vituity®
At the heart of better care.

WHY I'M AN OWNER

"At Vituity, I get to build the future of medicine. As a Fellowship director, I help physicians become true experts and leaders in their field.

- Kimberly Sokol, MD, MS, MACM
Co-Director of Clinical Teaching and Simulation Fellowship, Vituity

Vituity has always been **100% owned** by its physicians, and you **join as a Partner from day one**.

Learn more at vituity.com/EMcareers

Now hiring in: Arizona, California, Illinois, Indiana, Kansas, Missouri, Minnesota, Nevada, New Jersey, Oregon, South Carolina, Texas, Washington, and Wisconsin.

Received: 16 June 2022 | Revised: 2 September 2022 | Accepted: 12 September 2022

DOI: 10.1111/acem.14598

ORIGINAL CONTRIBUTION

Disparities in emergency department prioritization and rooming of patients with similar triage acuity score

Peter Lin[1] | **Nilay T. Argon PhD**[1] | **Qian Cheng MS**[1] | **Christopher S. Evans MD MPH**[2,3] | **Benjamin Linthicum DNP**[4] | **Yufeng Liu PhD**[1,5,6,7,8] | **Abhishek Mehrotra MD MBA**[4] | **Mehul D. Patel PhD**[4] | **Serhan Ziya PhD**[1]

[1]Department of Statistics and Operations Research, University of North Carolina, Chapel Hill, North Carolina, USA

[2]Information Services, ECU Health, Greenville, North Carolina, USA

[3]Department of Emergency Medicine, East Carolina University, Greenville, North Carolina, USA

[4]Department of Emergency Medicine, University of North Carolina, Chapel Hill, North Carolina, USA

[5]Department of Genetics, University of North Carolina, Chapel Hill, North Carolina, USA

[6]Department of Biostatistics, University of North Carolina, Chapel Hill, North Carolina, USA

[7]Carolina Center for Genome Sciences, University of North Carolina, Chapel Hill, North Carolina, USA

[8]Lineberger Comprehensive Cancer Center, University of North Carolina, Chapel Hill, North Carolina, USA

Correspondence
Nilay T. Argon, PhD, Department of Statistics and Operations Research, University of North Carolina, Chapel Hill, NC 27599, USA.
Email: nilay@unc.edu

Funding information
This work was partially supported by grant CMMI-1635574 from the National Science Foundation.

Abstract

Background: We identify patient demographic and emergency department (ED) characteristics associated with rooming prioritization decisions among ED patients who are assigned the same triage acuity score.

Methods: We performed a retrospective analysis of adult ED patients with similar triage acuity, as defined as an Emergency Severity Index (ESI) of 3, at a large academic medical center, during 2019. Violations of a first-come-first-served (FCFS) policy for rooming are identified and used to create weighted multiple logistic regression models and 1:M matched case–control conditional logistic regression models to determine how rooming prioritization is affected by individual patient age, sex, race, and ethnicity after adjusting for patient clinical and time-varying ED operational characteristics.

Results: A total of 15,781 ED encounters were analyzed, with 1612 (10.2%) ED encounters having a rooming prioritization in violation of a FCFS policy. Patient age and race were found to be significantly associated with being prioritized in violation of FCFS in both logistic regression models. The 1:M matched model showed a statistically significant relationship between violation of rooming prioritization with increasing age in years (adjusted odds ratio [aOR] 1.009, 95% confidence interval [CI] 1.005–1.013) and among African American patients compared to Caucasians (aOR 0.636, 95% CI 0.545–0.743).

Conclusions: Among ED patients with a similar triage acuity (ESI 3), we identified patient age and patient race as characteristics that were associated with deviation from a FCFS prioritization in ED rooming decisions. These findings suggest that there may be patient demographic disparities in ED rooming decisions after adjusting for clinical and ED operational characteristics.

KEYWORDS
emergency department, health disparities, triage

Supervising Editor: Dr. Jill Stoltzfus

INTRODUCTION

The emergency department (ED) triage process is a combination of objective and subjective rapid assessments that aim to identify and prioritize ED patients who need the most emergent or timely evaluation. Triage severity scales, such as the Emergency Severity Index (ESI),[1] assign patients to one of several different groups with more acute groups receiving priority over the less acute groups for treatment. Other triage scales, such as the Canadian Triage and Acuity Scale (CTAS),[2] also include guidance for how quickly patients should be treated. However, little systematic guidance exists for consistently prioritizing patients within the same ESI level, other than the use of a first-come-first-served (FCFS) policy among patients deemed initially to be of similar acuity. The FCFS paradigm among patients with similar triage acuity scores seems intuitive, but the process of a rapid triage assessment often uncovers subjective characteristics about a patient presentation that may influence the decision to violate a simplistic FCFS approach. This policy raises the question of what leads to rooming a patient in violation of this general FCFS guideline and whether or not this practice may lead to disparities in ED triage and timely access to emergency care. To date, there has been limited research investigating this potentially inequitable prioritization decision in the ED.

