INTEGRATIVE EMERGENCY SERVICES

A LINEAR DECOMPOSITION APPROACH TO EXPLAIN DIFFERENT WAITING-ROOM TIME AMONG PATIENTS WITH DIFFERENT RACES/ETHNICITIES IN EMERGENCY DEPARTMENT

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INTRODUCTION

- It has been reported that Non-Hispanic Black (NHB) and Hispanic/Latino (Hispanic) patients tended to wait longer in the Emergency Department (ED) before being seen by a provider when compared with Non-Hispanic White (NHW) patients.
- A prolonged length of waiting in the waiting room could further result in the increased rate of left before treatment complete, an indicator of poor quality of care.
- To better understand the factors that can affect the length of waiting among patients of different races/ethnicities, we aim to 1) analyze the length of waiting (LOW), 2) determine associated factors with prolonged LOW, and 3) further explore the different explainable factors leading to the prolonged LOW among NHB, NHW, and Hispanic ED patients.

METHOD

- This is a retrospective observational study. We included patients who presented at one urban tertiary hospital ED from January 1, 2019, to December 31, 2021. Patients were divided into three groups (NHW, NHB, and Hispanic) and their LOW were compared.
- Factors include patient demographics (age, gender, marital status, preferred language), clinical information (insurance, chronic disease conditions, mode of arrival), and hospital information (level us, of acuity, ED crowding status, weekday vs weekend, clinical hours vs after-hour).
- First, factors were analyzed to determine the association with prolonged LOW by using a multivariate linear regression model. Second, Blinder-Oaxaca post-linear decomposition on LOW was used to determine the different characteristics contribute to the prolonged LOW among patients of different races/ethnicities.

RESULTS

- A total of 310,253 patients were included into the final analysis with 107,757 NHW, 10,604 NHB, and 94,892 Hispanic ED patients separately.
- The average LOW in NHW was 42 minutes (SD 74 min), in NHB was 48 (76) minutes, and Hispanic was 57(83) minutes (p<0.0001).

RESULTS

- In comparison to NHW, being a NHB increased the LOW by 1.97 minutes and being a Hispanic increased the LOW by 3.37 minutes (p<0.001).

Table 1. General Characteristics of Study Population

	NHW (n=107,757)	NHB (n=107,604)	Hispanic (n=94,892)
Age			
Mean(SD)	46 (16)	44 (17)	42 (17)
Median (IQR)	46 [33, 58]	44 [30, 57]	41 [28, 54]
Gender --- n, %			
Male	57,177 (53)	55,614 (52)	45,806 (48)
Female	50,580 (47)	51,990 (48)	49,086 (52)
Marital status –n, %			
Single	55,525 (52)	70,735 (66)	45,143 (48)
Married	21,750 (20)	18,254 (17)	33,203 (35)
Others	30,482 (28)	18,615 (17)	16,546 (17)
Language --- n, %			
English	106,880 (99)	104,222 (97)	57,606 (61)
Spanish	223 (0.2)	27 (0.03)	37,019 (39)
Others	654 (0.6)	3,355 (3)	267 (0.3)
Insurance --- n, %			
Yes	72,843 (68)	73,630 (68)	51,070 (54)
No	34,914 (32)	33,974 (32)	43,822 (46)
Comorbid --- n, %			
No chronic disease	47,985 (45)	39,891 (37)	48,513 (51)
One chronic disease	16,642 (15)	18,940 (18)	14,236 (15)
Multimorbidity	43,130 (40)	48,773 (45)	32,143 (34)
Crowding status --- n, %			
Not-crowded	23,616 (22)	26,367 (25)	20,742 (22)
Crowded	40,785 (38)	41,287 (38)	35,663 (38)
Overly-crowded	43,356 (40)	39,950 (37)	38,487 (41)
Acuity level --- n, %			
ESI-1	5,138 (5)	4,460 (4)	3,739 (4)
ESI-2	33,296 (31)	26,297 (24)	21,400 (23)
ESI-3	60,980 (57)	65,871 (61)	63,119 (67)
ESI-4	7,470 (7)	10,096 (9)	6,194 (7)
ESI-5	873 (1)	880 (1)	440 (0.5)
Mode of arrival --- n, %			
Private car	43,528 (40)	49,035 (46)	55,052 (58)
Ambulance	43,360 (40)	36,757 (34)	20,937 (22)
Public transport	890 (1)	1,089 (1)	258 (0.3)
Ambulatory	8,745 (8)	9,885 (9)	9,183 (10)
Others	11,234 (10)	10,838 (10)	9,462 (10)
Clinical hour --- n, %			
Within hour (8a-5p)	54,471 (51)	54,683 (51)	49,266 (52)
Out of clinical hour	53,286 (49)	52,921 (49)	45,626 (48)
Week date --- n, %			
Weekday	79,561 (74)	79,529 (74)	69,888 (74)
Weekend	28,196 (26)	28,075 (26)	25,004 (26)
Distance to hospital --m			
Mean (SD)	39 (180)	22 (122)	20 (108)
Median (IQR)	13 (6, 22)	10 (5, 14)	10 (6, 15)

