

Statistical analysis of factors influencing patient length of stay in emergency departments

Mohammed Ba-Aoum

*Department of Industrial and Systems Engineering, Virginia Tech,
Blacksburg, Virginia, USA and*

King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia

Niyousha Hosseinichimeh and Konstantinos P. Triantis

*Department of Industrial and Systems Engineering, Virginia Tech,
Blacksburg, Virginia, USA*

Kalyan Pasupathy

*Department of Biomedical and Health Information Sciences,
University of Illinois at Chicago, Chicago, Illinois, USA, and*

Mustafa Sir and David Nestler

Mayo Clinic, Rochester, Minnesota, USA

Abstract

Purpose – Patient length of stay (LOS) is an important indicator of emergency department (ED) performance. Investigating factors that influence LOS could thus improve healthcare delivery and patient safety. Previous studies have focused on patient-level factors to explain LOS variation, with little research into service-related factors. This study examined the association between LOS and multi-level factors including patient-, service- and organization-level factors.

Design/methodology/approach – This study uses a retrospective observational design to identify a cohort of patients from arrival to discharge from ED. A year-long data regarding patients flow through ED were analyzed using analytics techniques and multi-regression models. The response variable was patient LOS, and the independent variables were patient characteristics, service-related factors and organizational variables.

Findings – The findings of this study showed that older patients, middle triage and hospitalization were all associated with longer LOS. Service-related factors such as complexity of care provided, initial ward designation and ward transfer had a significant impact as well. Finally, prolonged LOS was associated with a higher ratio of patients per medical doctor and per nurse. In contrast, a higher number of residents in the ED were associated with longer patient LOS.

Originality/value – Previous studies on patient LOS have focused on patient-level factors, with little research on service-related factors. This study has addressed that gap by examining the association between LOS and multi-level factors including patient-, service- and organization-level factors. Patient-level factors included demographics, acuity, arrival shift, arrival mode and discharge type. Service-level factors consisted of first ward, ward transfer and complexity of care provided. Organizational factors consisted of three ratios: patients per MD, patients per nurse and patients per resident. The results add to the current understanding of factors that increase patient LOS in EDs and contribute to the body of knowledge on ED performance, operation management and



quality of care. The study also provides practical and managerial insights that could be used to improve patient flow in EDs and reduce LOS.

Keywords Health care systems, Data analytics, Emergency department (ED), Overcrowding, Patient length of stay, Regression model, ED performance, Efficiency, Quality, ED service

Paper type Research paper

1. Introduction

Emergency departments (EDs) ensure that patients have access to treatment around the clock, seven days a week. Unlike visits to a medical clinic, urgent care is typically provided without advance notice, patient arrival rate and volume fluctuate throughout the day and from one day to another, and necessary resources are expensive. Thus, consistent pressure is placed on EDs around the world to improve their operational efficiency. What makes this matter more challenging is a downward trend in the number of EDs in the United States, despite an increase in ED visits. Between 1990 and 2009, the number of urban hospital EDs decreased by 27%, while ED visits increased by 44%; this increase was not solely due to a growing population, as ED visits have increased at a rate disproportionate to population growth (Barish and Arnold, 2012). The trend of hospital closures in the United States has continued in recent years, with an annual average of 21 closures between 2010 and 2015, and 47 closures in 2019. As a result of the COVID-19 pandemic, this trend in closures has accelerated as hospitals have faced financial difficulties, and it is likely that more hospitals will close in the near future (Saghafian *et al.*, 2022). All these challenges contribute to longer patient wait times and an increase in the volume of patients in EDs across the United States. According to a survey by the American Hospital Association, more than 50% of urban and teaching hospitals had EDs that were “at” or “over” capacity (Barish and Arnold, 2012).

The growing demand for emergency services commonly leads to overcrowding in EDs, which is an especially significant challenge facing healthcare delivery systems in the United States and has been described by the Institute of Medicine as a public health crisis (Di Somma *et al.*, 2015; Higginson *et al.*, 2011; Institute of Medicine, 2006). The term “crowding” in this context refers to the condition that arises when the demand for emergency services exceeds the available resources for patient care in a given ED (Crowding, 2006). Overcrowding occurs when the ED’s function is hampered primarily by an excessive number of patients waiting to be seen, undergoing assessment and treatment, or waiting to be discharged compared to the ED’s physical or staffing capacity (Yarmohammadian *et al.*, 2017). It has been demonstrated in prior research that overcrowding in EDs can have a variety of negative effects on the standard of care provided and the safety of patients; for example, it reduces the timeliness of care and increases the likelihood of mortality and morbidity (Hoyle, 2013; Miro *et al.*, 1999). In addition, severe crowding raises the risk of burnout among ED staff (Johnston *et al.*, 2016)—thus leading to wards being more understaffed and suffering from even more overcrowding and burnout—and increases the proportion of patients who arrive but are ultimately not seen by their providers (Rowe *et al.*, 2006; Stock *et al.*, 1994). Furthermore, crowding has various other knock-on effects, such as increasing the overall cost of care by increasing patient length of stay (LOS), which in turn leads to an increase in the likelihood of patient dissatisfaction. It also causes a loss of revenue due to ambulance diversion (Boudreaux and O’Hea, 2004; McHugh *et al.*, 2011). In this way, extreme examples of overcrowding could be considered comparable to a natural disaster based on the resulting harm to health and safety outcomes (Davis *et al.*, 2019).

Patient LOS is an essential indicator of an ED’s performance and has a strong correlation with overcrowding (Forster *et al.*, 2003; Yoon *et al.*, 2003). It refers to the total amount of time a patient spends in an ED, beginning with the patient’s first documented arrival and ending with the patient’s discharge (Forster *et al.*, 2003; Yoon *et al.*, 2003). In spite of the growing attention to factors contributing to patient LOS, there is a scarcity of data describing ED LOS

and associated service-related factors. Previous studies of patient LOS focused primarily on patient-level factors such as demographics, diagnosis and triage severity with sometimes contradictory results, and there is a dearth of research examining the association between LOS and service factors such as type of ward, ward transfers and complexity of care provided (Crossley and Sweeney, 2020; Kreindler *et al.*, 2016). This study addresses these gaps by examining the association between ED patient LOS and multi-level factors including demographic variables (gender and age), contextual factors related to patient arrival mode (walk-in, wheelchair and ambulance), arrival shift and triage diagnosis. Furthermore, from an operational and service viewpoint, the study includes variables that measure the complexity of care provided and the ratio of patients to service providers (medical doctors, nurses and residents) on arrival. The research questions that guided this study are as follows:

- RQ1. What patient-related factors have a significant association with patient length of stay?
- RQ2. What service-related factors have a significant association with patient length of stay?
- RQ3. What organizational factors have a significant association with patient length of stay?