The primary objective of this study was to determine patient demographics and ED operational conditions associated with prioritization in rooming decisions for patients who were triaged into a similar acuity category. Specifically, we test the null hypothesis that rooming prioritization, defined by an FCFS violation, does not vary by patient sex, race, or ethnicity when controlling for acuity and clinical and ED operational characteristics.

METHODS

We performed a retrospective analysis on data from a large academic medical center in the Southeastern United States from January 1, 2019, through December 31, 2019. The study ED had a total of 59 beds divided among five adult care areas (A, B, C, D, and behavioral health) and one pediatric care area. Two of the adult care areas (A and B) operated 24 hours, care area D operated only during peak hours and focused mainly on low-acuity patients, and the remaining two (C and behavioral health ED) were primarily dedicated to behavioral health patients. All patients are initially triaged by one or more dedicated triage nurses who have received training on a standardized triage process including assigning an ESI level and who have discretion on rooming order based on subjective and other operational characteristics including room/bed type availability. Clinicians are able to pull patients directly to the care areas although this occurs rarely in this ED. In 2019, the study ED had a total of 62,552 ED visits, which is similar to the average annual number of ED visits to 44 academic EDs across the United States surveyed in 2016.[3]

Patients were included in this study if they had an ESI score of 3 at time of triage; were evaluated in the two primary care areas (A or B); and had complete event time stamps recorded in the electronic health record (EHR) including ED arrival, end of triage, rooming, and first seen by a provider time. We only included patients who were assigned an ESI score of 3 as this represents a majority of patients seen in the ED and has proven difficult to determine which patients need more timely care within the same ESI classification.[4] We restricted our analysis to only patients evaluated in two care areas (A and B) that both operate continuously around the clock and are similar in terms of staffing by providers and nursing. Patients were excluded if they were less than 18 years old, if their chief complaint was categorized as "mental health," or if they arrived via emergency medical services (EMS), as these three groups of patients follow a separate workflow in ED rooming decisions. Lastly, patients with a sex other than male or female were also removed since their extremely low count (0.014% of the ED census during 2019) in comparison could create unstable model parameter estimation and consequently unreliable statistically significant results for sex. The final study data set contained 15,781 ED patient encounters. Table 1 summarizes patient characteristics of the study population.

Primary outcome

The primary outcome was to determine violations of a FCFS policy in rooming decisions. We use the convention that under the FCFS policy patients are roomed according to the order of their end of triage time stamps (corresponding to the time patients enter the waiting room). A patient is said to be *prioritized* in violation of FCFS if they were roomed at least 15 minutes before another patient who had arrived at the waiting room before them. We also say a patient is *deprioritized* if they were roomed after some prioritized patient despite entering the waiting room before that prioritized patient.

The specific margin of 15 min used in our definition of violation of FCFS was chosen based on clinical judgment of the authors who practice emergency medicine and have first-hand experience with the rooming process and nursing workflow at the study ED. We also performed a sensitivity analysis using margins of 10 and 20 min.

Model covariates

The chief complaint for each patient encounter was grouped into one of 17 categories.[5] The weighted Elixhauser comorbidity score[6,7] is then calculated for each patient encounter using the provided ICD-10 diagnosis codes and the comorbidity package[8] in R. Select patient demographic categories were collapsed into fewer levels to avoid extremely unbalanced categories and to reduce the number of required parameters in the models. For race, "Native American," "Pacific Islander," "patient refused," "unknown," and "other" were combined into an aggregate "other" category. For ethnicity, "patient refused" and "unknown" were placed into a "other" category. For chief complaints, "general/minor" and "environmental" were combined into a single category and the three different "ENT" categories were combined into a single