Table 2. Waiting room minutes comparison (Non-Hispanic White, Non-Hispanic Black, and Hispanic patients

	NHW	NHB	Hispanic
Overall waiting minutes			
Mean (SD)	42 (74)	48 (76)	57 (83)
Gender			
Male	39 (72)	44 (74)	51 (81)
Female	46 (76)	51 (77)	62 (84)
Marital status			
Single	40 (70)	46 (73)	52 (77)
Married	45 (75)	52 (79)	63 (87)
Others	45 (80)	49 (83)	59 (89)
Language			
English	42 (74)	47 (75)	53 (78)
Spanish	46 (91)	50 (75)	63 (90)
Others	54 (76)	62 (85)	66 (91)
Insurance			
Yes	40 (74)	46 (76)	54 (83)
No	47 (74)	51 (74)	60 (83)
Comorbid			
No	38 (66)	47 (69)	54 (77)
One	44 (73)	48 (73)	60 (83)
Multimorbidity	46 (82)	48 (82)	61 (92)
Crowding status			
Not-crowded	15 (25)	17 (27)	19 (29)
Crowded	33 (55)	38 (56)	44 (63)
Overly-crowded	66 (97)	78 (100)	90 (104)
Acuity-level			
ESI-1	3 (8)	3 (7)	4 (8)
ESI-2	14 (37)	18 (43)	20 (46)
ESI-3	59 (87)	61 (85)	72 (91)
ESI-4	55 (62)	56 (60)	61 (63)
ESI-5	43 (57)	50 (58)	57 (61)
Mode of arrival			
Private car	62 (81)	64 (80)	69 (86)
Ambulance	17 (53)	19 (56)	16 (50)
Public transportation	60 (73)	67 (79)	74 (101)
Ambulatory	61 (85)	64 (82)	75 (92)
Others	45 (75)	52 (79)	56 (84)
Clinical hours			
Within clinical hour	45 (79)	50 (80)	58 (89)
Out of clinical hour	39 (68)	45 (71)	56 (77)
Weekday vs. weekend			
Weekday	47 (79)	52 (81)	63 (89)
Weekend	30 (55)	35 (57)	39 (60)

Table 4. Decomposition of LOW by Patients with different races/ethnicities

Average LOW: NHW patients	**42.32 [41.88, 42.76], p<.001**	
Average LOW: NHB patients	47.65 [47.20, 48.10], p<.001	
Average LOW: Hispanic patients	56.92 [56.39, 57.45], p<.001	
	NHW vs. NHB	NHW vs. Hispanic
Differences in average waiting minutes	5.33 [4.70, 5.96], p<.001	14.60 [13.92, 15.29], p<.001
Demographics (age, sex, marital, language, insurance)	-0.25 (-4.7%) [-0.37, -0.14], p<.001	0.78 (5.3%) [0.36, 1.19], p<.001
Clinical information (chronic diseases)	0.40 (7.5%) [0.35, 0.45], p<.001	-0.44 (-3.0%) [-0.50, -0.38], p<.001
Hospital system (crowding, ESI, mode of arrival)	3.18 (59.7%) [2.87, 3.49], p<.001	10.93 (74.9%) [10.57, 11.28], p<.001
Total explained (%)	3.32 (62.3%) [2.99, 3.66], p<.001	11.26 (77.1%) [10.73, 11.79], p<.001
Total unexplained	2.00 (37.5%) [1.43, 2.58], p<.001	3.34 (22.9%) [2.64, 4.04], p<.001

