health Care* 24(4):169–176.

Daggy J, Lawley M, Willis D, Thayer D, Suelzer C, Delaurentis PC, Turkcan A, Chakraborty S, Sands L (2010) Using no-show modeling to improve clinic performance. *Health Informatics J.* 16(4):246–259.

Dai JG, Shi P (2019) Inpatient Overflow: An Approximate Dynamic Programming Approach. *Manuf. Serv. Oper. Manag.*:msom.2018.0730.

Delias P, Doumpos M, Grigoroudis E, Manolitzas P, Matsatsinis N (2015) Supporting healthcare management decisions via robust clustering of event logs. *Knowledge-Based Syst.* 84:203–213.

Demeere N, Stouthuysen K, Roodhooft F (2009) Time-driven activity-based costing in an outpatient clinic environment: Development, relevance and managerial impact. *Health Policy (New. York).* 92(2–3):296–304.

Deslauriers S, Raymond MH, Laliberté M, Lavoie A, Desmeules F, Feldman DE, Perreault K (2017) Access to publicly funded outpatient physiotherapy services in Quebec: waiting lists and management strategies. *Disabil. Rehabil.* 39(26):2648–2656.

Dexter F, Epstein RH, Marcon E, De Matta R (2005) Strategies to reduce delays in admission into a postanesthesia care unit from operating rooms. *J. Perianesthesia Nurs.* 20(2):92–102.

Diwas Singh KC, Scholtes S, Terwiesch C (2020) Empirical research in healthcare operations: Past research, present understanding, and future opportunities. *Manuf. Serv. Oper. Manag.* 22(1):73–83.

Dowd B, Karmarker M, Swenson T, Parashuram S, Kane R, Coulam R, Jeffery MM (2014) Emergency Department Utilization as a Measure of Physician Performance. *Am. J. Med. Qual.* 29(2):135–143.

Drew A. Linzer, Jefrey B. Lewis (2011) poLCA: An R Package for Polytomous Variable Latent Class Analysis. *J. Stat. Softw.* 42(10).

Edbrooke DL, Minelli C, Mills GH, Iapichino G, Pezzi A, Corbella D, Jacobs P, et al. (2011) Implications of ICU triage decisions on patient mortality: A cost-effectiveness analysis. *Crit. Care* 15(1).

Eilers GM (2004) Improving patient satisfaction with waiting time. *J. Am. Coll. Heal.* 53(1):41–48.

El-Sharo M, Zheng B, Yoon SW, Khasawneh MT (2015) An overbooking scheduling model for outpatient appointments in a multi-provider clinic. *Oper. Res. Heal. Care* 6:1–10.

Elkhuizen SG, Das SF, Bakker PJM, Hontelez JAM (2007) Using computer simulation to reduce access time for outpatient departments. *Qual. Saf. Heal. Care* 16(5):382–386.

Englander H, Weimer M, Solotaroff R, Nicolaidis C, Chan B, Velez C, Noice A, et al. (2017) Planning and designing the improving addiction care team (IMPACT) for hospitalized adults with substance use disorder. *J. Hosp. Med.* 12(5):339–342.

Eriksson CO, Stoner RC, Eden KB, Newgard CD, Guise JM (2017) The Association Between Hospital Capacity Strain and Inpatient Outcomes in Highly Developed Countries: A Systematic Review. *J. Gen. Intern. Med.* 32(6):686–696.

Feng YY, Wu IC, Chen TL (2017) Stochastic resource allocation in emergency departments with a multi-objective simulation optimization algorithm. *Health Care Manag. Sci.* 20(1):55–75.

Fernando SM, Bagshaw SM, Rochwerg B, McIsaac DI, Thavorn K, Forster AJ, Tran A, et al. (2019) Comparison of outcomes and costs between adult diabetic ketoacidosis patients admitted to the ICU and step-down unit. *J. Crit. Care* 50:257–261.

Ferrand YB, Magazine MJ, Rao US (2014) Partially Flexible Operating Rooms for Elective and Emergency Surgeries. *Decis. Sci.* 45(5):819–847.

Ferrat E, Audureau E, Paillaud E, Liuu E, Tournigand C, Lagrange JL, Canoui-Poitrine F, Caillet P, Bastuji-Garin S (2016) Four distinct health profiles in older patients with cancer: Latent class analysis of the prospective elcapa cohort. *Journals Gerontol. - Ser. A Biol. Sci. Med. Sci.* 71(12):1653–1660.

Ferrer RL (2007) Pursuing equity: Contact with primary care and specialist clinicians by demographics, insurance, and health status. *Ann. Fam. Med.* 5(6):492–502.

Fetter RB, Freeman JL (1986) Diagnosis related groups: product line management within hospitals. *Acad. Manage. Rev.* 11(1):41–54.

Fetter RB, Shin Y, Freeman JL, Averill RF, Thompson JD (1980) Case mix definition by diagnosis-related groups. *Med. Care* 18(Suppl 2):1–53.

Fogarty C, Cronin P (2008) Waiting for healthcare: A concept analysis. *J. Adv. Nurs.* 61(4):463–471.

Fop M, Murphy TB (2018) Variable selection methods for model-based clustering. *Stat. Surv.* 12:18–65.

Fop M, Smart KM, Murphy TB (2017) Variable selection for latent class analysis with application to low back pain diagnosis. *Ann. Appl. Stat.* 11(4):2080–2110.

