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# Predicting waiting and treatment times in emergency departments using ordinal logistic regression models

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ABSTRACT

*Background:* Since providing timely care is the primary concern of emergency departments (EDs), long waiting times increase patient dissatisfaction and adverse outcomes. Especially in overcrowded ED environments, emergency care quality can be significantly improved by developing predictive models of patients' waiting and treatment times to use in ED operations planning.
*Methods:* Retrospective data on 37,711 patients arriving at the ED of a large urban hospital were examined. Ordinal logistic regression models were proposed to identify factors causing increased waiting and treatment times and classify patients with longer waiting and treatment times.
*Results:* According to the proposed ordinal logistic regression model for waiting time prediction, age, arrival mode, and ICD-10 encoded diagnoses are all significant predictors. The model had 52.247% accuracy. The model for treatment time showed that in addition to age, arrival mode, and diagnosis, triage level was also a significant predictor. The model had 66.365% accuracy. The model coefficients had negative signs in the corresponding models, indicating that waiting times are negatively related to treatment times.
*Conclusion:* By predicting patients' waiting and treatment times, ED workloads can be assessed instantly. This enables ED personnel to be scheduled to better manage demand supply deficiencies, increase patient satisfaction by informing patients and relatives about expected waiting times, and evaluate performances to improve ED operations and emergency care quality.



## 1. Introduction

The significant increase in admissions to emergency departments (EDs) has led to ED overcrowding, which is a severe problem for healthcare systems worldwide. Overcrowding in EDs can have serious negative outcomes for patients and ED staff, such as reduced patient satisfaction [1], increased mortality [2], increased ambulance diversions [3], reduced staff morale and attention [4], and increased waiting and treatment times [5,6]. Of these issues, researchers have paid more attention to waiting and treatment times since EDs are highly sensitive to increased delays and waiting. Therefore, any interventions that can reduce these improve ED operations significantly.

One main goal of ED operations is minimizing the initial waiting time, defined as the time between a patient's registration and initial physician evaluation. Various studies have set targets for patients' initial waiting times in EDs. According to the triage system Emergency Severity Index (ESI) version 4, which categorizes patients based on their priorities from level 1 to 5, treatment patients should be treated within 1, 10, 30, 60, and 120 min respectively [7]. Treatment time, defined as the time from first physician assessment to final disposition decision, is another quality indicator for ED operations. To reduce or minimize waiting and treatment times, the first essential step is detailed recording and continuous reporting [8,9], which has become possible by integrating electronic warehouses into ED systems. Using these electronic medical records (EMR), researchers have analyzed the variables causing increased delays and waiting [10-15], while some studies have developed prediction models on ED time-related quality indicators [16-18]. Current studies also use data mining of EMR to analyze, model, and reduce ED times. This can help to reduce ED overcrowding and improve patient flow [19-22].

EMR systems allow hospitals and other health care organizations to collect a significant amount of data. However, most is raw data that is poorly structured and thus unsuitable for analysis [23]. Health data also has a very complicated structure [24] so the health care industry requires the application of data mining techniques to examine and analyze the raw data to extract useful information and knowledge. Based on the knowledge obtained, health organizations can take important decisions cost-effectively while providing complementary clinical solutions.

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The current study uses data mining techniques to develop models for classifying ED patients regarding their waiting and treatment times. The proposed models identify which characteristics are associated with longer waiting and treatment times in EDs. Grouping patients with similar characteristics and generating predictions based on both waiting and treatment times of each group can significantly improve ED operational planning.