RESULTS

Table 3. Factors associated with prolonged waiting by using multivariate linear regression

	Beta	SE	95% CI	P value
Intercept	-65.06	0.8037	[-66.64, -63.49]	<.001
Race				
NHW (ref)				
NHB	1.97	0.2975	[1.39-2.55]	<.001
Hispanic/Latino	3.37	0.3548	[2.67-4.07]	<.001
Gender				
Male (ref)				
Female	2.31	0.2478	[1.83, 2.80]	<.001
Age	0.21	0.009	[0.19, 0.23]	<.001
Marital status				
Single (ref)				
Married	0.67	0.3186	[0.05, 1.30]	0.034
Others	0.45	0.3414	[-0.22, 1.12]	0.186
Language				
English (ref)				
Spanish	2.28	0.4627	[1.37, 3.18]	<.001
Others	4.10	1.0523	[2.03, 6.16]	<.001
Insurance				
No	3.84	0.2734	[3.30, 4.37]	<.001
Yes (ref)				
Comorbidity				
No (ref)				
One	3.31	0.3592	[2.61, 4.02]	<.001
Multimorbidity	6.41	0.3132	[5.80, 7.02]	<.001
Crowding Status				
Not-crowded (ref)				
Crowded	22.09	0.3216	[21.46, 22.72]	<.001
Overly-crowded	62.21	0.3282	[61.57, 62.86]	<.001
Acuity-Level				
ESI-1 (ref)				
ESI-2	7.15	0.6333	[5.91, 8.39]	<.001
ESI-3	48.97	0.6143	[47.77, 50.18]	<.001
ESI-4	39.96	0.7482	[38.49, 41.42]	<.001
ESI-5	32.97	1.5635	[29.90, 36.03]	<.001
Mode of arrival				
Private-car	36.65	0.2963	[36.06, 37.23]	<.001
Ambulance (ref)				
Public transportation	34.92	1.4484	[32.08, 37.76]	<.001
Ambulatory	38.83	0.4671	[37.91, 39.74]	<.001
Others	27.34	0.4398	[26.48, 28.21]	<.001
Clinical hour				
Within clinical hour(ref)				
Out of clinical hour	2.84	0.2460	[2.35, 3.32]	<.001
Weekend/Weekday				
Weekend (ref)				
Weekday	4.62	0.2851	[4.07, 5.18]	<.001
Distance to hospital	-0.001	0.0009	[-0.003, 0.001]	0.326

CONCLUSION

- Factors affecting prolonged LOW in NHB and Hispanic ED patients are mainly due to ED crowding status, level of acuity patient assigned, and patient chronic conditions.
- However, apart from all these potential factors, there are still 23-38% of prolonged waiting minutes whose contributors are still uncertain.
- Finding such hidden factors leading to the prolonged LOW could potentially improve ED management in the future.

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CHAT-GPT USED IN EMERGENCY MEDICINE RESEARCH

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INTRODUCTION

- ChatGPT is an artificial intelligence (AI) language processing tool build upon large language models (LLMs)
- ChatGPT can be used in different areas of Emergency Medicine (EM) research. Several areas have been investigated with promising findings whereas the utility of applications for others remain uncertain.
- Areas with promising findings include natural language processing (NLP), patient education, drug design and clinical decision support.
- ChatGPT can be used to analyze and extract meaningful information from large amounts of medical text data, such as electronic health records, clinical notes, medical literature, and social media posts.
- ChatGPT can be used to develop predictive models and decision support tools that aid in diagnosis, treatment selection, and risk assessment.
- ChatGPT can be used to develop conversational agents that engage patients in health-related conversations, provide health education and support, and assist in self-management of chronic conditions.
- However, there are other ChatGPT applications related to EM research that have not been effectively applied or validated including, but not limited to, 1) generating literature searching strategies; 2) generating data mining coding; 3) providing statistical programming; 4) summarizing articles; 5) performing literature searching and reviewing; and 6) generating scientific manuscripts.
- Therefore, we aim to address these six areas by using ChatGPT versus manual checking/validating to determine its feasibility, applicability, and performance accuracies.