Foy R, Hempel S, Rubenstein L, Suttorp M, Seelig M, Shanman R, Shekelle PG (2010) Meta-analysis: Effect of interactive communication between collaborating primary care physicians and specialists. *Ann. Intern. Med.* 152(4):247–258.

Freeman M, Savva N, Scholtesa S (2017) Gatekeepers at work: An empirical analysis of a maternity unit. *Manage. Sci.* 63(10):3147–3167.

Froehle CM, Magazine MJ (2013) Improving Scheduling and Flow in Complex Outpatient Clinics. *Handb. Healthc. Oper. Manag.* 229–250.

Funkner AA, Yakovlev AN, Kovalchuk S V. (2017) Towards evolutionary discovery of typical clinical pathways in electronic health records. *Procedia Comput. Sci.* 119:234–244.

G S (1978) “Estimating the Dimension of a Model.” *Ann. Stat.* 6(2):461–464.

Garcia C dos S, Meincheim A, Faria Junior ER, Dallagassa MR, Sato DMV, Carvalho DR, Santos EAP, Scalabrin EE (2019) Process mining techniques and applications – A systematic mapping study. *Expert Syst. Appl.* 133:260–295.

Gershengorn HB, Chan CW, Xu Y, Sun H, Levy R, Armony M, Gong MN (2020) The Impact of Opening a Medical Step-Down Unit on Medically Critically Ill Patient Outcomes and Throughput: A Difference-in-Differences Analysis. *J. Intensive Care Med.* 35(5):425–437.

Gigantesco A, De Girolamo G, Santone G, Miglio R, Picardi A (2009) Long-stay in short-stay inpatient facilities: Risk factors and barriers to discharge. *BMC Public Health* 9(1):306.

Glowacka KJ, Henry RM, May JH (2009) A hybrid data mining/simulation approach for modelling outpatient no-shows in clinic scheduling. *J. Oper. Res. Soc.* 60(8):1056–1068.

Goldfield N (2010) The evolution of diagnosis-related groups (DRGs): From its beginnings in case-mix and resource use theory, to its implementation for payment and now for its current utilization for quality within and outside the hospital. *Qual. Manag. Health Care* 19(1):3–16.

Gorunescu F, Millard PH, McClean SI (2002) A queueing model for bed-occupancy management and planning of hospitals. *J. Oper. Res. Soc.* 53(1):19–24.

Grafe CJ, Horth RZ, Clayton N, Dunn A, Forsythe N (2020) How to Classify Super-Utilizers: A Methodological Review of Super-Utilizer Criteria Applied to the Utah Medicaid Population, 2016-2017. *Popul. Health Manag.* 23(2):165–173.

Green L (2006) Queueing analysis in healthcare; patient flow: Reducing delay in healthcare delivery. (Springer New York), 281–307.

Green L V. (2002) How Many Hospital Beds? *Inq. J. Heal. Care Organ. Provision, Financ.* 39(4):400–412.

Green L V. (2006) Capacity Planning and Management in Hospitals. *Oper. Res. Heal. Care*. (Kluwer Academic Publishers, Boston), 15–41.

Green L V, Nguyen V (2001) Strategies for cutting hospital beds: the impact on patient service. *Health Serv. Res.* 36(2):421–42.

Guerriero F, Guido R (2011) Operational research in the management of the operating theatre: A survey. *Health Care Manag. Sci.* 14(1):89–114.

Guest M (2017) Patient transfer from the intensive care unit to a general ward. *Nurs. Stand.* 32(10):45–51.

Günal MM, Pidd M (2010) Discrete event simulation for performance modelling in health care: A review of the literature. *J. Simul.* 4(1):42–51.

Gupta D, Natarajan MK, Gafni A, Wang L, Shilton D, Holder D, Yusuf S (2007) Capacity planning for cardiac catheterization: A case study. *Health Policy (New. York).* 82(1):1–11.

Halpern NA, Bettes L, Greenstein R (1994) Federal and nationwide intensive care units and healthcare costs: 1986-1992. *Crit. Care Med.* 22(12):2001–2007. https://insights.ovid.com/crossref?an=00003246-199412000-00019.

Halpern NA, Pastores SM, Thaler HT, Greenstein RJ (2006) Changes in critical care beds and occupancy in the United States 1985-2000: Differences attributable to hospital size. *Crit. Care Med.* 34(8):2105–2112.

Harper PR (2002) A framework for operational modelling of hospital resources. *Health Care Manag. Sci.* 5(3):165–173.

Harper PR, Shahani AK (2002) Modelling for the planning and management of bed capacities in hospitals. *J. Oper. Res. Soc.* 53(1):11–18.

Hasan I, Bahalkeh E, Yih Y (2020) Evaluating intensive care unit admission and discharge policies using a discrete event simulation model. *Simulation* 96(6):501–518.

Hashim MJ (2020) Provision of primary care by specialist physicians: A systematic review. *Fam. Med. Community Heal.* 8(1):e000247.

Hastings SN, Whitson HE, Sloane R, Landerman LR, Horney C, Johnson KS (2014) Using the Past to Predict the Future: Latent Class Analysis of Patterns of Health Service Use of Older Adults in the Emergency Department. *J. Am. Geriatr. Soc.* 62(4):711–715.

He L, Chalil Madathil S, Oberoi A, Servis G, Khasawneh MT (2019) A systematic review of research design and modeling techniques in inpatient bed management. *Comput. Ind. Eng.* 127:451–466.

Heincelman M, Schumann SO, Riley J, Zhang J, Marsden JE, Mauldin PD, Rockey DC (2016) Identification of High Utilization Inpatients on Internal Medicine Services. *Am. J. Med. Sci.* 352(1):63–70.