## 2. Methods

The data for this retrospective study were obtained from the emergency department of a tertiary-level public hospital in İzmir, Turkey. As one of the main region's main urban hospitals, it receives most of the city's emergency visits. In this hospital, initial assessment is initiated by a triage nurse who enters each patient's demographic characteristics and vital signs into the database. This ED uses the 3-level ESI system, which categorizes patients as red (urgent), yellow (emergent), or green (non-urgent). Since 2018, this ED has added an additional room for trauma patients. Thus, through registering arriving patients and recording their data, the triage nurse assigns them to one of four rooms. Higher-priority patients are generally directed to examination rooms for immediate treatment by physicians. Lower-priority patients must wait in waiting rooms until their turn comes. Patients are examined and treated in one of the four rooms by specialists and/or general practitioners, who prescribe further diagnostic measures for the nurses to perform. The physicians who treat the patients assign the diagnosis based on the International Classification of Diseases Version 10 (ICD-10), which is a medical classification system developed by the World Health Organization with codes for diseases, signs, and symptoms, abnormal findings, complaints, and external causes of injury or diseases [25]. When the required treatment is given, the patient is discharged from ED (to go home, be admitted to a hospital polyclinic or service, or transfer to another hospital).

In 2018, this ED received around 1250 daily arrivals. It was estimated that one month's data was sufficient for the study's design and purpose in that the observed variations in patient demographics, and waiting and treatment times are generalizable, and that data mining techniques can be applied. August 2018 was randomly selected for the study data.

The local institutional review board approved the study.

### *2.1. Study variables*

The independent variables were the patients' demographic characteristics (gender and age), and visit characteristics (triage category, arrival mode, and ICD-10 diagnosis). Gender, arrival mode, and diagnosis were measured on nominal scales while age and triage category were ordinal. For referral diagnosis, first-level ICD-10 was used, which has the form LXX, where L denotes a letter and X denotes a digit from 0 to 9. The respective categories of each variable were defined as follows:

- Gender: male, female
- Age: [0–14, 15–64, 65–84], ≥85
- Triage category: red, yellow, green, trauma
- Arrival mode: walk-in, by ambulance
- ICD-10 diagnosis: Certain infectious and parasitic diseases “A00-B99”, Neoplasms “C00-D49”, Diseases of the blood and blood-forming organs, and certain disorders involving the immune mechanism “D50-D89”, Endocrine, nutritional, and metabolic diseases “E00-E89”, Mental, behavioral and neurodevelopmental disorders “F01-F99”, Diseases of the nervous system “G00-G99”, Diseases of the eye and adnexa “H00-H59”, Diseases of the ear and mastoid process “H60-H95”, Diseases of the circulatory system “I00-I99”, Diseases of the respiratory system “J00-J99”, Diseases of the digestive system “K00-K95”, Diseases of the skin and subcutaneous tissue “L00-L99”, Diseases of the musculoskeletal system and connective tissue “M00-M99”, Diseases of the genitourinary system “N00-N99”, Pregnancy, childbirth, and the puerperium “O00-O9A”, Certain conditions originating in the perinatal period “P00-P96”, Congenital malformations, deformations, and chromosomal abnormalities “Q00-Q99”, Symptoms, signs, and abnormal clinical and laboratory findings, not elsewhere classified “R00-R99”, Injury, poisoning, and certain other consequences of external causes “S00-T88”, External causes of morbidity “V00-Y99”, Factors influencing health status and contact with health services “Z00-Z99”

Initial waiting time, hereafter waiting time, and treatment time were the two output variables used as quality indicators for ED performance. These variables were measured in minutes on a continuous scale for univariate analysis. For the proposed classification models, waiting and treatment times were converted into ordinal levels with thresholds for the levels of waiting time as 10 and 60 min respectively. Thresholds for the treatment time levels were defined as 10 and 120 min. The categorical definitions of the output variables of the two models were thus defined as follows:

- Waiting time: “Patients who wait less than 10 minutes”, “Patients whose waiting time is in the range of 10-60 minutes”, and “Patients who wait more than 60 minutes”
- Treatment time: “Patients who are treated for up to 10 minutes”, “Patients whose treatment time is in the range of 10-120 minutes”, and “Patients who are treated for longer than 120 minutes”

### *2.2. Statistical analysis and outcome measures*

Standard descriptive statistics were used to characterize the study sample with frequency and percentage distributions for the categories of independent and dependent variables. Waiting and treatment times were described with mean and standard deviation for each category. This analysis was also used to determine the appropriateness of the selected input variables since the significance of mean difference between categories of them was tested. Independent sample *t*-tests were used to test the significance of the differences between the categories of the binary input variables (gender, arrival mode) while ANOVA was used to test for the other input variables (age, triage category and ICD-10 codes). *P*-values less than 0.05 were considered as statistically significant. The relationship between waiting and treatment times for each category was tested by Pearson correlation analysis.