METHODS AND RESULTS

AREA 1: Generating a Literature Search Strategy

- Method: In this comparison study we used ChatGPT to write a searching strategy which was compared with librarian generating searching strategies (formal literature searching). In addition, we performed another 4 MEDLINE searches and 4 Google scholar searches using ChatGPT as well as manual searches by physicians.
- Results: The search strategies generated by ChatGPT matched perfectly with both the librarian's and physician's search strategy.

METHODS AND RESULTS

AREA 2: Generating Data Mining Codes

- Methods: we chose 10 data mining tasks. For example: "Ask for writing excel code to replace missing data with median value." or "Ask for writing steps to add 5 to each variables in column A", etc.
- Results: ChatGPT can generate steps in detail to teach how to perform these tasks. Overall, 8 out of 10 tasks were performed correctly.

AREA 3: Providing Statistical Programming

- Methods: using STATA commands, we chose 10 tasks for data analysis. For example: provided a binary outcome variable with several categorical variables and several continuous variables, ask ChatGPT to generate a logistic regression model using STATA.
- Results: ChatGPT can provided STATA programming correctly among 7 out of 10 tasks. When provided correct explanation of your variables, ChatGPT can differentiate the differences between categorical and continuous variables. However, if you provide incorrect information (such as binary variables including "0" as none, "1" as once, and "2" as twice), ChatGPT provided incorrect coding and programming.

AREA 4: Article Summarization

- Methods: we randomly selected 10 articles from PubMed, and asked ChatGPT to provide a summary of each article.
- Results: ChatGPT can provide a summary using background, method, results, and suggestion/conclusion in a similar format as article abstract with its own words. It can provide main results with numbers and statistical significance. It can also provide suggestions based on the study findings of each articles.

AREA 5: Perform Literature Review

- Methods: Using "Artificial intelligence and machine learning in Emergency Medicine" as a targeted review focus, we asked ChatGPT to provide a literature review using MEDLINE, Google scholar, Web of Science, Cochrane library, Scopus, and CINAHL. We compared the results with formal literature searches by a librarian.
- Results: The total number of articles provided by ChatGPT is more than the number of articles provided by the librarian. Further investigation of the list of articles reveals ChatGPT significantly provided incorrect information. Nearly 30% of articles had some levels of incorrect information, such as providing wrong author names, journal names, wrong publication years, wrong PMID number, etc.

METHODS AND RESULTS

AREA 6: Generating a Manuscript

- Methods: we asked ChatGPT: "can you write a manuscript using HINTS 5 Cycle 4 data to determine whether Non-Hispanic Whites use online medical records more than the Hispanic/Latino individuals".
- Results: ChatGPT can write an entire manuscript including an abstract, introduction, methods, results, and discussion. In the result section, ChatGPT can provide a simple table to compare two different patient populations. However, significant amounts of text were adapted from online material or other published articles, and unable to pass the plagiarism check provided by some journals (e.g., the American Journal of Emergency Medicine)

Below is a table summarizing the feasibility, accuracy, and applicability of these six ChatGPT applications

Table. A Comparison of Feasibility, Accuracy, and Applicability of ChatGPT used in Emergency Medicine Research

	Feasibility	Accuracy	Applicability
Generating searching strategy	√	√	√
Generating data mining codes	√	±	±
Providing statistical programming	√	±	±
Article summarization	√	√	√
Performing literature review	√	X	X
Generating manuscript	√	X	X

DISCUSSION/CONCLUSION

- We found that while ChatGPT can be applied to Emergency Medicine research, it should be used with caution. Users will need to have enough knowledge to be able to recognize incorrect information. All findings generated from ChatGPT required manual validations.
- In addition, to minimize the errors generated by ChatGPT, users are recommended to provide as detailed information/steps as possible to guide ChatGPT to enhance its performance and accuracy.