Hejl A, Høgh P, Waldemar G (2002) Potentially reversible conditions in 1000 consecutive memory clinic patients. *J. Neurol. Neurosurg. Psychiatry* 73(4):390–394.

Helm JE, Ahmadbeygi S, Van Oyen MP (2011) Design and analysis of hospital admission control for operational effectiveness. *Prod. Oper. Manag.* 20(3):359–374.

Helm JE, Van Oyen MP (2014) Design and Optimization Methods for Elective Hospital Admission. 62(6):1265–1282.

Hick JL, Christian MD, Sprung CL (2010) Chapter 2. Surge capacity and infrastructure considerations for mass critical care. *Intensive Care Med.* 36(SUPPL. 1):11–20.

Higginson I, Whyatt J, Silvester K (2011) Demand and capacity planning in the emergency department: How to do it. *Emerg. Med. J.* 28(2):128–135.

Hillier FS, Editor S, The N, Of P, Chain S, Where M (2006) *Patient Flow: Reducing Delay in Healthcare Delivery* Hall RW, ed. (Springer US, Boston, MA).

Hodges JR, Berrios GE, Breen K (2010) The multidisciplinary memory clinic approach. Berrios GE, Hodges JR, eds. *Mem. Disord. Psychiatr. Pract.* (Cambridge University Press, Cambridge), 101–121.

Høgh P, Waldemar G, Knudsen GM, Bruhn P, Mortensen H, Wildschiødtz G, Bech RA, Juhler M, Paulson OB (1999) A multidisciplinary memory clinic in a neurological setting: Diagnostic evaluation of 400 consecutive patients. *Eur. J. Neurol.* 6(3):279–288.

Howell E, Bessman E, Kravet S, Kolodner K, Marshall R, Wright S (2007) Improving patient care. Active bed management by hospitalists and emergency department throughput.

Hripcsak G, Albers DJ (2013) Next-generation phenotyping of electronic health records. *J. Am. Med. Informatics Assoc.* 20(1):117–121.

Hsia RY, Niedzwiecki M (2017) Avoidable emergency department visits: A starting point. *Int. J. Qual. Heal. Care* 29(5):642–645.

Huang Y, Hanauer DA (2014) Patient no-show predictive model development using multiple data sources for an effective overbooking approach. *Appl. Clin. Inform.* 5(3):836–860.

Huang Z, Lu X, Duan H (2011) Mining association rules to support resource allocation in business process management. *Expert Syst. Appl.* 38(8):9483–9490.

Hulshof PJH (2013) *Integrated Decision Making in Healthcare*

Hulshof PJH, Kortbeek N, Boucherie RJ, Hans EW, Bakker PJM (2012) Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS. *Heal. Syst.* 1(2):129–175.

Iwata H, Hirano S, Tsumoto S (2014) Construction of clinical pathway based on similarity-based mining in hospital information system. *Procedia Comput. Sci.* 31:1107–1115.

J. Morrice D, F. Bard J, M. Koenig K (2019) Designing and scheduling a multi-disciplinary integrated practice unit for patient-centred care. *Heal. Syst.*:1–24.

Jaeker JAB, Tucker AL (2017) Past the point of speeding up: The negative effects of workload saturation on efficiency and patient severity. *Manage. Sci.* 63(4):1042–1062.

Jiang B, Tang J, Yan C (2017) Outpatient capacity allocation considering adding capacity to match high patient demand. *J. Syst. Sci. Syst. Eng.* 26(4):487–516.

Johannessen KA, Alexandersen N (2018) Improving accessibility for outpatients in specialist clinics: Reducing long waiting times and waiting lists with a simple analytic approach. *BMC Health Serv. Res.* 18(1):827.

Johnston KJ, Allen L, Melanson TA, Pitts SR (2017) A “Patch” to the NYU Emergency Department Visit Algorithm. *Health Serv. Res.* 52(4):1264–1276.

Kaier K, Mutters NT, Frank U (2012) Bed occupancy rates and hospital-acquired infections-should beds be kept empty? *Clin. Microbiol. Infect.* 18(10):941–945.

Kane BYJ (2012) Health Costs: How the U.S. Compares With Other Countries. *PBS News Hour* 22:1–18.

Kang J, Ciecierski CC, Malin EL, Carroll AJ, Gidea M, Craft LL, Spring B, Hitsman B (2014) A latent class analysis of cancer risk behaviors among U.S. college students. *Prev. Med. (Baltim).* 64:121–125.

Kc DS, Terwiesch C (2009) Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Manage. Sci.* 55(9):1486–1498.

Kelarev A V., Stranieri A, Yearwood JL, Jelinek HF (2012) Empirical study of decision trees and ensemble classifiers for monitoring of diabetes patients in pervasive healthcare. *Proc. 2012 15th Int. Conf. Network-Based Inf. Syst. NBIS 2012*:441–446.

Kelen GD, Kraus CK, McCarthy ML, Bass E, Hsu EB, Li G, Scheulen JJ, Shahan JB, Brill JD, Green GB (2006) Inpatient disposition classification for the creation of hospital surge capacity: a multiphase study. *Lancet* 368(9551):1984–1990.

Kenagy JW, Berwick DM, Shore MF (1999) Service quality in health care. *J. Am. Med. Assoc.* 281(7):661–665.

Khan MU, Choi JP, Shin H, Kim M (2008) Predicting breast cancer survivability using fuzzy decision trees for personalized healthcare. *Proc. 30th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS'08 - "Personalized Healthc. through Technol.*:5148–5151.