Ordinal logistic regression analysis was used to model the ED waiting and treatment times. The model classified patients into predetermined, ordered categories of the output variable. Since this study aimed to identify the characteristics of patients with shorter and longer waiting and treatment times, the model was appropriate. Additionally, since the output variables of the models, waiting and treatment times, were classified into three different levels which were ordered, this method was chosen. The performances of the proposed classification models are reported based on model accuracies. This metric shows the percentage of correctly classified instances, formulated as follows:

$$accuracy = \frac{N_c}{N_c + N_{ic}} * 100\%$$

where $N_c$ shows the number of correct classifications and $N_{ic}$ represents the number of incorrect classifications. For the proposed waiting time model, the number of correct predictions, $N_c$, was given by the number of patients whose actual waiting time (<10, 10–59, or ≥60 min) fell within the same predicted waiting interval category. A similar calculation was made for treatment time accuracy. In addition to reporting model accuracies, classification tables are presented to show in which categories the models performed better or worse. The statistical analysis was conducted using SPSS statistical software (version 16.0).

## 3. Results

### 3.1. Univariate analysis

Table 1 presents the frequency and percentage distributions based on the model input variables.

Table 1 shows nearly equal numbers of male and female ED arrivals while almost 10% of arrivals were elderly patients who are at least 65 years old. Almost all arrivals were walk-in patients. Just over half of arrivals were non-urgent, and triaged into green areas accordingly. The most frequent ICD-10 diagnosis group codes were M00-M99 followed by J00-J99.

Table 2 presents the descriptive statistics of the waiting and treatment times for each category of the input variables. It also shows the significance of the differences between the categories for both waiting and treatment times.

Table 2 shows that males have significantly longer waiting times but significantly shorter treatment times. Waiting times decrease significantly with increasing age whereas treatment times increase significantly with age. Patients arriving by ambulance wait significantly less time than walk-in patients but their treatment times are significantly longer. Red room patients (urgent) wait the shortest time, followed by trauma, yellow, and green room patients. Red room patients also have the longest treatment times, followed in order by yellow, trauma, and green room patients. Patients with ICD-10 diagnoses H60-H95, J00-J99, and L00-L99 wait significantly longer than others but have significantly shorter treatment times. Conversely, patients with ICD-10 diagnoses E00-E89, O00-O9A, and P00-P96 wait significantly less time but have significantly longer treatment times. Overall, there are statistically significant differences in waiting and treatment times between the categories of all the input variables ($p < 0.05$).

Table 3 shows the correlations between waiting and treatment times for each category along with the statistical significance.

Table 3 shows that, for each category of the input variables gender, age, arrival mode and triage category, there is a significant negative correlation between waiting and treatment times. That is, as waiting times decrease, treatment times are expected to increase and vice versa. This pattern is similar for the ICD-10 codes, except for A00-B99, C00-D49, H00-H59, O00-O9A, P00-P96 and Z00-Z99.

Table 4 presents the frequency and percentage distributions for the three ordinal categories of waiting and treatment times.

### 3.2. Ordinal logistic regression (OLR) analysis

The ordinal logistic regression analysis classified patients into one of the predefined output categories based on waiting and treatment times. Table 5 presents the results of the two models.

The OLR analysis showed that age, arrival mode, and ICD-10 diagnosis all significantly predicted both waiting and treatment times. However, the signs of parameter estimates were opposite in the two proposed models. That is, the parameters for age, arrival mode, and ICD-10 codes had negative signs in the waiting time model whereas they were positive in the treatment time model. More specifically, this shows that increasing age decreases the likelihood of a patient being classified in the longer waiting time groups but increases the likelihood of being classified in the longer treatment time groups. Likewise, arriving by ambulance significantly decreases the likelihood of being classified in the longer waiting time groups but increases the likelihood of being classified in the longer treatment time groups.