The objective of this study was to examine the association between LOS and multi-level factors including patient-, service- and organization-level factors. Data for this study came from an ED in a large academic medical center in the United States and was analyzed using data analytics techniques and a multivariate regression model. The study hypothesized that a variety of factors, including patient characteristics, service-related factors and organizational factors would influence the LOS of ED patients. Understanding the factors that influence patient LOS could have significant implications for improving the quality of healthcare delivery in an ED and addressing challenges related to overcrowding. This paper adds to the current understanding of factors that increase ED patient LOS and contributes to the body of knowledge on ED performance, operation management, quality of care and patient safety. The study and its results can provide operation managers in EDs and healthcare quality specialists with insights that could be used to reduce LOS and overcrowding. The findings could help design evidence-based interventions to reduce LOS as well as inform operational procedures and improve patient flow in EDs. This work could also serve as a stepping-stone toward developing predictive models of LOS with multi-level factors.

The rest of the study is organized as follows: [Section 2](#) reviews the relevant literature on factors that have a significant association with longer patient LOS. [Section 3](#), the methodology, covers the study setting and design, illustrates data collection and cleaning, and explains the variables chosen for the study and the test used to examine linearity assumptions. [Section 4](#) presents the analysis and results, and [Section 5](#) discusses the findings and compares them to previous research findings. Finally, the conclusion ([Section 6](#)) summarizes the study and discusses its contributions, implications, limitations and recommendations for future research.

2. Literature review

EDs in the United States and around the world are constantly under pressure to improve performance and efficiency in order to respond to an increasing number of patient visits in a timely manner. From acceptance and initial assessment to running tests, prescribing medication and releasing patients to go home, an inpatient unit or an intensive care unit, EDs offer a wide range of services. As a result, several factors influence an ED's performance and the LOS of the patient. Prolonged patient LOS is regarded as an indicator of poor hospital

performance (Pitts *et al.*, 2014) and has been linked to a higher mortality rate (Singer *et al.*, 2011). Thus, improving care timeliness has been one of the primary strategies used over the last decade to reduce overcrowding and improve ED performance (Morley *et al.*, 2018).

A previous major study found that measuring patient wait times at various process stages in the ED—such as time spent in triage, treatment room and discharge—helped with identifying and correcting ED inefficiencies (Smeltzer and Curtis, 1987). More recent studies have identified other possible causes of prolonged LOS such as increased patient attendance, number of consultations, consultation delay and hospital bed shortages for patients needing admission (e.g. Bergs *et al.*, 2014; Mahsanlar *et al.*, 2014; van der Linden *et al.*, 2013). Other studies have concentrated on patient characteristics linked to longer LOS. For instance, research has shown that patients over the age of 65 have a longer LOS than younger patients (e.g. Hosseinienejad *et al.*, 2017; Vegting *et al.*, 2015). On the other hand, condition-specific subpopulation studies have shown that, with the exception of patients who had suffered trauma, age had no impact on LOS (e.g. Biber *et al.*, 2012). These studies do not necessarily refute the well-established effect of age on LOS, but they do highlight the complexities of the relationship between age and certain health conditions.

Some studies of the general patient population found that female patients had longer LOS (e.g. Chaou *et al.*, 2016; Ding *et al.*, 2010), while other studies found no significant difference based on gender (e.g. Casalino *et al.*, 2013). It has also been demonstrated that the patient's triage level can affect their LOS in an ED. For instance, Chaou *et al.* (2016) found that patients who had higher triage based on the emergency severity index had a longer LOS in the discharge patient group. However, the study found contradictory results for higher acuity (Level 1 vs Level 5) in the admission patient group, and other studies have found that patients with intermediate triage (Levels 3 or 4) generally stayed the longest in the ED (e.g. Vegting *et al.*, 2015; Yoon *et al.*, 2003). A longer stay has also been associated with a need for laboratory and radiology tests (e.g. van der Linden *et al.*, 2013; Yoon *et al.*, 2003).

3. Methodology

3.1 Setting

The setting for this work was an ED in a large academic medical center in the United States that operates a total of 51 beds, which are located in different wards. These beds are available to patients of all ages including those suffering from mental illness. The ED has a large number of patients suffering from severe or acute emergencies, and it is certified to provide the highest level of care possible (known as Trauma Level I). These patients are treated by specialists who are trained for the most serious illnesses and injuries. There are a total of 54 medical professionals on this team including nurses, physician assistants, residents and doctors.

3.2 Study design and data collection

This study employed a retrospective observational design to find a group of patients and follow them from the time they checked into the ED until they were discharged. The dataset was gathered throughout the fiscal year 2016–2017. This dataset, which has not been made public yet, contains a plethora of information that can be used to gain a deeper understanding of healthcare services. Over 79,000 patient arrivals and observations were included in the raw data pool. These observations were collected over the course of three daily shifts of eight hours each, seven days a week. The data were recorded across seven wards (East, West, North, South, Pediatric, Center 1 and Center 2), two of which were operationalized for mental illness (North and South), one for children (Pediatric) and the remaining four for adults. The measurements covered 21 factors that were associated with the ED, staff scheduling and patients (adults and children). As shown in Table 1, the study looked at 13 factors relating to