Khanna S, Boyle J, Good N, Lind J (2012) Unravelling relationships: Hospital occupancy levels, discharge timing and emergency department access block. *EMA - Emerg. Med. Australas.* 24(5):510–517.

Khorasanian D, Dexter F, Moslehi G (2018) Analyses of the phase I postanesthesia care unit baseline capacity and effect of disruptions to its beds or nurse availability on operating room workflow. *Int. J. Plan. Sched.* 2(4):350.

Kim SH, Chan CW, Olivares M, Escobar GJ (2016) Association among ICU Congestion, ICU Admission Decision, and Patient Outcomes. *Crit. Care Med.* 44(10):1814–1821.

Kim SH, Tong J, Peden C (2020) Admission control biases in hospital unit capacity management: How occupancy information hurdles and decision noise impact utilization. *Manage. Sci.* 66(11):5151–5170.

Kim SH, Vel P, Whitt W, Cha WC (2015) Poisson and non-Poisson properties in appointment-generated arrival processes: The case of an endocrinology clinic. *Oper. Res. Lett.* 43(3):247–253.

Kim SH, Whitt W, Cha WC (2018) A Data-Driven Model of an Appointment-Generated Arrival Process at an Outpatient Clinic. *INFORMS J. Comput.* 30(1):181–199.

Klassen KJ, Rohleder TR (2001) Combining operations and marketing to manage capacity and demand in services. *Serv. Ind. J.* 21(2):1–30.

Klassen KJ, Yoogalingam R (2009) Improving Performance in Outpatient Appointment Services with a Simulation Optimization Approach. *Prod. Oper. Manag.* 18(4):447–458.

Klonsky ED, Olino TM (2008) Identifying Clinically Distinct Subgroups of Self-Injurers Among Young Adults: A Latent Class Analysis. *J. Consult. Clin. Psychol.* 76(1):22–27.

Knopman D, Donohue JA, Gutterman EM (2000) Patterns of Care in the Early Stages of Alzheimer's Disease: Impediments to Timely Diagnosis. *J. Am. Geriatr. Soc.* 48(3):300–304.

Kolker A (2009) Process Modeling of ICU Patient Flow: Effect of Daily Load Leveling of Elective Surgeries on ICU Diversion. *J. Med. Syst.* 33(1):27–40.

Kortbeek N, Braaksma A, Smeenk FHF, Bakker PJM, Boucherie RJ (2015) Integral resource capacity planning for inpatient care services based on bed census predictions by hour. *J. Oper. Res. Soc.* 66(7):1061–1076.

Kortbeek N, van der Velde MF, Litvak N (2017) Organizing multidisciplinary care for children with neuromuscular diseases at the Academic Medical Center, Amsterdam. *Heal. Syst.* 6(3):209–225.

Kouroukis T, Ratcliffe J, Running K, Sussman J (2017) Developing and evaluating new models of care in hematology. *J. Clin. Oncol.* 35(8_suppl):53–53.

Kritchanchai D, Hoeur S (2018) Simulation modeling for facility allocation of outpatient department. *Int. J. Healthc. Manag.* 11(3):193–201.

Kuntz L, Mennicken R, Scholtes S (2015) Stress on the ward: Evidence of safety tipping points in hospitals. *Manage. Sci.* 61(4):754–771.

Laganga LR, Lawrence SR (2007) Clinic overbooking to improve patient access and increase provider productivity. *Decis. Sci.* 38(2):251–276.

Laganga LR, Lawrence SR (2012) Appointment overbooking in health care clinics to improve patient service and clinic performance. *Prod. Oper. Manag.* 21(5):874–888.

LaGanga LR, Lawrence SR (2012) Appointment Overbooking in Health Care Clinics to Improve Patient Service and Clinic Performance. *Prod. Oper. Manag.* 21(5):874–888.

Land T (2020) Ambulatory Networks: Innovating and Transforming Healthcare Delivery. *Front. Health Serv. Manage.* 37(2):1–2.

Landon BE, Wilson IB, McInnes K, Landrum MB, Hirschhorn LR, Marsden P V., Cleary PD (2005) Physician specialization and the quality of care for human immunodeficiency virus infection. *Arch. Intern. Med.* 165(10):1133–1139.

Lane BH, Mallow PJ, Hooker MB, Hooker E (2020) Trends in United States emergency department visits and associated charges from 2010 to 2016. *Am. J. Emerg. Med.* 38(8):1576–1581.

Lantz PM (2020) "Super-Utilizer" Interventions: What They Reveal About Evaluation Research, Wishful Thinking, and Health Equity. *Milbank Q.* 98(1):31–34.

Lee HK, Li J, Musa AJ, Bain PA (2016) A Markov chain model to evaluate patient transitions in small community hospitals. *Autom. Sci. Eng. (CASE), 2016 IEEE Int. Conf.* (vii):675–680.

Lee HK, Musa AJ, Bain PA, Nelson K, Baker C, Li J (2019) A Queueing Network Model for Analysis of Patient Transitions Within Hospitals. *IEEE Trans. Autom. Sci. Eng.* 16(1):6–20.

Lee L, Hillier LM, McKinnon Wilson J, Gregg S, Fathi K, Sturdy Smith C, Smith M (2018) Effect of Primary Care-Based Memory Clinics on Referrals to and Wait-Time for Specialized Geriatric Services. *J. Am. Geriatr. Soc.* 66(3):631–632.