Two variables differed in predictive power for the two models. First, while gender was not a significant predictor ($p$-value = 0.261) in the waiting time model, it was a significant positive predictor in the treatment time model ($p$-value = 0.056, at 90% confidence interval). That is, a female patient is significantly more likely than a male patient to be classified in the longer treatment groups. Second, triage category produced an unexpected result. Triage category had no significant effect on waiting time classification ($p$-value = 0.153) whereas it was a significant negative predictor in the treatment time model ($p$-value = 0.000). That is, a patient categorized as red (i.e. urgent) is significantly less likely than a green group patient (i.e. non-urgent) to be classified in the longer treatment time groups. Finally, interpreting the model signs for ICD-10 diagnoses was more complicated because the variable is not ordinal.

Table 6 presents the classification matrixes for the predictive performance of the OLR models for waiting and treatment time.

Table 6 shows that each model performed significantly better than classifying patients into any of the three output groups randomly when the probability of correct classification would be just 33.3%. Additionally, the treatment time classification was more accurate (accuracy = 66.365%) than the waiting time classification (accuracy = 52.247%). The waiting time model gave the most accurate predictions for patients in the 10–60-min group, with 10,815 of 15,064 (71.794%) patients being correctly classified (see Table 4). The treatment time model gave the most accurate predictions for patients in the <10-min group, with 18,930 of 20,928 (90.453%)

**Table 1**
Frequency and percentage distributions based on the model inputs

| Variable | Categories | Frequency | Percentage | Variable | Categories | Frequency | Percentage |
|---|---|---|---|---|---|---|---|
| Gender | Male | 18,349 | 48.657 | ICD-10 Diagnosis | A00-B99 | 1232 | 3.267 |
| | Female | 19,362 | 51.343 | | C00-D49 | 23 | 0.061 |
| Age | [0–14] | 6110 | 16.202 | | D50-D89 | 88 | 0.233 |
| | [15–64] | 28,004 | 74.259 | | E00-E89 | 103 | 0.273 |
| | [65–84] | 3153 | 8.361 | | F01-F99 | 427 | 1.132 |
| | ≥85 | 444 | 1.177 | | G00-G99 | 581 | 1.541 |
| Arrival mode | Walk in | 36,034 | 95.553 | | H00-H59 | 76 | 0.202 |
| | Ambulance | 1677 | 4.447 | | H60-H95 | 487 | 1.291 |
| Triage levels | Trauma | 5401 | 14.322 | | I00-I99 | 642 | 1.702 |
| | Red | 1472 | 3.903 | | J00-J99 | 7240 | 19.199 |
| | Yellow | 11,435 | 30.323 | | K00-K95 | 2143 | 5.683 |
| | Green | 19,403 | 51.452 | | L00-L99 | 971 | 2.575 |
| | | | | | M00-M99 | 7779 | 20.628 |
| | | | | | N00-N99 | 1859 | 4.930 |
| | | | | | O00-O9A | 44 | 0.117 |
| | | | | | P00-P96 | 76 | 0.202 |
| | | | | | R00-R99 | 5520 | 14.638 |
| | | | | | S00-T88 | 1319 | 3.498 |
| | | | | | V00-Y99 | 1771 | 4.696 |
| | | | | | Z00-Z99 | 5330 | 14.134 |

**Table 2**
Descriptive statistics for waiting and treatment times by input variable category and significances of differences