TABLE 1 Characteristics of the study population and prioritized patients

	Study population (ESI 3 patients seen at care areas A and B)	Prioritized patients within the study population	Percentage prioritized
Sample size	15,781	1612	10.21
Age (years)	47.73 (±17.87)	49.72 (±18.44)	—
Age group (years)			
18–40	6124 (38.81)	577 (35.79)	9.42
40–55	4259 (26.99)	402 (24.94)	9.44
55–70	3487 (22.10)	393 (24.38)	11.27
>70	1911 (12.11)	240 (14.89)	12.56
Sex			
Male	6681 (42.34)	704 (43.67)	10.54
Female	9100 (57.66)	908 (56.33)	9.98
Race			
Caucasian	8015 (50.79)	925 (57.38)	11.54
African American	4529 (28.70)	410 (25.43)	9.05
Asian	283 (1.79)	24 (1.49)	8.48
Other	2954 (18.72)	253 (15.70)	8.56
Ethnicity			
Hispanic or Latino	2576 (16.32)	219 (13.59)	8.50
Not Hispanic or Latino	13,069 (82.81)	1377 (85.42)	10.54
Other	136 (0.86)	16 (0.99)	11.76
Complaint category			
Cardiovascular	2278 (14.44)	251 (15.57)	11.02
Ear, nose, throat	624 (3.95)	59 (3.66)	9.46
General/environmental	1321 (8.37)	187 (11.6)	14.16
Gastrointestinal	3796 (24.05)	315 (19.54)	8.30
Genitourinary	977 (6.19)	71 (4.40)	7.27
Neurologic	1298 (8.23)	140 (8.68)	10.79
Obstetrics/gynecology	555 (3.52)	54 (3.35)	9.73
Ophthalmology	312 (1.98)	73 (4.53)	23.40
Orthopedic	1565 (9.92)	146 (9.06)	9.33
Respiratory	1132 (7.17)	104 (6.45)	9.19
Skin	1182 (7.49)	131 (8.13)	11.08
Substance	214 (1.36)	17 (1.05)	7.94
Trauma	527 (3.34)	64 (3.97)	12.14

Note: Data are reported as mean (±SD) or *n* (%). The last column is column 3 divided by column 2 times 100.

category. Lastly, the average time from the end-of-triage time stamp to first-seen-by-provider time stamp is calculated for patients who enter the waiting room during the same hourly block as a proxy for measuring ED crowding. The day of week and the time of day in six 4-h blocks (12 a.m. to 4 a.m., 4 a.m. to 8 a.m., 8 a.m. to 12 p.m., 12 p.m. to 4 p.m., 4 p.m. to 8 p.m., and 8 p.m. to 12 a.m.) were also used as covariates.

Modeling technique

We first fitted a weighted logistic regression model on the data set for the study population (sample size 15,781) to identify patient characteristics and ED conditions that relate to whether a patient is prioritized in violation of FCFS. Prioritized patients in violation of FCFS received a response of 1, and all other patients (including those who were roomed according to FCFS and those who were deprioritized in violation of FCFS) were assigned a response of 0. Patient-level covariates in the model included patient age, sex, race, ethnicity, chief complaint category, and the weighted Elixhauser comorbidity score. ED-level operational covariates included the day of week and time of day when patients were roomed and average time from the end of triage to first provider time for the hourly block when that patient was roomed. Weights are assigned to each patient encounter according to the response that was assigned. If this model was to remain unweighted, the imbalance between the two different classes (10.21% prioritized vs. 89.79% others) could lead to bias and affect the significance of the different predictors.[9] This model was fitted using maximum likelihood estimation with the glm function in R.[10]

We also created a matched 1:M case–control logistic regression model[11] to assess the differences between the prioritized and deprioritized patients. Compared to the previous logistic regression model, the 1:M modeling technique can be more robust to potential unmeasured confounders which are not included in the covariates and reduce bias in the statistical analysis.[12] For this matched model, we excluded patients who were not involved in a FCFS violation keeping only prioritized and deprioritized patients. Patients are grouped into various strata, with each stratum consisting of one prioritized patient and any deprioritized patients that had been present in the waiting room before this prioritized patient, resulting in 1612 strata. Hence, with this model, we directly matched each prioritized patient with multiple patients who were in the waiting room at the same time, had similar triage acuity, and had arrived earlier than this prioritized patient. This conditional logistic regression model with varying M is then formed with only the patient-related variables included. The model was then fitted using a Cox proportional hazards model.[13–16] For more details on this matched case–control model, interested readers are referred to the Supplementary Material.

Submodels corresponding to both types of logistic regression models were then created, with each submodel dropping one predictor from the full model. Likelihood ratio tests (LRTs) were then performed to determine the significance of each predictor ($p \leq 0.001$) assuming the remaining predictors are already accounted for in both types of models. After determining predictor significance, we then determined the direction of significance for those predictors by examining the coefficients of different models. We also conducted a multicollinearity analysis for both models and concluded that there is no indication of any serious multicollinearity (Supplemental Material Table S1).

All calculations and analysis were performed using R[10] 4.0.2. This study was exempted from full review by the institutional review board at the University of North Carolina at Chapel Hill.