Leeftink AG, Bikker IA, Vliegen IMH, Boucherie RJ (2018) Multi-disciplinary planning in health care: a review. *Heal. Syst.*:1–24.

Leeftink AG, Vliegen IMH, Hans EW (2019) Stochastic integer programming for multi-disciplinary outpatient clinic planning. *Health Care Manag. Sci.* 22(1):53–67.

Lehmann TNO, Aebi A, Lehmann D, Balandraux Olivet M, Stalder H (2007) Missed appointments at a Swiss university outpatient clinic. *Public Health* 121(10):790–799.

Leifer BP (2003) Early Diagnosis of Alzheimer's Disease: Clinical and Economic Benefits. *J. Am. Geriatr. Soc.* 51(5s2):S281–S288.

Li L, Benton W. (2003) Hospital capacity management decisions: Emphasis on cost control and quality enhancement. *Eur. J. Oper. Res.* 146(3):596–614.

Li X, Beullens P, Jones D, Tamiz M (2009) An integrated queuing and multi-objective bed allocation model with application to a hospital in China. *J. Oper. Res. Soc.* 60(3):330–338.

Lismont J, Janssens AS, Odnoletkova I, vanden Broucke S, Caron F, Vanthienen J (2016) A guide for the application of analytics on healthcare processes: A dynamic view on patient pathways. *Comput. Biol. Med.* 77:125–134.

Liss DT, Chubak J, Anderson ML, Saunders KW, Tuzzio L, Reid RJ (2011) Patient-reported care coordination: Associations with primary care continuity and specialty care use. *Ann. Fam. Med.* 9(4):323–329.

Liu N, Ziya S, Kulkarni VG (2010) Dynamic Scheduling of Outpatient Appointments Under Patient No-Shows and Cancellations. *Manuf. Serv. Oper. Manag.* 12(2):347–364.

Long EF, Mathews KS (2018) The Boarding Patient: Effects of ICU and Hospital Occupancy Surges on Patient Flow. *Prod. Oper. Manag.* 27(12):2122–2143.

Luyt CE, Combes A, Aegerter P, Guidet B, Trouillet JL, Gibert C, Chastre J (2007) Mortality among patients admitted to intensive care units during weekday day shifts compared with "off" hours. *Crit. Care Med.* 35(1):3–11.

M.F. L, W.T. S, Y.W. Y, See K.C. AO - Liew MFO http://orcid. org/000. 0002 8880 004X (2020) Safe patient transport for COVID-19. *Crit. Care* 24(1):94.

Madraki G, Bahalkeh E, Judd R (2015) Efficient algorithm to find makespan under perturbation in operation times. *IIE Annu. Conf. Expo 2015*. (Institute of Industrial and Systems Engineers (IISE)), 1474–1481.

Mans R, Schonenberg H, Leonardi G, Panzarasa S, Cavallini A, Quaglini S, Aalst W van der (2008) Process mining techniques: An application to stroke care. *Stud. Health Technol. Inform.* 136:573–578.

Mans RS, van der Aalst WMP, Vanwersch RJB (2015) *Process Mining in Healthcare* (Springer International Publishing, Cham).

Marcon E, Kharraja S, Smolski N, Luquet B, Viale JP (2003) Determining the number of beds in the postanesthesia care unit: A computer simulation flow approach. *Anesth. Analg.* 96(5):1415–1423.

Marlene Gyldmark CP (1995) A review of cost studies of intensive care units. *Crit. Care Med.* 23(5):964–972.

Martin Prodel, Vincent Augusto, Xie X (2013) Hospitalization Admission Control of Emergency Patients Using Markovian Decision Processes and Discrete Event Simulation. *Proc. 2014 Winter Simul. Conf.*:1433–1444.

Mathews KS, Long EF (2015a) A conceptual framework for improving critical care patient flow and bed use. *Ann. Am. Thorac. Soc.* 12(6):886–894.

Mathews KS, Long EF (2015b) A conceptual framework for improving critical care patient flow and bed use. *Ann. Am. Thorac. Soc.* 12(6):886–894.

Mayer ML (2008) Disparities in geographic access to pediatric subspecialty care. *Matern. Child Health J.* 12(5):624–632.

Mayfiel J, Reiber G, Sanders L, Janisse D, Pogach L (1998) Preventive Foot Care in People With Diabetes. *Diabetes Care* 21(12):2178–2179.

McConnell KJ, Richards CF, Daya M, Bernell SL, Weathers CC, Lowe RA (2005) Effect of increased ICU capacity on emergency department length of stay and ambulance diversion. *Ann. Emerg. Med.* 45(5):471–478.

Mehrotra A, Forrest CB, Lin CY (2011) Dropping the baton: Specialty referrals in the United States. *Milbank Q.* 89(1):39–68.

Mehrotra A, Keehl-Markowitz L, Ayanian JZ (2008) Implementing open-access scheduling of visits in primary care practices: A cautionary tale. *Ann. Intern. Med.* 148(12):915–922.

Melnykov V, Maitra R (2010) Finite mixture models and model-based clustering. *Stat. Surv.* 4(none):80–116.

Moore CG, Wilson-Witherspoon P, Probst JC (2001) Time and money: Effects of no-shows at a family practice residency clinic. *Fam. Med.* 33(7):522–527.

Mutlu S, Benneyan J, Terrell J, Jordan V, Turkcan A (2015) A co-availability scheduling model for coordinating multi-disciplinary care teams. *Int. J. Prod. Res.* 53(24):7226–7237.