IDENTIFYING RACIAL DISPARITIES IN SEXUAL ASSAULT IN TARRANT COUNTY

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INTRODUCTION

- Data from the CDC reports a lifetime prevalence of sexual assault as about 1 in 5 for Black surviviors (22%) and 1 in 7 for Hispanics (14.6%). Unfortunately, this percentage only accounts for the number of women who report their abuse.[1]
- Some evidence suggests Black women are at an increased risk of sexual victimization and negative health sequelae compared with White women.[2]
- JPS has a dedicated Forensics Department, including a full nursing team, patient advocates, physicians, and community partners. This team performs sexual assault exams 24/7.
- 2 in 5 women in Texas have experienced sexual assault. 1 in 5 men in Texas have experienced sexual assault.[3]

PATIENT POPULATION

Tarrant County Population Demographics:[4]

- 43.7% White or Caucasian
- 18.5% Black or African American
- 30.2 Hispanic or Latino
- 6% Asian
- 3.9% Other

"You are not the darkness you endured. You are the light that refused to surrender."
– John Mark Green

RESULTS

JAN 2022 - JAN 2023

During the year 2022, JPS served 483 sexual assault patients with the following demographics:

- 39% White or Caucasian
- 27% Hispanic or Latino
- 28% Black or African American
- 2% Asian/Pacific Islander
- 4.2% Other

RESULTS

- The data shows JPS sees a higher population of Black or African American victims of sexual assault when compared to general Tarrant County population demographics.
- Though we do not have data from the other hospital who also performs sexual assault exams in Tarrant County, this finding is concerning for a population at higher risk for sexual assault seen at JPS

IMPLICATIONS

- Currently, JPS does not offer specialized care to Black or African American persons who are victims of sexual assault. After identifying a discrepancy in the demographics and acknowledging the increased risk of negative health sequelae compared to White or Caucasian victims, the JPS Forensics Department plans to work with community partners to provide and expand the services offered at JPS.
- It is important to address these disparities through policies and programs that address systemic inequalities and supporting survivors of all races and backgrounds, as well as promoting awareness.
- We hope to serve as a model for changing the approach in caring for survivors of violence regardless of race or ethnicity.

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THE ROLE OF ELECTRONIC HEALTH INTERACTIONS IN PATIENT-CENTERED COMMUNICATION: A CROSS SECTIONAL ANALYSIS FROM THE HEALTH INFORMATION NATIONAL TRENDS SURVEY (HINTS)

INTEGRATIVE EMERGENCY SERVICES

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INTRODUCTION

- Patient-provider communication can be assessed by patient-centered communication (PCC) score.
- Results from previous studies show that better PCC is linked to higher patient satisfaction, higher patient compliance, increased health-related self-efficacy, and better clinical outcomes.
- In recent years, after reviewing qualitative studies with key informants, a conceptual model for eHealth has been developed including three prominent but overlapping eHealth domains. It includes 1) using digital technologies to monitor, track, and inform health, 2) using digital technologies to enable health communications between patients and healthcare providers, and 3) data enabling health.
- With rapid development of electronic health (eHealth) interactions, we are uncertain of its role in PCC. Therefore, we aim to determine the association of PCC and eHealth using national representative survey data.

METHOD

- This is a cross sectional analysis using the Health Information National Trends Survey 5 (HINTS 5) cycle 1 to cycle 4 data (2017-2020).
- Seven specific questions were used for PCC assessment, and eHealth communication was divided into two types including private-eHealth (i.e., using online medical record) and public-eHealth (i.e., sharing health information online) communication.
- All independent variables were imputed by multiple imputation by chained equations (MICE).
- A multivariate logistic regression was performed to determine the association between PCC and eHealth communication after the adjustment of other social, demographic, and clinical variables.
- All analyses including data merging, data imputation, and final analyses were performed by STATA 14.2 (College Station, TX).
- Strengthening of the reporting of observational studies in epidemiology (STROBE) reporting guidelines were followed in describing study methods and findings

RESULTS

- Four cycles of HINTS 5 data were merged with a total of 16,092 weighted participants, including 3,285 participants from cycle 1, 3,504 from cycle 2, 5,438 from cycle 3, and 3,865 from cycle 4. 3,037 participants. We analyzed a total of 13,055 weighted participants representing a 791,877,728 unweighted population.
- The missing data rates from all variables range from 0.17% to 12.59% with a median of 1.89%.
- The adjusted odds ratio (AOR) of private-eHealth communication associated with PCC was 1.17 (95% CI 1.02-1.35, p=0.027). The AOR of public-eHealth communication associated with PCC was 0.84 (95% CI 0.71-0.99, p=0.043).