RESULTS

During the study period 15,781 ED visits met the inclusion criteria. Included ED visits were composed of patients with mean age of 47.73 years, 57.66% of whom were female and 28.70% of whom were African American. The two most common chief complaint categories were gastrointestinal and cardiovascular (Table 1). A total of 1612 (10.2%) ED encounters were prioritized in violation of FCFS among patients with an ESI score of 3, where certain patient groups were more frequently prioritized than others. For example, Table 1 shows that 12.56% of patients who are more than 70 years old were prioritized whereas 9.42% of patients who are 18–40 years of age received priority. Similarly, according to Table 1, 11.54% of Caucasians were prioritized whereas only 9.05% of African Americans received priority. Both logistic and 1:M case–control logistic regression models were found to be statistically significant overall, with goodness-of-fit tests for the weighted logistic regression model and the LRT for the entire 1:M model both returning a p-value of <0.001.

The weighted logistic regression model found that patient age, race, chief complaint category, weighted Elixhauser score, day of week, time of day, and hourly average time from end of triage to provider were statistically significant with p-values of ≤0.001, whereas sex and ethnicity were not at this level of statistical significance (Table 2). In particular, older patients were more likely to be prioritized with an adjusted odds ratio (aOR) of 1.005 (95% confidence interval [CI] 1.002–1.007) for a 1-year increase in age. In addition, the likelihood of prioritization was significantly lower for African Americans when compared to Caucasians with an aOR of 0.751 (95% CI 0.688–0.818). Among the patient chief complaint categories, cardiovascular, general/environmental, neurologic, ophthalmology, and trauma were heavily associated with prioritization compared to the gastrointestinal complaints. Lastly, each of the ED operational characteristics were found to be statistically significant. After the patient covariates were accounted for, the model still found that significant associations existed between ED-level operational covariates and patient prioritization. The likelihood of prioritization changed depending on the day of week and time of day. In addition, it was also associated with average time until provider, with an aOR of 1.017 for an increase of 1 min.

Table 3 shows the results for the matched 1:M conditional logistic regression model. Using this approach, we found similar results to the weighted logistic regression model in terms of patient characteristics that correlate with rooming priority. The race predictor was overall significant and most notably the aORs for African Americans and others being prioritized compared to Caucasians were 0.636 (95% CI 0.545–0.743) and 0.561 (95% CI 0.401–0.784), respectively. Also, the aOR for a 1-year increase in age was 1.009 (95% CI 1.005–1.013). Table 3 also shows that patients who were prioritized did not seem to have statistically significant differences from patients who were deprioritized in terms of sex and ethnicity. Similar relationships with increased ORs for certain chief complaints were observed in this model including general/environmental, neurological, trauma, and ophthalmology when compared to gastrointestinal chief complaints.

We performed a sensitivity analysis around the margin of 15 min used in our definition of violation of FCFS. Specifically, we repeated the statistical analysis with margins of 10 and 20 min and observed similar results. There were 1776 (11.3%) prioritized ED encounters when using a margin of 10 min and 1474 (9.3%) when using a margin of 20 min. Additionally, to test the robustness of our results that were obtained under the assumption that age is a continuous variable, we repeated our analysis by using age as a categorical variable. The aOR and p-values remained comparable to the case where age was modeled as a continuous variable. The results from these two sensitivity analyses are provided in the Supplemental Material Tables S1 through S7.

TABLE 2 Coefficients, aOR, and LRT p-values for the weighted logistic regression model 3

Predictor	aOR	95% CI	LRT p-values	Two-sided p-values
Age	1.005	(1.002–1.007)	<0.001*	<0.001*
Sex (baseline: female)			0.072	
Male	1.072	(0.994–1.156)		0.072
Race (baseline: Caucasian)			<0.001*	
African American	0.751	(0.688–0.818)		<0.001*
Asian	0.715	(0.538–0.951)		0.021
Other	0.782	(0.648–0.942)		0.010
Ethnicity (baseline: not Hispanic or Latino)			0.341	
Hispanic or Latino	0.879	(0.723–1.069)		0.197
Other	1.099	(0.724–1.669)		0.656
Complaint category (baseline: gastrointestinal)			<0.001*	
Cardiovascular	1.247	(1.102–1.410)		<0.001*
Ear, nose, throat	1.231	(1.006–1.507)		0.044
General/environmental	1.546	(1.341–1.783)		<0.001*
Genitourinary	0.830	(0.693–0.993)		0.042
Neurologic	1.377	(1.190–1.593)		<0.001*
Obstetrics/gynecology	1.168	(0.941–1.450)		0.159
Ophthalmology	3.605	(2.838–4.579)		<0.001*
Orthopedic	0.989	(0.858–1.139)		0.877
Respiratory	1.273	(1.085–1.493)		0.003
Skin	1.166	(1.003–1.355)		0.046
Substance abuse	0.944	(0.678–1.313)		0.731
Trauma	1.434	(1.169–1.759)		0.001*
Weighted Elixhauser score	1.014	(1.006–1.020)	<0.001*	<0.001*
Day of week (baseline: Monday)			<0.001*	
Tuesday	1.125	(0.989–1.280)		0.073
Wednesday	0.987	(0.864–1.127)		0.846
Thursday	1.269	(1.113–1.447)		<0.001*
Friday	1.187	(1.042–1.353)		0.010
Saturday	0.623	(0.538–0.723)		<0.001*
Sunday	0.654	(0.564–0.760)		<0.001*
Time of day (baseline: 12 p.m. to 4 p.m.)			<0.001*	
12 a.m. to 4 a.m.	0.801	(0.705–0.911)		0.001*
4 a.m. to 8 a.m.	0.057	(0.041–0.080)		<0.001*
8 a.m. to 12 p.m.	0.271	(0.233–0.315)		<0.001*
4 p.m. to 8 p.m.	0.981	(0.878–1.097)		0.739
8 p.m. to 12 a.m.	1.207	(1.083–1.346)		0.001*
Hourly average end of triage to provider	1.017	(1.016–1.018)	<0.001*	<0.001*