Table 1.
Variables examined

Category	Variable	Description
Patients	Gender	Patient gender: male or female
	Age	Patient age: below 21, 21–65 and above 65
	Emergency severity index	Five-level ED triage algorithm, from 1 (most urgent) to 5 (least urgent), based on acuity and resource needs
	Arrival mode	How patient arrived: walk-in, wheelchair or ambulance
	Discharge type	Discharge home, inpatient admission or hospital observation
	Arrival shift	Shift when a patient arrived: Shift 1: 12:00 a.m. to 8:00 a.m., Shift 2: 8:00 a.m. to 4:00 p.m., Shift 3: 4:00 p.m. to 12:00 a.m.
Service	Length of stay	The time a patient spent in the ED starting from registration
	First treatment ward	Initial ward where a patient was treated (Center 1, Center 2, East, West, Pediatric)
	Ward transfer	Whether a patient was transferred to another ward (yes or no)
	Care complexity (ED level)	Complexity of care provided to a patient, where a higher value represented higher complexity (Levels 1–5 and critical care)
Organizational	Patients per MD	Number of patients per MD when a patient arrived
	Patients per nurse	Number of patients per nurse when a patient arrived
	Patients per resident	Number of patients per resident when a patient arrived

patients’ characteristics, the services they received and the number of physicians, nurses and residents available to provide those services.

The data were timestamped and therefore processed to identify the daily shift for the entire year. The variables represented in [Table 1](#) were classified as discrete or continuous and some were organized into groups. Discrete variables consisted of gender, age, emergency severity index, arrival mode, discharge type, first treatment ward, ward transfer and complexity of care provided.

The gender variable consisted of two groups, male and female. In the ED literature, older adults are typically defined as anyone over the age of 65, whereas the identified upper limit in pediatrics is 21 years of age ([Hardin and Hackell, 2017](#); [Kreindler et al., 2016](#)). With this in mind, the study divided patients’ ages into three groups: younger than 21, 21 to 65 and older than 65. An additional patient characteristic variable was the emergency severity index, a tool for triaging patients according to the severity of their case, with a range from 1 (the most urgent) to 5 (the least urgent). The arrival modes were wheelchair, walk-in and ambulance. The final designation of the patient (discharge type) included discharge home, inpatient admission and hospital observation. The patient arrival hours were divided into three eight-hour shifts: Shift 1 (12:00 a.m. to 8:00 a.m.), Shift 2 (8:00 a.m. to 4:00 p.m.) and Shift 3 (4:00 p.m. to 12:00 a.m.). The study excluded weekend arrivals since wards had different operation schedules during the weekend.

The service-related variables took into account the treatment ward, ward transfer and the complexity of the service provided. Although the ED had seven wards, this study excluded the two mental illness wards because they typically had significantly longer LOS than other wards (i.e. an 11-hour average LOS in a mental illness ward compared to an average of four hours in a nonmental illness ward). The remaining five wards—Pediatric, East, West, Center 2 and Center 4—were included in the study. Patients who were younger than 21 years old could receive specialized pediatric care in the Pediatric ward, while patients of any age could receive care comparable to that provided in the other four wards.

The complexity of care was measured using the ED level, a billing-related code that represents the complexity of care provided, with a higher ED level representing greater complexity ([American College of Emergency Physicians, n.d.](#); [Pitts, 2012](#)). Note that the emergency severity index (illness severity) and the ED level (complexity of care) measure

different concepts. For instance, a highly severe trauma patient does not necessarily imply high complexity from a clinical decision-making perspective (Sir *et al.*, 2017). As a result, the study included both variables to ensure that one covered the severity of a patient's situation based on triage assessment and the other (care complexity) measured the complexity of care provided and resources consumed.

LOS was selected as the response variable in this study, while the remaining variables were analyzed as predictors (see Table 1). Other continuous variables represented the organizational staff level when a patient arrived at the ED. These variables included the number of patients treated by a physician (MD), the number of patients treated by a nurse and the number of patients treated by a resident.

3.3 Data cleaning and diagnostic test

The dataset was reviewed before analysis, uncovering issues such as missing values, visits entered by error and negative values for patient arrival time, which indicated arrival before the timeframe of the study. Any missing or negative time values were excluded from analysis. Initial visualization, descriptive and univariate analyses were carried out on the data, and bivariate analysis employed LOS as the dependent variable. Figure A1 in appendix shows the plot for LOS to check for outliers or noisy observations. Observations with LOS of more than 24 h were considered outliers since an ED should treat outpatients, while patients who need to stay more than 24 h are usually admitted to the hospital. A total of 44 LOS observations exceeded a 24-hour stay. Based on final diagnosis, a majority (37) was for mental illness patients (24 with suicidal ideation, eight with depression and five with hallucinations) who accessed the general ward, and some were transferred to a behavioral health ward. Observations with LOS exceeding 24 h were omitted since these were most likely relevant to mental illness or behavioral issues, which was beyond the scope of this study. In addition, three observations assigned an emergency severity index level of "direct admit to inpatient" were eliminated since these patients did not access the ED. Also, observations with discharge type "left without being seen," "left before treatment complete" or "death" were excluded since they did not reflect the whole ED treatment process. Figure A2 in appendix shows the plot for LOS after eliminating outliers.

Scatter plots and box plots were used to test the assumption of normality as well as the correlation between the response and the predictors. These plots can be found in Figures A3 and A4 of appendix. The findings presented in Figure A3 indicate that the continuous variables must be transformed in order to satisfy the linearity assumption. As a result, log transformation was applied to LOS, patients per MD, patients per nurse and residents per patient. Figure A4 displays the final results of the transformation.

A correlation test was used to determine the relationship between the continuous variables incorporated into the model (see Table 2). Hypotheses were developed to determine whether LOS changed significantly for different predictor variable categories. Independent-samples *t*-tests were used for hypothesis testing. After checking the correlation and linearity assumption, the researcher developed a multilinear regression model to estimate the relationship between LOS (the response variable) and the other variables, serving as the model's explanatory variables. The study utilized various data

	Patients per MD	Patients per nurse	Patients per resident
Patients per MD	1.00	0.58	0.55
Patients per Nurse		1.00	0.46
Patients per Resident			1.00

Table 2.
Correlation results

analytics techniques (e.g. visualization, transformation and anomaly detection) in the data wrangling stage and then used regression modeling to answer the research questions. Given the empirical and exploratory nature of this study, regression modeling was sufficient to answer the research questions. The next stage of this research will include using machine learning to predict patient LOS, which will build on the results of this study and expand it to other modeling techniques. R-Studio was used for processing the data and for the regression analysis.