Naghib S, Van Der Starre C, Gischler SJ, Joosten KFM, Tibboel D (2010) Mortality in very long-stay pediatric intensive care unit patients and incidence of withdrawal of treatment. *Intensive Care Med.* 36(1):131–136.

Naiker U, FitzGerald G, Dulhunty JM, Rosemann M (2018) Time to wait: A systematic review of strategies that affect out-patient waiting times. *Aust. Heal. Rev.* 42(3):286–293.

Najjar A, Reinharz D, Girouard C, Gagné C (2018) A two-step approach for mining patient treatment pathways in administrative healthcare databases. *Artif. Intell. Med.* 87:34–48.

NEJM Catalyst (2017) What Is Patient-Centered Care? *NEJM Catal.*:1–6.

Ng SHX, Rahman N, Ang IYH, Sridharan S, Ramachandran S, Wang DD, Tan CS, Toh SA, Tan XQ (2019) Characterization of high healthcare utilizer groups using administrative data from an electronic medical record database. *BMC Health Serv. Res.* 19(1):452.

Nguyen TBT, Sivakumar AI, Graves SC (2015) A network flow approach for tactical resource planning in outpatient clinics. *Health Care Manag. Sci.* 18(2):124–136.

O'Neill S, Calderon S, Casella J, Wood E, Carvelli-Sheehan J, Zeidel ML (2012) Improving outpatient access and patient experiences in academic ambulatory care. *Acad. Med.* 87(2):194–199.

Oseran AS, Lage DE, Jernigan MC, Metlay JP, Shah SJ (2019) A "Hospital-Day-1" Model to Predict the Risk of Discharge to a Skilled Nursing Facility. *J. Am. Med. Dir. Assoc.* 20(6):689–695.e5.

Pagnoni A, Parisi S, Lombardo S (2001) Analysis of patient flows via data mining. *Stud. Health Technol. Inform.* 84:1379–1383.

Parikh A, Gupta K, Wilson AC, Fields K, Cosgrove NM, Kostis JB (2010) The Effectiveness of Outpatient Appointment Reminder Systems in Reducing No-Show Rates. *Am. J. Med.* 123(6):542–548.

Patterson B, Marks M, Martinez-Garcia G, Bidwell G, Luintel A, Ludwig D, Parks T, et al. (2020) A novel cohorting and isolation strategy for suspected COVID-19 cases during a pandemic. *J. Hosp. Infect.* 105(4):632–637.

Peterson CL, Burton R (2009) The U.S. health care spending: comparisons with other OECD countries. *Choice Rev. Online* 46(05):46-2795-46–2795.

Pettengill J, Vertrees J (1982) Reliability and validity in hospital case-mix measurement. *Health Care Financ. Rev.* 4(2):101–128.

Pham JC, Patel R, Millin MG, Kirsch TD, Chanmugam A (2006) The Effects of Ambulance Diversion: A Comprehensive Review. *Acad. Emerg. Med.* 13(11):1220–1227.

Pizer SD, Prentice JC (2011) What are the consequences of waiting for health care in the veteran population? *J. Gen. Intern. Med.* 26 Suppl 2(S2):676–682.

Polito A, Combescure C, Levy-Jamet Y, Rimensberger P (2019) Long-stay patients in pediatric intensive care unit: Diagnostic-specific definition and predictors Ehrman R, ed. *PLoS One* 14(10):e0223369.

Ponis ST, Delis A, Gayialis SP, Kasimatis P, Tan J (2013) Applying discrete event simulation (DES) in healthcare: The case for outpatient facility capacity planning. *Int. J. Healthc. Inf. Syst. Informatics* 8(3):58–79.

Porcu M, Giambona F (2017) Introduction to Latent Class Analysis With Applications. *J. Early Adolesc.* 37(1):129–158.

Prentice JC, Pizer SD (2007) Delayed access to health care and mortality. *Health Serv. Res.* 42(2):644–662.

Prin M, Wunsch H (2014) The role of stepdown beds in hospital care. *Am. J. Respir. Crit. Care Med.* 190(11):1210–1216.

Quentin W, Scheller-Kreinsen D, Geissler A, Busse R (2012) Appendectomy and diagnosis-related groups (DRGs): Patient classification and hospital reimbursement in 11 European countries. *Langenbeck's Arch. Surg.* 397(2):317–326.

Ratcliffe A, Gilland W, Marucheck A (2012) Revenue management for outpatient appointments: Joint capacity control and overbooking with class-dependent no-shows. *Flex. Serv. Manuf. J.* 24(4):516–548.

Rau CL, Tsai PFJ, Liang SFM, Tan JC, Syu HC, Jheng YL, Ciou TS, Jaw FS (2013) Using discrete-event simulation in strategic capacity planning for an outpatient physical therapy service. *Health Care Manag. Sci.* 16(4):352–365.

Rebuge Á, Ferreira DR (2012) Business process analysis in healthcare environments: A methodology based on process mining. *Inf. Syst.* 37(2):99–116.

Reeve H, Baxter K, Newton P, Burkey Y, Black M, Roland M (1997) Long-term follow-up in outpatient clinics. 1: The view from general practice. *Fam. Pract.* 14(1):24–28.

Reid M, Cohen S, Wang H, Kaung A, Patel A, Tashjian V, Williams DL, Martinez B, Spiegel BMR (2015) Preventing patient absenteeism: Validation of a predictive overbooking model. *Am. J. Manag. Care* 21(12).

Van Riet C, Demeulemeester E (2015) Trade-offs in operating room planning for electives and emergencies: A review. *Oper. Res. Heal. Care* 7:52–69.