Abbreviations: aOR, adjusted odds ratio; LRT, likelihood ratio test.
*Significant at ≤0.001.

DISCUSSION

In our study of a large academic medical center ED, we employed two modeling techniques that independently found patient and ED operational characteristics that were associated with prioritization of rooming decisions among distinct patient groups compared to patients with similar triage acuity scores. Our findings add to the current literature on triage and rooming decisions in the ED by notably using robust modeling techniques that adjust for both patient-level characteristics and department-level characteristics that may

TABLE 3 Coefficients, aOR, and LRT results for the matched 1:M logistic regression model

Predictor	aOR	95% CI	LRT p-values	Two-sided p-values
Age	1.009	(1.005–1.013)	<0.001*	<0.001*
Sex (baseline: female)			0.640	
Male	1.032	(0.903–1.180)		0.640
Race (baseline: Caucasian)			<0.001*	
African American	0.636	(0.545–0.743)		<0.001*
Asian	0.702	(0.419–1.175)		0.178
Other	0.561	(0.401–0.784)		<0.001*
Ethnicity (baseline: not Hispanic or Latino)			0.394	
Hispanic or Latino	1.075	(0.760–1.520)		0.683
Other	1.632	(0.814–3.271)		0.167
Complaint category (baseline: gastrointestinal)			<0.001*	
Cardiovascular	1.311	(1.059–1.623)		0.013
Ear, nose, throat	1.259	(0.876–1.809)		0.213
General/environmental	1.583	(1.235–2.028)		<0.001*
Genitourinary	0.938	(0.677–1.300)		0.701
Neurologic	1.591	(1.221–2.073)		<0.001*
Obstetrics/gynecology	1.292	(0.897–1.862)		0.168
Ophthalmology	4.695	(3.115–7.079)		<0.001*
Orthopedic	1.096	(0.850–1.413)		0.479
Respiratory	1.445	(1.075–1.942)		0.015
Skin	1.358	(1.038–1.777)		0.025
Substance abuse	0.314	(0.177–0.557)		<0.001*
Trauma	1.444	(1.002–2.081)		0.049
Weighted Elixhauser score	1.017	(1.005–1.029)	0.004	0.004

Abbreviations: aOR, adjusted odds ratio; LRT, likelihood ratio test.
*Significant at ≤0.001.

influence rooming decisions of patients with a similar ESI triage acuity. To the best of our knowledge, this is the first study that specifically examines demographic disparities in rooming decisions. Prior work on disparities in EDs has been restricted to specific types of patients or applications. For instance, Tamayo-Sarver et al.,[17] Heins et al.,[18] Singhal et al.[19] found that ED opioid prescriptions were influenced by race. Chest pain patients have been found to be treated differently based on their race.[20,21] Lastly, Schrader and Lewis[22] and Vigil et al.[23] found that there have been significant differences in the triage acuity scores assigned to similar patients of different races and ethnicities.

There also exist a few papers in the literature that studied prioritization in rooming decisions in EDs. Ashour and Okudan[24] and Claudio and Okudan[25] use multiattribute utility theory to help nurses decide prioritization and select the next patient to be roomed. However, in both papers, the authors study subjective assessment made by a triage nurse about various criteria including patient vital signs or demographics which helped them determine the relative importance of these criteria and cutoffs used to make decisions. In such situations, triage nurses may be unaware of biases or tendencies to prioritize particular groups of patients. Our models use empirical data of how patients were triaged and roomed in a busy academic ED, and all data were retrieved from the EHR in a manner that captures real-world practice patterns and limits the possibility of decision making being influenced by the knowledge of the topic under study. Ding et al.[26] and Li et al.[27] both examined prioritization of patients using the CTAS in Canada, which includes fractile response objectives for each triage level within some target wait time. Both papers placed emphasis on the relation between prioritization and the patient wait time with respect to the target wait time of the associated triage category. Neither paper investigated demographic disparities associated with rooming decisions.