| Variable | Categories | Waiting Time (minutes) | | Treatment Time (minutes) | |
|---|---|---|---|---|---|
| | | $\mu$, $\sigma$ | $p$-value | $\mu$, $\sigma$ | $p$-value |
| Gender | Male | 41.262, 61.859 | 0.035 | 61.458, 116.288 | 0.000 |
| | Female | 39.957, 58.334 | | 69.310, 121.500 | |
| Age | [0–14] | 43.847, 60.009 | 0.000 | 56.091, 111.234 | 0.000 |
| | [15–64] | 41.502, 61.529 | | 58.922, 111.025 | |
| | [65–84] | 28.944, 46.561 | | 125.015, 158.404 | |
| | ≥85 | 21.153, 36.133 | | 186.349, 185.567 | |
| Arrival mode | Walk in | 42.286, 60.826 | 0.000 | 58.077, 109.310 | 0.000 |
| | Ambulance | 4.205, 16.729 | | 224.769, 188.327 | |
| Triage levels | Trauma | 30.125, 61.430 | 0.000 | 76.120, 106.475 | 0.000 |
| | Red | 4.658, 13.348 | | 242.763, 189.537 | |
| | Yellow | 39.705, 53.837 | | 103.679, 128.939 | |
| | Green | 46.755, 63.846 | | 26.575, 84.162 | |
| ICD-10 Encoded Diagnosis | A00-B99 | 20.986, 43.399 | 0.000 | 22.393, 78.753 | 0.000 |
| | C00-D49 | 36.253, 64.168 | | 186.348, 191.324 | |
| | D50-D89 | 30.394, 42.247 | | 111.662, 129.759 | |
| | E00-E89 | 21.463, 36.293 | | 133.606, 150.671 | |
| | F01-F99 | 56.845, 69.349 | | 46.033, 95.161 | |
| | G00-G99 | 51.367, 65.976 | | 65.180, 141.593 | |
| | H00-H59 | 32.054, 41.082 | | 48.715, 95.381 | |
| | H60-H95 | 59.180, 67.672 | | 21.292, 55.374 | |
| | I00-I99 | 37.059, 61.368 | | 120.110, 188.661 | |
| | J00-J99 | 58.704, 69.079 | | 32.819, 93.957 | |
| | K00-K95 | 49.051, 59.829 | | 54.247, 114.318 | |
| | L00-L99 | 60.408, 72.229 | | 31.273, 84.227 | |
| | M00-M99 | 39.026, 57.512 | | 58.907, 107.643 | |
| | N00-N99 | 37.650, 51.299 | | 105.345, 137.837 | |
| | O00-O9A | 12.342, 22.166 | | 147.535, 109.492 | |
| | P00-P96 | 9.532, 15.021 | | 119.710, 109.751 | |
| | R00-R99 | 37.025, 47.460 | | 140.018, 141.356 | |
| | S00-T88 | 37.789, 57.346 | | 54.069, 101.910 | |
| | V00-Y99 | 33.019, 56.959 | | 75.334, 113.448 | |
| | Z00-Z99 | 21.331, 57.368 | | 43.901, 103.143 | |

**Table 3**
Correlations between waiting and treatment times for each input category and statistical significances

| Variable | Categories | Correlation coefficient | Variable | Categories | Correlation coefficient |
|---|---|---|---|---|---|
| Gender | Male | $-0.151^{**}$ | ICD-10 Encoded | A00-B99 | −0.016 |
| | Female | $-0.173^{**}$ | Referral Diagnosis | C00-D49 | −0.281 |
| Age | [0–14] | $-0.149^{**}$ | | D50-D89 | $-0.253^{*}$ |
| | [15–64] | $-0.151^{**}$ | | E00-E89 | $-0.315^{**}$ |
| | [65–84] | $-0.204^{**}$ | | F01-F99 | $-0.266^{**}$ |
| | ≥85 | $-0.242^{**}$ | | G00-G99 | $-0.276^{**}$ |
| Arrival | Walk in | $-0.138^{**}$ | | H00-H59 | −0.166 |
| mode | Ambulance | $-0.189^{*}$ | | H60-H95 | $-0.166^{**}$ |
| Triage | Trauma | $-0.182^{**}$ | | I00-I99 | $-0.252^{**}$ |
| levels | Red | $-0.073^{*}$ | | J00-J99 | $-0.170^{**}$ |
| | Yellow | $-0.189^{**}$ | | K00-K95 | $-0.177^{**}$ |
| | Green | $-0.067^{*}$ | | L00-L99 | $-0.122^{**}$ |
| | | | | M00-M99 | $-0.159^{**}$ |
| | | | | N00-N99 | $-0.175^{**}$ |
| | | | | O00-O9A | −0.041 |
| | | | | P00-P96 | 0.037 |
| | | | | R00-R99 | $-0.222^{**}$ |
| | | | | S00-T88 | $-0.227^{**}$ |
| | | | | V00-Y99 | $-0.295^{**}$ |
| | | | | Z00-Z99 | 0.009 |