Multicollinearity between predictors was examined via the variance inflation factor (VIF) function to look for a relationship between predictors that could impact the analysis and results. The rule of thumb for VIF is that any variable with a score greater than 5 or 10 indicates a multicollinearity issue. However, the results showed no multicollinearity (see [Table 3](#)).

4. Analysis and results

4.1 Description of variables

[Table 4](#) presents the demographic information for the discrete variables. A total of 42,462 observations were analyzed for the entire year. As mentioned above, this work considered five wards: Center 1, which served 11,328 patients (26.68%), Center 2, which served 9,911 (23.34%), East ($N = 4,927$, 11.6%), West ($N = 10,475$, 24.67%) and the Pediatric ward ($N = 5,821$, 13.71%) during the year on weekdays. Out of all patients admitted to the ED, 51.95% were female and 48% were male. In terms of age, 7,241 patients were below 21 (17.05%), 22,060 were 21–65 (51.95%) and 13,161 were older than 65 (31%). Similarly, patients were categorized based on severity level. The largest group was Level 3, with 27,140 patients (63.92%), followed by Level 2 ($N = 8,210$, 19.33%) and Level 4 ($N = 6,529$, 15.38%).

The smallest groups were Level 1 ($N = 360$, 0.85%) and Level 5 ($N = 223$, 0.52%). The majority of patients arrived during Shift 2 ($N = 19,502$, 45.93%) or Shift 3 ($N = 19,502$, 45.9%), and the fewest arrived during Shift 1 ($N = 640$, 15.09%). The most common methods of arrival were walk-in ($N = 21,362$, 50.31%), while arrivals via wheelchair ($N = 10,465$, 24.65%) and ambulance ($N = 10,635$, 25.04%) were nearly equal. The biggest category for patient discharge was discharge home ($N = 27,859$, 65.61%), followed by inpatient admission ($N = 9,314$, 21.93%) and hospital observation ($N = 5,289$, 12.46%). Patients were most likely admitted to Center 1 ($N = 11,328$, 26.68%), followed by West ($N = 10,475$, 24.67%), Center 2 ($N = 9,911$, 23.34%), Pediatric ($N = 5,821$, 13.71%) and East ($N = 4,927$, 11.6%). In this sample, only 1.02% ($N = 433$) of patients were transferred to another ward.

Table 3.
Multicollinearity based
on VIF function

	GVIF	DF	GVIF ^{1/(2*DF)}
Gender	1.014	1	1.007
Age	3.489	2	1.367
Emergency Severity Index	1.909	4	1.084
Arrival Shift	1.778	2	1.155
Arrival Mode	1.550	2	1.116
Discharge Type	1.891	2	1.173
First Ward	3.651	4	1.176
Ward Transfer	1.021	1	1.010
Care Complexity	3.666	5	1.139
Patients per MD	3.468	1	1.862
Patients per Nurse	3.243	1	1.801
Patients per Resident	2.298	1	1.516

Category	Variable	N	%	Patient length of stay in EDs
Patient Gender	Male	20,404	48.05	
	Female	22,058	51.95	
Patient Age	<21	7,241	17.05	
	21–65	22,060	51.95	
	>65	13,161	31.00	
Patient Severity Level	Level 1	360	0.85	
	Level 2	8,210	19.33	
	Level 3	27,140	63.92	
	Level 4	6,529	15.38	
	Level 5	223	0.52	
Arrival Shift	Shift 1	6,408	15.09	
	Shift 2	19,502	45.93	
	Shift 3	16,552	38.98	
Patient Arrival Mode	Walk-in	21,362	50.31	
	Wheelchair	10,465	24.65	
	Ambulance	10,635	25.04	
Patient Discharge	Discharge home	27,859	65.61	
	Inpatient admission	9,314	21.93	
	Hospital observation	5,289	12.46	
Ward	Center 1	11,328	26.68	
	Center 2	9,911	23.34	
	East	4,927	11.6	
	West	10,475	24.67	
	Pediatric	5,821	13.71	
Ward Transfer	Yes	433	1.02	
	No	42,029	98.98	
Care Complexity (ED level)	ED Level 1	112	0.26	
	ED Level 2	1,409	3.32	
	ED Level 3	10,106	23.8	
	ED Level 4	12,939	30.47	
	ED Level 5	17,294	40.73	
	Critical Care	602	1.42	

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Table 4.
Demographic
information of nominal
variables

Table 5 gives a statistical description of the continuous variables. The mean for patient LOS was 4.06 h ($SD = 2.09$). Based on interquartile range values, 25% of patients had a LOS lower than 2.52 h and 75% had a LOS lower than 5.25 h. Regarding organizational staff-level variables, the mean number of patients was 11.99 per MD ($SD = 3.188$), 1.59 per nurse ($SD = 0.45$) and 5.035 per resident ($SD = 1.839$).

4.2 Regression model results

The outcomes of the three multi-regression models are presented in Table 6. The following patient variables were included in Model 1: gender, age, emergency severity index, arrival shift, arrival mode and discharge type. The variables in Model 1 were expanded upon in

Continuous variable	Mean	SD	Minimum	Q1	Median	Q3	Maximum	Table 5. Statistical description of continuous variables
Length of Stay	4.06	2.09	0.18	2.52	3.77	5.25	23.97	
Patients per MD	11.99	3.188	3.57	9.94	11.64	13.73	54.3	
Patients per Nurse	1.59	0.45	0.44	1.34	1.57	1.81	23.97	
Patients per Resident	5.035	1.839	1.083	4.066	4.066	5.69	38.43	