Lastly, Batt and Terwiesch[28] focused on using FCFS violations to determine why some patients leave without being seen rather than investigating disparities in rooming decisions at the ED. They argued that FCFS violations may be due to load balancing for providers in the ED because blocks of rooms are assigned to different doctors and nurses in the study ED, and the nurses in charge of rooming may choose to select patients who require less resources to room in a block that already has more severe patients.

The findings from both of our models suggest that racial disparities in rooming decisions exist in this ED. In particular, the weighted logistic regression model showed that African Americans were less likely to be prioritized in violation of FCFS for rooming when compared to Caucasians. Furthermore, our matched 1:M model found that African Americans and others were less likely to be prioritized compared to Caucasians, with respective aORs of 0.636 and 0.561. In addition, the matched model concluded that African Americans and others were more likely to be deprioritized than Caucasians. We also found that older patients were prioritized more than younger patients. The aOR for a 1-year increase in age were 1.005 and 1.009 for the weighted logistic model and matched model, respectively. Neither model found sex and ethnicity to be significant predictors of prioritization in rooming decisions in this ED. When compared to gastrointestinal chief complaints, certain chief complaints, including general/environmental, neurologic, and trauma, were associated with increased odds of prioritization in both modeling techniques. Of note, ophthalmological chief complaints were much more likely to get prioritized over gastrointestinal complaints, which in part can be explained by having a dedicated eye care room that patients with other chief complaints would not be roomed in. The weighted logistic model also brings up that prioritization may change depending on the ED's operating characteristics. In particular, there was more prioritization during Thursdays but less during the weekends when compared to the reference day of Monday. In addition, there was more prioritization during the evening and less during the morning in comparison to the reference hours of noon to 4 p.m. Lastly, when the ED seemed to be more crowded (as measured by the average time taken to see a provider), the likelihood of prioritization increased. These results suggest that prioritization became more frequent as the ED became more crowded.

It is important to note that violations of FCFS rooming decisions should not be uniformly viewed as problematic, but rather as means to give insight into subtle differences in how patients may experience variations in triage and timeliness of care depending on patient and ED characteristics. Additionally, it is not possible to use our EHR data to definitively assess on a case-by-case basis whether a prioritization was justified based on clinical condition (e.g., age-related frailty). However, the data can identify trends in subgroups of patients who are more likely to be prioritized in aggregate, i.e., sex, race, and ethnicity in this study, which would not be clinically justifiable. As patients are prioritized ahead of patients with similar triage scores, there will be other patients who will face longer wait times, and in some cases this may increase delays in timely diagnosis and treatment. This especially becomes pressing as the ED becomes more crowded, which our results suggest is a scenario where the rate of prioritization in violation of FCFS may also increase.

LIMITATIONS

This study has several limitations that are important to acknowledge. Patient race and ethnicity were abstracted from what was recorded in the EHR during routine clinical care and thus were not prospectively collected for this research purpose. Although this is a limitation, our data set had less than 1% of ED patients with missing race or ethnicity data and at the study ED, patient demographics are collected by ED registration staff who are required to complete training on how to collect demographic information.

Our findings are based on data from a single academic ED and excluded patients arriving to the ED via EMS and, therefore, may not generalize to other settings. To draw firmer conclusions about the existence of disparities, similar models should be generated using data from other EDs and other ED patient groups and with patient demographic data having higher fidelity than routine clinical data captured in the EHR. These additional results would allow us to further generalize our conclusions and to further determine whether a different patient population leads to differences in prioritization in ED rooming.

Additionally, it is possible that our model was not able to account for unmeasured variables that differentially affect the recognized triage acuity of a patient's condition. For example, we do not explicitly adjust for specific comorbidities that differentially affect patients of a given race/ethnicity including end-stage renal disease or sickle cell disease. In our study we utilized a weighted Elixhauser score; however, this only captures the likelihood of a patient's mortality across common comorbidities but does not assess specific individual comorbidities in isolation. Some insight from the models could also be possibly explained by the layout of the ED rather than bias toward a particular type of patient. Some patients, by nature of their complaint, cannot be roomed in certain care areas such as those with chief complaints that require private rooms for adequate evaluation. Additionally, even though ophthalmology-related patients were prioritized more, this is readily explained by the specialized care areas only suited for eye complaints. To ensure robustness, we conducted a sensitivity analysis by excluding the eye complaints and observed that our main conclusions have not changed (Tables S8 and S9 in the Supplementary Material). Lastly, our data did not account for individual patient triage vital signs and other nondiscrete data such as free-text triage nursing notes to further assess the potential severity of a patient's condition that is more easily appreciated in real time by triage staff.