Rodrigues F, Zaric GS, Stanford DA (2018) Discrete event simulation model for planning Level 2 "step-down" bed needs using NEMS. *Oper. Res. Heal. Care* 17:42–54.

Rodríguez-Carvajal M, Mora D, Doblas A, García M, Domínguez P, Tristancho A, Herrera M (2011) Impact of the premature discharge on hospital mortality after a stay in an intensive care unit. *Med. Intensiva (English Ed.* 35(3):143–149.

Rojas E, Munoz-Gama J, Sepúlveda M, Capurro D (2016) Process mining in healthcare: A literature review. *J. Biomed. Inform.* 61:224–236.

Saghafian S, Austin G, Traub SJ (2015) Operations research/management contributions to emergency department patient flow optimization: Review and research prospects. *IIE Trans. Healthc. Syst. Eng.* 5(2):101–123.

Salzarulo PA, Mahar S, Modi S (2016) Beyond patient classification: Using individual patient characteristics in appointment scheduling. *Prod. Oper. Manag.* 25(6):1056–1072.

Schafermeyer RW, Asplin BR (2003) Hospital and emergency department crowding in the United States. *Emerg. Med. (Fremantle).* 15(1):22–7.

Schilling PL, Campbell DA, Englesbe MJ, Davis MM (2010) A comparison of in-hospital mortality risk conferred by high hospital occupancy, differences in nurse staffing levels, weekend admission, and seasonal influenza. *Med. Care* 48(3):224–232.

Schmidt A, Bachner F, Rainer L, Zuba M, Bobek J, Lepuschütz L, Ostermann H, Winkelmann J, Quentin W (2018) Ambulatory care on the rise? Lessons from the Austrian health care reforms. *Eurohealth (Lond).* 24(4):21–24.

Schoen C, Osborn R, Squires D, Doty M, Pierson R, Applebaum S (2011) New 2011 survey of patients with complex care needs in eleven countries finds that care is often poorly coordinated. *Health Aff.* 30(12):2427–2436.

Schroeder SA (2007) We can do better - Improving the health of the American people. *N. Engl. J. Med.* 357(12):1221–1228.

Schwarz G (1978) “Estimating the Dimension of a Model.” *Ann. Stat.* 6(2):461–464.

Shaikh SA, Robinson RD, Cheeti R, Rath S, Cowden CD, Rosinia F, Zenarosa NR, Wang H (2018) Risks predicting prolonged hospital discharge boarding in a regional acute care hospital. *BMC Health Serv. Res.* 18(1).

Shao X, Li J, Wiegmann DA (2013) A Markov chain approach to study flow disruptions on surgery in emergency care. *2013 IEEE Int. Conf. Autom. Sci. Eng.*:990–995.

Shi P, Chou MC, Dai JG, Ding D, Sim J (2015) Models and Insights for Hospital Inpatient Operations: Time-Dependent ED Boarding Time. *Manage. Sci.* (May):150422112841002.

Shi P, Helm J, Deglise-Hawkinson J, Pan J (2018) Timing it Right: Balancing Inpatient Congestion Versus Readmission Risk at Discharge. *SSRN Electron. J.*

Shoaib M, Prabhakar U, Mahlawat S, Ramamohan V (2020) A discrete-event simulation model of the kidney transplantation system in Rajasthan, India. *Heal. Syst.*

Singh KCD, Terwiesch C (2012) An econometric analysis of patient flows in the cardiac intensive care unit. *Manuf. Serv. Oper. Manag.* 14(1):50–65.

Slade EP, Dixon LB, Semmel S (2010) Trends in the duration of emergency department visits, 2001-2006. *Psychiatr. Serv.* 61(9):878–884.

Song H, Tucker AL, Graue R, Moravick S, Yang JJ (2019) Capacity Pooling in Hospitals: The Hidden Consequences of Off-Service Placement. *Manage. Sci.*:mnsc.2019.3395.

Song H, Tucker AL, Graue R, Moravick S, Yang JJ (2020) Capacity pooling in hospitals: The hidden consequences of off-service placement. *Manage. Sci.* 66(9):3825–3842.

Southern WN, Arnsten JH (2015) Increased Risk of Mortality among Patients Cared for by Physicians with Short Length-of-Stay Tendencies. *J Gen Intern Med* 30(6):712–720.

Staats BR, Gino F (2012) Specialization and variety in repetitive tasks: Evidence from a Japanese bank. *Manage. Sci.* 58(6):1141–1159.

Steorts RC (2009) Tree Based Methods: Classification Trees.

Studnicki J (1991) Measuring service line competitive position. A systematic methodology for hospitals. *Health Prog.* 72(6):68–72.

Survey AN (2014) Transfers of Patient Care Between House Staff on Internal Medicine Wards. 166:1173–1177.

Tan AL, Chiew CJ, Wang S, Abdullah HR, Lam SS, Ong ME, Tan HK, Wong TH (2019) Risk factors and reasons for cancellation within 24 h of scheduled elective surgery in an academic medical centre: A cohort study. *Int. J. Surg.* 66:72–78.

Tan T, Netessine S (2012) When Does the Devil Make Work? An Empirical Study of the Impact of Workload on Worker Productivity. *SSRN Electron. J.*

Tian Y, Xu B, Yu G, Li Y, Liu H (2017) Age-adjusted charlson comorbidity index score as predictor of prolonged postoperative ileus in patients with colorectal cancer who underwent surgical resection. *Oncotarget* 8(13):20794–20801.