* corr. significant at 95%
** corr. sig. at 99%

**Table 4**
Frequency and percentage distributions by waiting and treatment times

| Waiting time | | | Treatment time | | |
|---|---|---|---|---|---|
| Categories (in minutes) | Frequency | Percentage | Categories (in minutes) | Frequency | Percentage |
| <10 | 14,391 | 38.161 | <10 | 20,928 | 55.496 |
| [10–60) | 15,064 | 39.946 | [10−120) | 8904 | 23.611 |
| ≥60 | 8256 | 21.893 | ≥120 | 7879 | 20.893 |

patients being correctly classified (see Table 4). The two models' least accurate predictions where for the ≥60-min waiting time group (only 760 of 8256–9.205%- patients correctly classified) and the 10–120-min treatment group (only 925 of 8904–10.389%- patients correctly classified).

## 4. Discussion

This study proposed two models to classify patients based on their waiting and treatment times in the emergency department of a metropolitan hospital in Izmir, Turkey. The first noteworthy result concerns the huge volume of ED arrivals as the patient volume for this hospital is considerably greater than for many of other EDs, both in Turkey and other countries [26-29]. This indicates that overcrowding is a major problem for this ED, so models to plan operations more efficiently may lead to considerable improvements in patient care.

Another important result is that more than half of the arrivals are triaged into green areas for non-urgent patients, which is a higher proportion than reported for other EDs [4,12,30,31]. Conversely, considerably fewer patients arrive by ambulance (5%) than in most other EDs studied [4,32,33]. This indicates another important problem in EDs, particularly in Turkey: unnecessary admissions leading to redundant use of EDs. Non-urgent arrivals are most frequently from four particularly common diagnosis groups, namely diseases of the respiratory system "J00-J99", musculoskeletal system [22,33,34], symptoms, signs and abnormal clinical and laboratory findings "R00-R99",

**Table 5**
OLR models results

| Input variable | OLR model for waiting time | | | | OLR model for treatment time | | | |
|---|---|---|---|---|---|---|---|---|
| | Parameter estimate | p-value | 95% confidence interval | | Parameter estimate | p-value | 95% confidence interval | |
| | | | Lower bound | Upper bound | | | Lower bound | Upper bound |
| Gender | −0.022 | 0.261 | −0.061 | 0.016 | 0.041 | 0.056 | −0.001 | 0.084 |
| Age | −0.116 | 0.000 | −0.154 | −0.079 | 0.151 | 0.000 | 0.111 | 0.190 |
| Arrival mode | −3.398 | 0.000 | −3.616 | −3.180 | 1.215 | 0.000 | 1.095 | 1.335 |
| Triage level | 0.016 | 0.153 | −0.006 | 0.037 | −0.950 | 0.000 | −0.973 | −0.926 |
| ICD-10 diagnosis | −0.067 | 0.000 | −0.071 | −0.063 | 0.054 | 0.000 | 0.049 | 0.058 |
| | Model fitting information: Chi-square = 3740.277; p-value: 0.000 | | | | Model fitting information: Chi-square = 10,504.755; p-value: 0.000 | | | |
| | Model summary: Cox & Snell R square = 0.194; Nagelkerke R square = 0.207 | | | | Model summary: Cox & Snell R square = 0.343; Nagelkerke R square = 0.382 | | | |

**Table 6**
Classification matrixes of the OLR models

| OLR model for waiting time | | | | OLR model for treatment time | | | |
|---|---|---|---|---|---|---|---|
| Waiting time categories | <10 | [10–60) | ≥60 | Treatment time categories | <10 | [10–120) | ≥120 |
| <10 | 8128 | 5849 | 414 | <10 | 18,930 | 545 | 1453 |
| [10–60) | 3990 | 10,815 | 259 | [10–120) | 5479 | 925 | 2500 |
| ≥60 | 2050 | 5446 | 760 | ≥120 | 2409 | 298 | 5172 |
| Accuracy: 52.247% | | | | Accuracy: 66.365% | | | |

and factors influencing health status and contact with health services “Z00-Z99” [35].