Variable	Category	Model 1 (Personal level)	Model 2 (Service-related)	Model 3 (Organizational)
Intercept		0.783*** [0] (0.029)	−0.108* [0] (0.054)	−0.896*** [0] (0.061)
Gender	Male	−0.062*** [−0.054] (0.005)	−0.037*** [−0.033] (0.005)	−0.037*** [−0.032] (0.004)
Age	>65	0.023*** [0.019] (0.006)	0.02*** [0.016] (0.006)	0.021*** [0.017] (0.005)
	<21	−0.347*** [−0.228] (0.007)	−0.194*** [−0.127] (0.011)	−0.166*** [−0.109] (0.01)
Emergency Severity Index	Level 2	0.284*** [0.196] (0.028)	0.109*** [0.075] (0.027)	0.138*** [0.095] (0.026)
	Level 3	0.362*** [0.303] (0.028)	0.266*** [0.223] (0.027)	0.303*** [0.254] (0.026)
	Level 4	0.104*** [0.066] (0.028)	0.234*** [0.147] (0.028)	0.271*** [0.171] (0.027)
	Level 5	−0.207*** [−0.026] (0.044)	0.137** [0.017] (0.043)	0.151*** [0.019] (0.041)
Arrival Shift	Shift 2	0.194*** [0.169] (0.007)	0.219*** [0.191] (0.007)	0.131*** [0.114] (0.008)
	Shift 3	0.162*** [0.138] (0.008)	0.204*** [0.174] (0.007)	0.058*** [0.049] (0.008)
Arrival Mode	Wheelchair	0.11*** [0.083] (0.007)	0.060*** [0.052] (0.006)	0.064*** [0.049] (0.006)
	Ambulance	−0.029*** [−0.022] (0.007)	−0.149*** [−0.113] (0.007)	−0.151*** [−0.115] (0.007)
Discharge Type	Observation	0.283*** [0.163] (0.008)	0.1*** [0.058] (0.008)	0.092*** [0.053] (0.008)
	Inpatient	0.212*** [0.153] (0.007)	0.046*** [0.033] (0.007)	0.037*** [0.026] (0.007)
First Ward	Center 2		0.037*** [0.027] (0.007)	0.034*** [0.025] (0.006)
	East		−0.031*** [−0.017] (0.008)	−0.045*** [−0.025] (0.008)
	Pediatric		−0.108*** [−0.065] (0.012)	−0.162*** [−0.097] (0.012)
	West		−0.019** [−0.014] (0.007)	−0.014* [−0.01] (0.006)
Ward Transfer	Yes		0.339*** [0.059] (0.023)	0.337*** [0.059] (0.022)
Care Complexity	Level 2		0.343*** [0.107] (0.048)	0.333*** [0.104] (0.046)
	Level 3		0.669*** [0.497] (0.046)	0.64*** [0.476] (0.044)
	Level 4		1.078*** [0.866] (0.047)	1.039*** [0.835] (0.045)
	Level 5		1.223*** [1.049] (0.047)	1.185*** [1.016] (0.045)
	Critical Care		0.963*** [0.199] (0.052)	0.948*** [0.196] (0.049)

Table 6.
Regression model
results

(continued)

Variable	Category	Model 1 (Personal level)	Model 2 (Service-related)	Model 3 (Organizational)
Patients per MD				0.338*** [0.148] (0.017)
Patients per Nurse				0.344*** [0.147] (0.016)
Patients per Resident				−0.054*** [−0.027] (0.012)
R^2		0.198	0.311	0.367
Adjusted R^2		0.198	0.31	0.367
F		807.126	831.921	947.953

Note(s): Standard error is reported in parentheses (), and standardized coefficient values are reported in square brackets []

*Significance at 90%, **significance at 95% and ***significance at 99%

Table 6.

Model 2, which resulted in the addition of three service-related variables: first treatment ward, ward transfer and care complexity (ED level). In addition to the variables that were present in Model 2, Model 3 added the following organizational staff-level variables: the number of patients per MD, patients per nurse and patients per resident.

Variables related to patient characteristics explained approximately 20% of the variance in LOS, as shown in Table 6 under the Model 1 results. Male patients had a shorter LOS than female patients. Similarly, patients over the age of 65 had a longer LOS than those between the ages of 21 and 65. Patients under the age of 21 spent less time in the hospital than other age groups, which could be attributed to the presence of a specialized pediatric ward. The emergency severity index variable had a bell-shaped relationship with LOS, where patients with triage Levels 2 and 3 had the highest LOS, followed by Level 4 (which had a slightly higher LOS than Level 1) and Level 5 (which had the lowest LOS compared to Level 1). However, once the care complexity variable was introduced in Model 2, the sign for Level 5 shifted from negative to positive, indicating that it had a longer LOS than Level 1. This could be due to omitted variable bias in Model 1. In EDs, patients triaged with Level 1 have the highest acuity and are seen more quickly than patients triaged with other levels.

In terms of arrival shift, patients who arrived during Shift 2 (8:00 a.m. to 4:00 p.m.) had the longest LOS, followed by Shift 3 (4:00 p.m. to 12:00 a.m.) and then Shift 1 (12:00 a.m. to 8:00 a.m.). As for arrival mode, patients who came by wheelchair had higher LOS than those who walked in, and patients who arrived by ambulance had lower LOS than walk-ins. Patients requiring observation or inpatient services also spent more time in the ED than those who were discharged home. Based on the partial R-squared results shown in Table 7, age explained most of the variance in the model, followed by discharge type and emergency severity index.

Model 2 added service-related variables, such as initial treatment ward, ward transfer and care complexity. Overall, this model explained 30% of variance. The results showed a significant difference in LOS based on initial treatment ward. Compared to Center 1, the East, West and Pediatric wards had lower LOS, while Center 2 had higher LOS. This could be due to differences in operational efficiency between wards or services provided, especially in the case of the pediatric pod. Patients who transferred wards also had longer LOS, and patients with a higher level of care stayed longer as well. Patients triaged with severity Level 5 had the highest LOS, followed by Level 4, patients receiving critical care, Level 3, Level 2 and Level 1. Based on the results shown in Table 7, care complexity measured at the ED level was the strongest determinant of patient LOS in the ED, followed by arrival shift and arrival mode.