Table 1. Patient-centered and eHealth Communication Comparisons prior-to and during COVID-19 Pandemic Phases

	Prior-to COVID Pandemics (2017-2019) 95% CI	During COVID Pandemics (2020) 95% CI	Percentage Difference 95% CI
Internet access --- yes (Wt%)	84.58(83.43, 85.74)	87.88(86.31, 89.45)	3.30(1.35,5.25)
Usual sources of care --- yes (Wt%)	73.66(71.91, 75.41)	70.92(68.33, 73.51)	-2.73(-5.86, 0.39)
Private-eHealth communication --- yes (Wt%)	42.13(40.26, 44.00)	46.12(43.31, 48.93)	3.98(0.60, 7.37)
Public-eHealth communication --- yes (Wt%)	18.60 (17.19, 20.00)	19.56(17.22, 21.91)	0.97(-1.76, 3.70)
Individual perception of PCC --- ideal (Wt%)	53.63(51.82, 55.44)	53.86(50.78, 56.94)	0.23(-3.34, 3.80)

Table 2. PCC and eHealth Communication Comparisons among Participants of Different Race/Ethnicities

	NHW	NHB	Hispanic/Latino	NHA	Others
Internet access --- yes (Wt%)	88.18	76.63	78.75	86.33	89.74
Usual sources of care --- yes (Wt%)	78.74	67.78	55.98	61.38	66.76
Private-eHealth communication --- yes (Wt%)	46.34	35.39	33.56	49.18	41.30
Public-eHealth communication --- yes (Wt%)	18.24	20.83	19.31	19.22	21.86
Individual perception of PCC ---excellent (Wt%)	55.13	56.52	50.65	37.94	51.40

RESULTS

Table 3. Association Between PCC and eHealth Communication

	Adjusted Odds Ratio with 95% CI	P value
Public-eHealth communication		
No	Reference	
Yes	0.84 [0.71, 0.99]	0.043
Private-eHealth communication		
No	Reference	
Yes	1.17 [1.02, 1.35]	0.027
Usual source of Care		
No	Reference	
Yes	1.36 [1.15, 1.59]	<0.001
Internet access		
No	Reference	
Yes	0.79 [0.65, 0.96]	0.019
Insurance coverage		
No	Reference	
Yes	1.06 [0.75, 1.50]	0.750
Age		
18-34	Reference	
35-49	0.89 [0.71, 1.11]	0.312
50-64	0.92 [0.75, 1.13]	0.418
65-74	1.09 [0.88, 1.36]	0.434
75+	0.87 [0.67, 1.12]	0.271
Gender		
Male	Reference	
Female	1.10 [0.96, 1.25]	0.158
Race/ethnicity		
NHW	Reference	
NHB	1.17 [0.95, 1.44]	0.144
Hispanic/Latino	0.94 [0.77, 1.14]	0.502
NHA	0.55 [0.40, 0.75]	<0.001
Others	0.93 [0.65, 1.34]	0.700
Marital status		
Single	Reference	
Married	1.03 [0.87, 1.23]	0.710
Others	1.21 [0.99, 1.47]	0.058
Education level		
Less than High school	Reference	
High school to some college	1.12 [0.86, 1.47]	0.392
College and above	0.95 [0.71, 1.27]	0.707
Income level		
<$20,000	Reference	
$20,000-49,999	1.18 [0.96, 1.44]	0.115
$50,000-99,999	1.13 [0.90, 1.40]	0.288
≥$100,000+	1.48 [1.17, 1.88]	0.001

DISCUSSION/CONCLUSION

- We found that eHealth communication was associated with PCC varies.
- This study showed that private-eHealth interaction was positively associated with PCC, whereas public-eHealth interaction was found to be negatively associated with PCC.