Regarding the waiting and treatment times, with the analysis reveals gender differences in that female arrivals have shorter waiting times but longer treatment times than males. This may be related to human psychological factors that need further investigation. Similar to previous studies [12,13,22,30], waiting times decreased significantly with both age, seriousness of triage category, and for patients arriving by an ambulance whereas treatment times significantly increased in these groups.

This study makes a novel contribution to the literature by analyzing the effects of these factors comparatively on both waiting and treatment times. It also analyzed the relationship between waiting and treatment times for each level of the input variables, finding significant negative relationships between waiting and treatment times for the majority of groups. That is decreased waiting times can predict increased treatment times in EDs. Regarding ICD-10 diagnosis, significantly lower waiting and higher treatment times were recorded for endocrine, nutritional, and metabolic diseases “E00-E89”, diseases of the circulatory system “I00-I99”, pregnancy, childbirth, and the puerperium “O00-O9A”, certain conditions originating in the perinatal period “P00-P96”, and symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified “R00-R99”.

Most of these univariate analysis results were supported by the two OLR models proposed here. The models showed that age, arrival mode, and ICD-10 codes all significant predicted patients waiting and treatment times. More specifically, triage category significantly predicted treatment time but not waiting time. Despite the significant gender differences in both waiting and treatment times, gender was not a significant predictor in either model. This finding suggests that the effects of age, arrival mode, and ICD-10 diagnosis suppress the effects of triage category and gender in predicting waiting time while the effect of gender is suppressed by the other four variables in predicting treatment time.

In addition to the significance of the predictors, the signs of the model coefficients were also useful in interpreting the model results. For predicting waiting time, the negative coefficients for gender, age, arival mode, and ICD-10 codes show that being female, older, arriving by ambulance, and having higher ICD-10 codes predict shorter waiting times. For treatment time prediction, the coefficients are positive, indicating the opposite interpretation. That is, these factors increase treatment time.

The prediction accuracies of the waiting and treatment time models were respectively as 52.247% and 66.365%. These performances were somehow lower compared to existing literature [22] classifying ED patients based on their LOS values and having around 69% accuracy levels. However, it should be noted that while this study presents waiting and treatment time classification for three levels meaning that patients were categorized into three different time intervals, the cited study was designated to classify patients into one of two levels. From this viewpoint, since the performances of the classification models generally decrease when number of categories of dependent variable increase, this study should be seen as improving the prediction performances of the existing literature.

## 5. Limitations

There are several limitations. First, the data come from only one institution, which limits the ability to generalize the findings to other EDs. Secondly, although the sample size was adequate for the research design, the models could not include monthly or seasonal variations, particularly for frequency distributions based on ICD-10 diagnoses. Third, the input variables are all widely used model parameters in the ED literature. However, other parameters could be added to improve the models' predictive performance. Finally, since this study used secondary data from the EMR of one hospital, which limited the researchers to using only the recorded variables in the models.

## 6. Conclusion

This study identified the main factors increasing or reducing waiting and treatment times in Eds. Two models were proposed that very accurately predicted patients' waiting and treatment times based on data from a large urban ED in Turkey. This shows that OLR models can be used to improve prediction performance in ED contexts. Focusing on the factors that increase patient waiting and treatment times may provide insights into practice that can be used to improve the efficiency of ED operations. This in turn can increase patient well-being and satisfaction. More specifically, patient satisfaction could be improved by informing each patient about their expected waiting and treatment times as soon as they register. The proposed models should also be used as a decision support tool to help ED decision makers plan ED operations and manage ED resources more effectively, based on the total estimated waiting and treatment times in each ED area. This may also accelerate patient flow so as to reduce ED overcrowding.

## Ethics committe approval

Ethics committe approval of this study was received from İzmir Katip Çelebi University Non-Interventional Clinical Studies Institutional Review Board at its board meeting 19.04.2017.

## Declaration of Competing Interest

The authors declares no conflict of interest.

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