Finally, Model 3 added patients per MD, patients per nurse and patients per resident as variables and explained around 37% of LOS variance. In this model, for every 1% increase in

Table 7.
Partial R-squared
results for the model

Variable	Model 1	Model 2	Model 3
Gender	0.004	0.002	0.002
Age	0.058	0.008	0.007
Emergency Severity Index	0.037	0.015	0.018
Arrival Shift	0.016	0.022	0.008
Arrival Mode	0.010	0.023	0.024
Discharge Type	0.038	0.003	0.003
First Ward		0.004	0.007
Ward Transfer		0.005	0.005
Care Complexity		0.128	0.131
Patients per MD			0.010
Patients per Nurse			0.010
Patients per Resident			0.000

the number of patients per MD, LOS increased by 0.338%, and for every 1% increase in patients per nurse, LOS increased by 0.344%. However, for every 1% increase in patients per resident, LOS decreased by 0.054%. The model had an *F*-value of 947.953 and *R*² of 36.7%. The three variables showed a significant impact on LOS. The first two variables had a positive relation with LOS, while the third had an inverse relationship, as explained later in the discussion section. Based on the partial *R*² results shown in Table 7, ED care level remained the variable with the strongest influence on LOS. Adjusted *R*² had almost the same value as *R*² due to the large sample size (*N* = 42,462), as explained in the following equation:

$$Adjusted R_{squared} = 1 - \left[\frac{(1 - R_{squared})(n - 1)}{N - P - 1} \right]$$

where:

N = number of observations

P = number of independent regressors

All variables showed a significant difference from the base. Partial *R*² values are presented in Table 7 to compare across variables.

A diagnostic of the residuals of Model 3 is shown in Figure A5 in appendix. The residual output showed the variance was relatively constant, and no clear pattern was apparent. For the normal Q-Q plot, there was a lower tail and an outlier, but it was acceptable overall. In addition, the histogram had an overall acceptable shape, albeit slightly right skewed. Hence, the residual and Q-Q plot showed no violation of linear regression assumptions.

5. Discussion

Model 3 was chosen for the discussion because it incorporates the service variables and controls for other variables that may impact LOS. The base model values for the regression were gender (female), age (21–65), emergency severity index (Level 1), shift (Shift 1), arrival mode (walk-in), discharge type (discharge home), first ward (Center 1), ward transfer (no) and care complexity (Level 1). The model had an *F* of 947.953 and *R*² of 36.7%. Given the exploratory and empirical nature of this study, the emphasis was on examining the significance of the relationship between the factors under consideration and LOS rather than developing a model that would explain the majority of the variability or predict the response with high accuracy. Hence, any interpretation of an *R*² value depends on the purpose of the research and the application domain. When compared to regression studies in pure technical engineering topics, regression

modeling studies in health systems and social science typically report low R^2 values. [Cohen \(1988\)](#) established a rule for interpreting R^2 in behavioral and social science, stating that a model with R^2 greater than 0.26 is considered substantial. In this study, the value of R^2 was 0.36, which would be considered adequate in this application context and sufficient for the research purpose. [Table 8](#) presents the results in relation to related literature.

The results of the model reaffirmed previous research concerning patient characteristics that influence LOS. For instance, some studies have shown that age and gender both had a similar impact on LOS, such that patients over the age of 65 had longer LOS than younger patients, and female patients had longer LOS than male patients (e.g. [Baum and Rubenstein, 1987](#); [Hosseinienejad et al., 2017](#); [Latham and Ackroyd-Stolarz, 2014](#)). However, [Casalino et al. \(2013\)](#) found no significant differences between ED patients based on gender that could be related to the sample chosen or due to the fact that the difference was relatively small. Concerning the connection between acuity and LOS, the findings of the present study provided support for earlier research, indicating that patients who were classified as either nonurgent or critically ill had shorter LOS than patients who were triaged in the middle, that is, those who were in Emergency Severity Index Levels 2 and 3 (e.g. [Yoon et al., 2003](#)).

Variable	Results	Literature
Gender	Female patients had longer LOS	Female patients had longer LOS in Chaou et al. (2016) and Ding et al. (2010) , while Casalino et al. (2013) found no significant difference
Age	Patients over 65 had longer LOS, followed by 21–65 and under 21	Age can influence LOS (Hosseinienejad et al., 2017 ; Latham and Ackroyd-Stolarz, 2014) but usually not in condition-specific subpopulation studies (Biber et al., 2012)
Emergency Severity Index (ESI)	Level 3 had higher LOS, followed by 4, 2, 1, and 5	Nonurgent and critical patients had lower LOS (Ding et al., 2010 ; Yoon et al., 2003)
Arrival Shift	Shift 2 (8:00 a.m. to 4:00 p.m.) had longer LOS, followed by 3 (4:00 p.m. to 12:00 a.m.) and 1 (12:00–8:00 a.m.)	Daytime arrivals had longer LOS (Chaou et al., 2016 ; Sarıyer et al., 2020)
Arrival Mode	Wheelchair arrivals had higher LOS, followed by walk-ins and ambulance arrivals	Ambulance arrivals had shorter waits but longer treatment (Ding et al., 2010)
Discharge Type	Patients requiring observation or inpatient services had longer LOS than those discharged home	Need for admission showed higher LOS (Gardner et al., 2007 ; Kreindler et al., 2016)
First Ward	Center 2 had higher LOS, followed by Center 1, East, West and Pediatric	Treatment location and ward efficiency affected LOS (Sir et al., 2017)
Ward Transfer	Ward transfers had longer LOS	Multiple consultations or wrong initial designation affected LOS (Ross et al., 2019)
Care Complexity	Patients with Level 5 care had higher LOS, followed by 4, 3, 2 and 1. Care complexity was the strongest LOS determinant	Care complexity was the most significant factor (Sir et al., 2017)
Patients per MD/ Nurse	More MDs/nurses per patient was associated with lower LOS	Maximum patients per provider or minimum providers affected LOS (Sir et al., 2017)
Patients per Resident	More residents per patient was associated with higher LOS	Higher LOS was associated with more residents and lower LOS with higher physician seniority (Brouns et al., 2015 ; Fiallos et al., 2017)

Table 8.
Connections to the
literature

Ding *et al.* (2010) came to the same conclusion, finding that patients in Level 3 had the longest wait times. In terms of the type of discharge, the findings supported the conclusions of earlier studies that need for admission was associated with longer LOS (e.g. Gardner *et al.*, 2007; Kreindler *et al.*, 2016). Driesen *et al.* (2018) considered this to be due to organizational factors related to hospital capacity and outside the influence of the ED.