USING ARTIFICIAL INTELLIGENCE/MACHINE LEARNING ALGORITHMS TO PREDICT LEFT BEFORE TREATMENT COMPLETE IN THE EMERGENCY DEPARTMENT

INTEGRATIVE EMERGENCY SERVICES

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INTRODUCTION

- Left before treatment complete (LBTC) is defined as patients who present to the Emergency Department (ED) seeking healthcare and leave before their healthcare is complete. LBTC includes patients who leave before or after the medical screening exam, those who leave against medical advice (AMA), and those who elope.
- LBTC is an important metric for both ED operations and quality of care. Factors that affect LBTC have been reported in the past with controversial findings.
- Identifying factors that affect the daily departmental LBTC could potentially help administrators and ED leaders implementing interventions to reduce LBTC.
- Predicting LBTC could provide an early alert to administrators and ED leadership warning them of an upcoming surge and allow them to act early to avoid the surge or mobilize their team and resources to enter their Surge Plan.
- We aim to 1) validate factors that affect LBTC, 2) predict LBTC rates using different machine learning algorithms, and 3) identify the best machine learning model for LBTC predictions.

METHOD

- Data was retrieved from a publicly funded hospital ED whose annual ED volume ranges between 120,000 to 130,000.
- ED metrics were collected including LBTC, daily patient volume, boarding time, acuity level, total ED length of stay, and every stage of ED stay (i.e., triage time, waiting room time, provider time, disposition time, etc.).
- From January 1, 2019, to December 31, 2022, all ED metric data was harvested. A prediction model was generated by machine learning using 70% data as the training model and 30% data as the testing model.
- We used seven different machine supervised learning algorithms including linear regression, decision tree regression, random forest regression, gradient boosting, K-Nearest Neighbors, multi-layer perceptron, and support vector regression.

METHODS

- Mean Absolute Error (MAE, the mean difference between predicted LBTC rate to the real LBTC rate) was used to determine the accuracy of model prediction.
- Important features were calculated to determine risk factors associated with LBTC.
- In terms of machine learning, we used Python 3.8 to predict LBTC with different regression models. The MAE was measured in each model to determine the best machine learning algorithm.
- We also used regular statistical software (STATA 14.2 version) for general characteristic variables analyses.

RESULTS

A total of 1461 daily operation metrics were analyzed. The overall LBTC rate was 8.1%. The top three factors affecting LBTC were longer waiting room time, longer boarding time, and number of main ED patients. The linear regression model yielded the best prediction with the smallest MAE (1.453). When such a model is used for daily LBTC rate prediction, a less than 1.5% daily LBTC rate difference can be predicted. Meanwhile, once the optimal LBTC rate is set, we can generate a formula to predict any other variables (for example: if LBTC=4.0%, ED volume=350, main ED volume=250, ED total LOS=4h, waiting room=45min, the targeted total boarding hours daily= approximately 500 hours)