CONCLUSIONS

Using a statistical modeling approach, we identified that patient age and race were statistically associated with prioritization in rooming decisions among patients with similar triage acuity score at an ED of a large academic medical center in the Southeastern United States. The findings from our two statistical models highlight that differences in patient race and age are vulnerable to deviations from a first-come-first-served prioritization scheme, even after accounting for other differences in patient-level and ED-level characteristics. Future study is needed in ways to mitigate disparities in rooming decisions across different patient groups.

AUTHOR CONTRIBUTIONS

Peter Lin conceived and designed the study, managed the data, analyzed numerical results, constructed the statistical models, and drafted the manuscript. Nilay T. Argon conceived and designed the study, analyzed numerical results, provided statistical expertise, acquired funding, and revised the manuscript. Qian Cheng conceived and designed the study, managed the data, analyzed numerical results, and reviewed the manuscript. Christopher S. Evans conceived and designed the study, provided clinical interpretations of the results, provided insights into the operational management of emergency department, and revised the manuscript. Benjamin Linthicum conceived and designed the study, acquired data, provided clinical expertise, and reviewed the manuscript. Yufeng Liu conceived and designed the study, analyzed numerical results, provided statistical expertise, and revised the manuscript. Abhishek Mehrotra conceived and designed the study, provided clinical interpretations of the results, provided insights into the operational management of emergency department, and reviewed the manuscript. Mehul D. Patel conceived and designed the study, analyzed numerical results, provided statistical expertise, and revised the manuscript. Serhan Ziya conceived and designed the study, analyzed numerical results, provided statistical expertise, acquired funding, and revised the manuscript.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

ORCID

Peter Lin https://orcid.org/0000-0002-2330-8396
Nilay T. Argon https://orcid.org/0000-0002-6814-0849
Christopher S. Evans https://orcid.org/0000-0003-1499-2867
Yufeng Liu https://orcid.org/0000-0002-1686-0545
Abhishek Mehrotra https://orcid.org/0000-0002-9119-831X
Mehul D. Patel https://orcid.org/0000-0002-1281-3207
Serhan Ziya https://orcid.org/0000-0003-1558-6051