The findings showed that patient arrival time had an effect on LOS, which has been previously documented (e.g. Sanyer *et al.*, 2020). Arrival during the day shift, for example, has been shown to be associated with longer LOS than arrival at night (Chaou *et al.*, 2016), in agreement with the findings of this study. In terms of the arrival mode, patients arriving by ambulance had a shorter LOS than walk-ins. This could be because patients arriving by ambulance were often tracked more quickly than walk-in patients, who usually had to wait for treatment. According to Ding *et al.* (2010), patients who arrived by ambulance had shorter wait times but longer treatment times than those who arrived by other means.

In terms of service-related variables, the findings supported previous research that identified care complexity measured at the ED level as the most significant factor influencing LOS (e.g. Sir *et al.*, 2017). The ward transfer variable was not directly addressed in previous studies. However, multiple consultations could be one reason for transfer and has been shown to be significant in determining LOS (Ross *et al.*, 2019). Further investigation into potential reasons for ward transfer could be done to address this issue. As patients who needed to be transferred from one ward to another tended to stay longer, improving triage and initial assessment could reduce such errors and, as a result, patient LOS. Location of treatment and differences in operational efficiency between wards had an impact on LOS as well.

The results showed organizational staff-level variables to be significant in determining LOS, corroborating previous research. Sir *et al.* (2017), for example, demonstrated that patients who received services with the same level of complexity had significantly different LOS, depending on whether maximum number of patients per provider or minimum number of providers was used in the analysis. Fiallos *et al.* (2017) found performance variations between physicians within and between each patient complaint group, and when ED physicians were not assisted by residents, their performance scores improved, which could be explained by the widely held belief that teaching reduces the pace of care in the ED. Furthermore, Brouns *et al.* (2015) found that lower physician seniority was related to longer LOS in elderly patients. This is consistent with the finding of the current study that an increase in LOS was associated with an increase in the number of residents.

In general, the results demonstrated how the multifactorial nature of ED patient LOS was determined by a combination of patient, service complexity and organizational variables. Further investigation could be done to assess the practical significance of the difference in LOS between male and female patients and explore factors increasing ward transfer. The findings suggested that improving the triage system to direct patients to the appropriate ward could increase ED efficiency. Improving the process for discharging patients to inpatient or observation units might also reduce the demand for ED beds. Another improvement would be to categorize patients ahead of time based on the complexity of the treatment required and route them appropriately to balance workload in various wards.

6. Conclusion

This study examined the association between LOS and multi-level factors including patient-, service- and organization-level factors. A year's worth of data from an ED in a large academic medical center in the United States was analyzed using a multi-regression model. The LOS for patients in the ED served as the response variable, while the independent variables included patient variables (such as age, gender, severity level, arrival mode, arrival shift and discharge

type), service-related variables (such as ward transfer and complexity of care provided), and organizational staff variables (patients per MD, patients per nurse and patients per resident). The results supported previous findings regarding patient factors influencing LOS. For instance, patients over 65 had longer LOS than younger patients, and female patients had longer LOS than male patients. In terms of the relationship between acuity and LOS, the findings revealed that patients who were classified as nonurgent (Level 5) or critically ill (Level 1) had shorter LOS than those who were triaged in the middle, i.e. in Levels 2 and 3. In addition, discharge type had a significant impact on LOS, where patients discharged to inpatient or observation units had longer LOS than patients who were sent home. The complexity of provided services and number of patients per service provider had a positive and significant correlation with LOS as well. As the complexity of the required service increased, the longer a patient stayed in the ED, and patients who needed to be transferred from one ward to another tended to stay longer. Finally, LOS increased as the number of patients per MD or per nurse increased, while there was an inverse relationship between LOS and number of patients per resident.

Increased LOS in the ED can result in significant costs and has implications for patient safety, making timely care a critical issue for improving care delivery and avoiding overcrowding. An understanding of the factors associated with longer LOS based on real-world data is a critical first step toward developing evidence-based interventions to address prolonged LOS and overcrowding. Previous studies of patient LOS in EDs rarely took service-related and organizational factors into account. As a result, the findings of this study contribute to the current understanding of the factors influencing patient LOS and add to the current understanding of ED operation management, quality of care and patient flow. In particular, this study provides insights into service-related factors influencing LOS based on an unpublished dataset to researchers in ED and professionals such as industrial engineers, operation managers and quality specialists. The findings highlighted the multifaceted nature of patient LOS. When designing any intervention to address overcrowding, managers should take into account the complexity, interdependence and dynamic nature of the patient's LOS. In terms of managerial implications, the findings suggested that improving the triage system to direct patients to the appropriate ward could reduce patient LOS and thus increase ED efficiency. Improving the process for discharging patients to inpatient or observation units may also reduce patient LOS by lowering ED bed occupancy. Another managerial implication would be to classify patients ahead of time based on the complexity of the treatment required and route them accordingly to balance the workload across various wards. The findings of this study could be used as a proof of concept in future studies to develop a more precise predictive model for long ED LOS that considers multiple types of factors.

While the study included factors related to patients, services, the organization and crowding in the ED, there could be other factors associated with LOS not included in this study that require further research. For instance, more demographic variables could be included such as patient ethnicity and insurance type. It would also be beneficial to identify a causal relationship between the predictors and LOS. Future research could focus on particular patient conditions, especially with patients who are receiving highly complex care (for example, ED Care Levels 3–5), investigate the causal relationships and interdependencies that emerge as services become more complex and determine how to make those services more efficient. A simulation or network model could shed light on some of the underlying causes of long-term LOS. Because the number of people using EDs and the severity of their illnesses are both on the rise, researchers could also investigate overcrowding from a dynamic perspective over the course of multiple years. This is necessary because EDs must find ways to manage change and allocate enough resources to meet the demands of this challenge over the long term.