Table 1. Different Mean Absolute Errors among Different Machine Learning

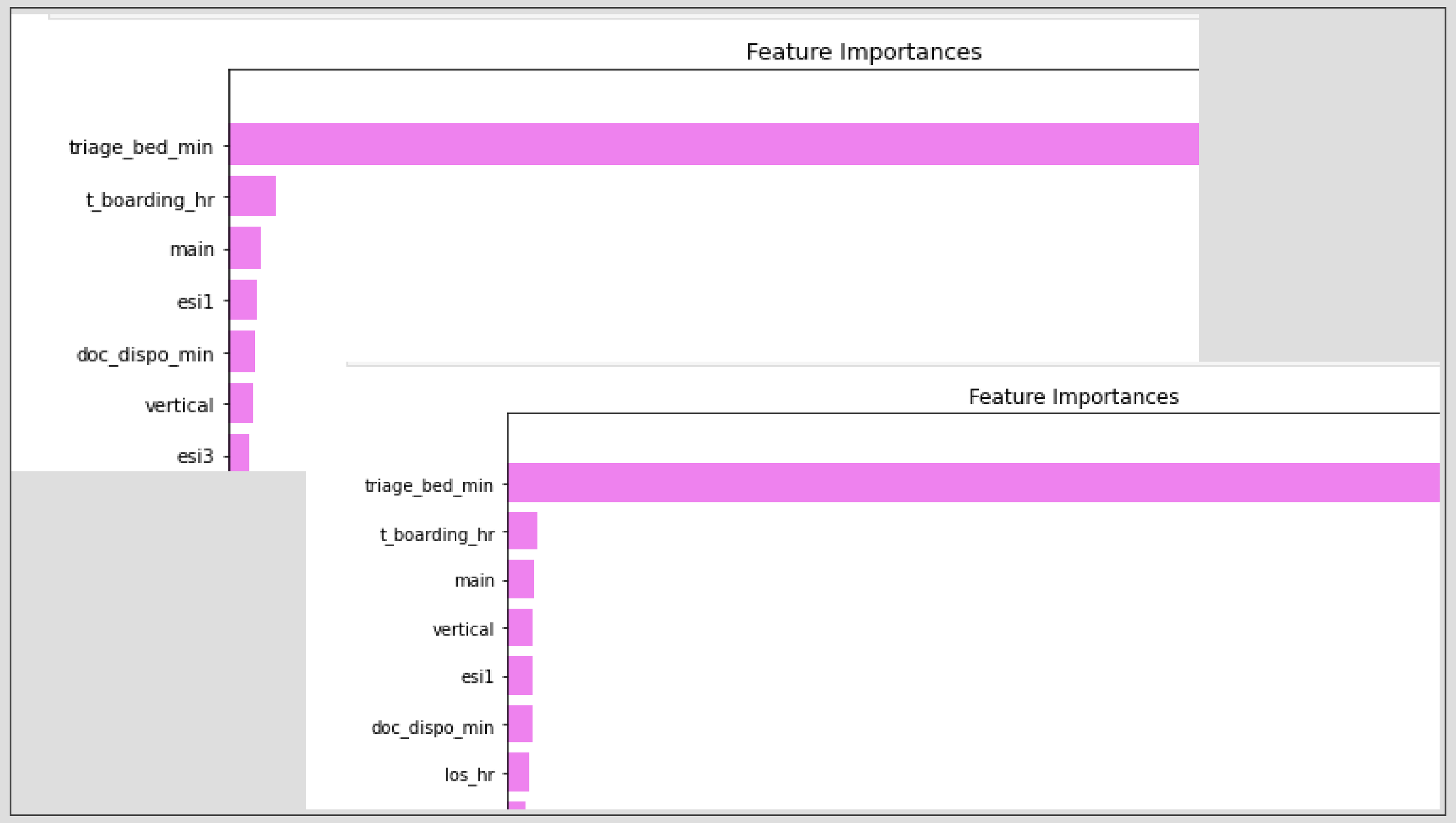
	Training Set	Testing Set
Linear Regression	1.485 %	1.453 %
Gradient Boosting Regression	1.087 %	1.507 %
Random Forest Regression	0.732 %	1.509 %
Multi-layer Perceptron Regression	1.528 %	1.511 %
Support Vector Regression	1.585 %	1.523 %
K-Nearest Neighbors Regression	1.369 %	1.588 %
Decision Tree Regression	0.513 %	2.091 %

RESULTS

Table 2. Sample Comparison between Predicted LBTC and Real-time LBTC

Sample Random Number	Real-time LBTC Rate	Predicted LBTC Rate	Difference
774	4.84	5.57	0.13%
396	5.57	4.47	-1.10%
1297	9.68	9.05	-0.63%
647	11.11	10.18	-0.93%
491	3.61	5.04	1.43%

Figure 1. Factors affecting LBTC in different machine learning prediction models. (2 of 7)



DISCUSSION/CONCLUSION

- ED waiting time, boarding time, and main ED volumes are the top three factors that affect the ED LBTC rate.
- These factors are validated consistently with the use of different machine learning algorithms. Among all machine learning algorithms, using linear regression model yielded the best prediction accuracy.
- This study identified risks affecting LBTC and built up the machine learning prediction model, thus serving as a foundation to predict and further implement interventions to decrease LBTC in ED operations.
- Following this study, ED operations focused on decreasing ED waiting time by promoting a “pull to full” process, yielding a significant decrease in LBTC as the model suggests. Success!