REFERENCES

1. Wuerz RC, Milne LW, Eitel DR, Travers D, Gilboy N. Reliability and validity of a new five-level triage instrument. *Acad Emerg Med*. 2000;7(3):236-242. doi:10.1111/j.1553-2712.2000.tb01066.x
2. Murray MJ. The Canadian Triage and Acuity Scale: a Canadian perspective on emergency department triage. *Emerg Med (Fremantle)*. 2003;15(1):6-10. doi:10.1046/j.1442-2026.2003.00400.x
3. Peterson SM, Harbertson CA, Scheulen JJ, Kelen GD. Trends and characterization of academic emergency department patient visits: a five-year review. *Acad Emerg Med*. 2019;26(4):410-419. doi:10.1111/acem.13550
4. Howard PK. Prioritizing patients with acuity 3. *J Emerg Nurs*. 2011;37(3):296-297. doi:10.1016/j.jen.2011.02.010
5. Grafstein E, Bullard MJ, Warren D, Unger B, CTAS National Working Group. Revision of the Canadian emergency department information system (CEDIS) presenting complaint list version 1.1. *CJEM*. 2008;10(2):151-173. doi:10.1017/s1481803500009878
6. Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. *Med Care*. 1998;36(1):8-27. doi:10.1097/00005650-199801000-00004
7. van Walraven C, Austin PC, Jennings A, Quan H, Forster AJ. A modification of the Elixhauser comorbidity measures into a point system for hospital death using administrative data. *Med Care*. 2009;47(6):626-633. doi:10.1097/MLR.0b013e31819432e5
8. Gasparini A. Comorbidity: an R package for computing comorbidity scores. *J Open Source Softw*. 2018;3(23):648. doi:10.21105/joss.00648
9. King G, Zeng L. Logistic regression in rare events data. *Polit Anal*. 2001;9(2):137-163. doi:10.1093/oxfordjournals.pan.a004868
10. R Core Team, *R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing*, 2022. Accessed September 18, 2022. http://www.R-project.org/
11. Hosmer DW, Lemeshow S. *Applied Logistic Regression*. John Wiley & Sons, Inc; 2000.
12. Rubin DB. Matching to remove bias in observational studies. *Biometrics*. 1973;29(1):159-183. doi:10.2307/2529684
13. Therneau T. A package for survival analysis in R. *R Package Version*. 2021;3:2-13. https://CRAN.R-project.org/package=survival
14. Therneau TM, Grambsch PM. *Modeling Survival Data: Extending the Cox Model*. Springer; 2000.
15. Gail MH, Lubin JH, Rubinstein LV. Likelihood calculations for matched case-control studies and survival studies with tied death times. *Biometrika*. 1981;68(3):703-707. doi:10.1093/biomet/68.3.703
16. Logan JA. A multivariate model for mobility tables. *Am J Sociology*. 1983;89(2):324-349. doi:10.1086/227868
17. Tamayo-Sarver JH, Hinze SW, Cydulka RK, Baker DW. Racial and ethnic disparities in emergency department analgesic prescription. *Am J Public Health*. 2003;93(12):2067-2073. doi:10.2105/ajph.93.12.2067
18. Heins JK, Heins A, Grammas M, Costello M, Huang K, Mishra S. Disparities in analgesia and opioid prescribing practices for patients with musculoskeletal pain in the emergency department. *J Emerg Nurs*. 2006;32(3):219-224. doi:10.1016/j.jen.2006.01.010
19. Singhal A, Tien YY, Hsia RY. Racial-ethnic disparities in opioid prescriptions at emergency department visits for conditions commonly associated with prescription drug abuse. *PLoS One*. 2016;11(8):e0159224. doi:10.1371/journal.pone.0159224
20. Pezzin LE, Keyl PM, Green GB. Disparities in the emergency department evaluation of chest pain patients. *Acad Emerg Med*. 2007;14(2):149-156. doi:10.1197/j.aem.2006.08.020
21. Hambrook JT, Kimball TR, Khoury P, Cnota J. Disparities exist in the emergency department evaluation of pediatric chest pain. *Congenit Heart Dis*. 2010;5(3):285-291. doi:10.1111/j.1747-0803.2010.00414.x
22. Schrader CD, Lewis LM. Racial disparity in emergency department triage. *J Emerg Med*. 2013;44(2):511-518. doi:10.1016/j.jemermed.2012.05.010
23. Vigil JM, Alcock J, Coulombe P, et al. Ethnic disparities in emergency severity index scores among U.S. Veteran's affairs emergency department patients. *PLoS One*. 2015;10(5):e0126792. doi:10.1371/journal.pone.0126792
24. Ashour OM, Okudan GE. Patient Sorting through Emergency Severity Index and Descriptive variables' Utility. Proceedings of *IIE Annual Conference and Expo*; June 5–9, 2010; Cancun, Mexico
25. Claudio D, Okudan GE. Utility function-based patient prioritization in the emergency department. *Eur J Ind Eng*. 2010;4(1):59-77. doi:10.1504/EJIE.2010.029570
26. Ding Y, Park E, Nagrajan M, Grafstein E. Patient prioritization in emergency department triage systems: an empirical study of the Canadian triage and acuity scale (`). *Manuf Serv Oper Manag*. 2019;21(4):723-741. doi:10.1287/msom.2018.0719
27. Li W, Sun Z, Hong LJ. Who is next: patient prioritization under emergency department blocking. *Oper Res* 2021;0(0). doi:10.1287/opre.2021.2187

28. Batt RJ, Terwiesch C. Waiting patiently: an empirical study of queue abandonment in an emergency department. *Manag Sci*. 2015;61(1):39-59. doi:10.1287/mnsc.2014.2058

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Lin P, Argon NT, Cheng Q, et al. Disparities in emergency department prioritization and rooming of patients with similar triage acuity score. *Acad Emerg Med*. 2022;29:1320-1328. doi: 10.1111/acem.14598

PennState Health
Emergency Medicine Residency Program Director

Penn State Health Milton S. Hershey Medical Center is seeking an Emergency Medicine Residency Program Director to join our exceptional academic team located in Hershey, PA. This is an excellent opportunity to join an outstanding academic program with a national reputation and inpact the lives of our future Emergency Medicine physicians.

What We're Offering:

- Competitive salary and benefits
- Sign-On Bonus
- Relocation Assistance
- Leadership for Emergency Medicine Residency Program
- Comprehensive benefit and retirement options

What We're Seeking:

- MD, DO, or foreign equivalent
- BC/BE by ABEM or ABOEM
- Leadership experience
- Outstanding patient care qualities
- Ability to work collaboratively within a diverse academic and clinical environment

FOR MORE INFORMATION PLEASE CONTACT:

Heather Peffley, PHR CPRP
Physician Recruiter
Penn State Health

Email: hpeffley@pennstatehealth.psu.edu
Website: careers.pennstatehealth.org

What the Area Offers:

Located in a safe family-friendly setting, Hershey, PA, our local neighborhoods boast a reasonable cost of living whether you prefer a more suburban setting or thriving city rich in theater, arts, and culture. Known as the home of the Hershey chocolate bar, Hershey's community is rich in history and offers an abundant range of outdoor activities, arts, and diverse experiences. We're conveniently located within a short distance to major cities such as Philadelphia, Pittsburgh, NYC, Baltimore, and Washington DC.