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Appendix

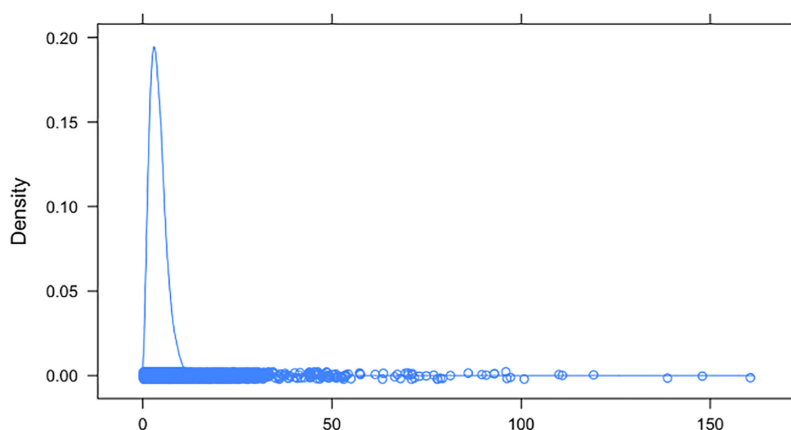


Figure A1.
Length of stay in hours
before cleaning outliers

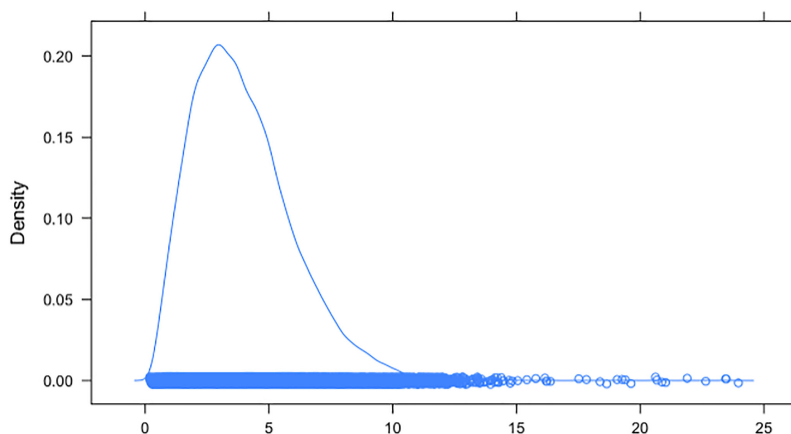


Figure A2.
Length of stay after
cleaning outliers

Figure A3.
Visualization of
response and predictor
variables before
transformation

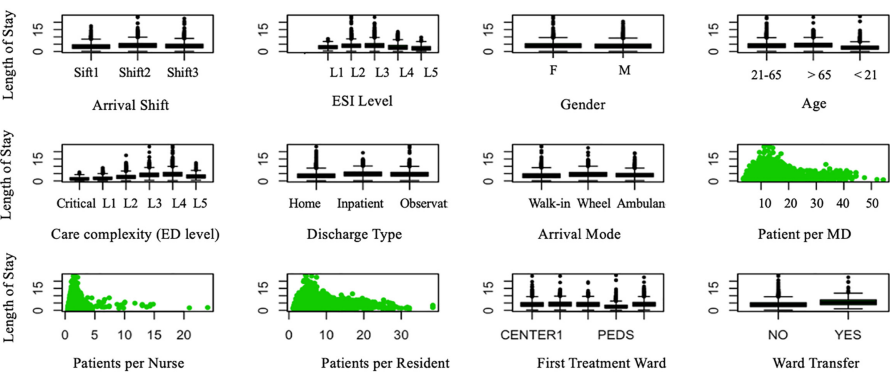
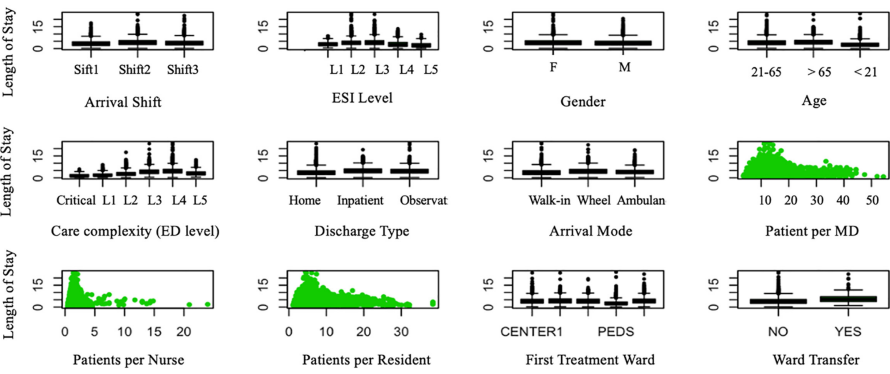


Figure A4.
Visualization of
response and predictor
variables after
transformation



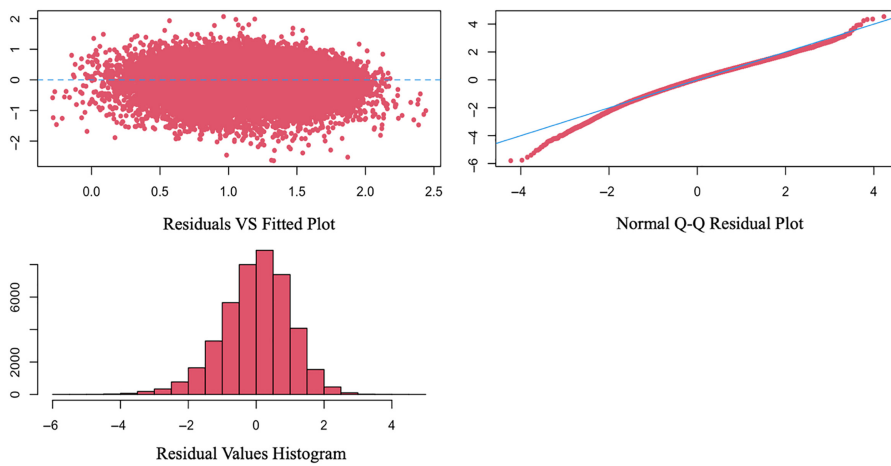


Figure A5.
Diagnostic of model 3

Corresponding author

Mohammed Ba-Aoum can be contacted at: mbaaoum@vt.edu

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