Tierney LT, Conroy KM (2014) Optimal occupancy in the ICU: A literature review. *Aust. Crit. Care* 27(2):77–84.

U.S. D of H and HS (2013) *National Ambulatory Medical Care Survey: 2013 State and National Summary Tables*

Valentin A, Ferdinande P (2011) Recommendations on basic requirements for intensive care units: Structural and organizational aspects. *Intensive Care Med.* 37(10):1575–1587.

Vanberkel PT, Blake JT (2007) A comprehensive simulation for wait time reduction and capacity planning applied in general surgery. *Health Care Manag. Sci.* 10(4):373–385.

Verhey FRJ, Jolles J, Ponds RWHM, Rozendaal N, Plugge LA, De Vet RCW, Vreeling FW, Van Der Lugt PJM (1993) Diagnosing dementia: a comparison between a monodisciplinary and a multidisciplinary approach. *J. Neuropsychiatry Clin. Neurosci.* 5(1):78–85.

Vikander T, Parnicky K, Demers R, Frisof K, Chase N (1986) New-patient no-shows in an urban family practice center: Analysis and intervention. *J. Fam. Pract.* 22(3):263–268.

Villa S, Barbieri M, Lega F (2009) Restructuring patient flow logistics around patient care needs: Implications and practicalities from three critical cases. *Health Care Manag. Sci.* 12(2):155–165.

Vitikainen K, Street A, Linna M (2009) Estimation of hospital efficiency-Do different definitions and casemix measures for hospital output affect the results? *Health Policy (New. York).* 89(2):149–159.

Weatherall M, Shirtcliffe P, Travers J, Beasley R (2010) Use of cluster analysis to define COPD phenotypes. *Eur. Respir. J.* 36(3):472–474.

De Weerdt J, Vanden Broucke SKLM, Vanthienen J, Baesens B (2012) Leveraging process discovery with trace clustering and text mining for intelligent analysis of incident management processes. *2012 IEEE Congr. Evol. Comput. CEC 2012*. (IEEE), 1–8.

Weissman JS, Moy E, Campbell EG, Gokhale M, Yucel R, Causino N, Blumenthal D (2003) Limits to the safety net: Teaching hospital faculty report on their patients' access to care. *Health Aff.* 22(6):156–166.

Wild C, Narath M (2005) Evaluating and planning ICUs: Methods and approaches to differentiate between need and demand. *Health Policy (New. York).* 71(3):289–301.

Wolfs CAG, Dirksen CD, Severens JL, Verhey FRJ (2006) The added value of a multidisciplinary approach in diagnosing dementia: A review. *Int. J. Geriatr. Psychiatry* 21(3):223–232.

Woodger O (2017) *New Perspectives on Long Stay Patients in the Pediatric Intensive Care Unit : Definition , Characteristics and Impact*. (Carleton University, Ottawa, Ontario).

Woodger O, Menon K, Yazbeck M, Acharya A (2018) A Pragmatic Method for Identification of Long-Stay Patients in the PICU. *Hosp. Pediatr.* 8(10):636–642.

Wu AW, Young Y, Skinner EA, Diette GB, Huber M, Peres A, Steinwachs D (2001) Quality of care and outcomes of adults with asthma treated by specialists and generalists in managed care. *Arch. Intern. Med.* 161(21):2554–2560.

Xiao Y, Romanelli M, Lindsey MA (2019) A latent class analysis of health lifestyles and suicidal behaviors among US adolescents. *J. Affect. Disord.* 255:116–126.

Yang KK, Lam SSW, Low JMW, Ong MEH (2016) Managing emergency department crowding through improved triaging and resource allocation. *Oper. Res. Heal. Care* 10:13–22.

Yang M, Xie J, Zhang H, Chen Y, Xie S, Peng R, Jia Y, Chen Y, Wang L (2020) Qualitative analyses of the reasons why patients do not attend scheduled inpatient appointments in a hospital in Guangzhou, China. *Risk Manag. Healthc. Policy* 13:2857–2865.

Yoo S, Cho M, Kim E, Kim S, Sim Y, Yoo D, Hwang H, Song M (2016) Assessment of hospital processes using a process mining technique: Outpatient process analysis at a tertiary hospital. *Int. J. Med. Inform.* 88:34–43.

Young-Wolff KC, Hellmuth J, Jaquier V, Swan SC, Connell C, Sullivan TP (2013) Patterns of Resource Utilization and Mental Health Symptoms Among Women Exposed to Multiple Types of Victimization. *J. Interpers. Violence* 28(15):3059–3083.

Yu H, Wang P, Zheng H, Luo J, Liu J (2020) Impacts of congestion on healthcare outcomes: an empirical observation in China. *J. Manag. Anal.* 7(3):344–366.

Zailinawati AH, Ng CJ, Nik-Sherina H (2006) Why do patients with chronic illnesses fail to keep their appointments? A telephone interview. *Asia-Pacific J. Public Heal.* 18(1):10–15.

Zhang X (2018) Application of discrete event simulation in health care: A systematic review. *BMC Health Serv. Res.* 18(1).

Zhu S, Fan W, Yang S, Pei J, Pardalos PM (2019) Operating room planning and surgical case scheduling: a review of literature. *J. Comb. Optim.* 37(3):757–805.

Zimmerman J, Seneff M, Wood S, Alzola C, Wagner D, Draper E (1999) A comparison of outcome and resource use for step-down unit and ICU patients. *Crit. Care Med.* 27(1 SUPPL.):154A.