Real-Time Prediction of Waiting Time in the Emergency Department, Using Quantile Regression

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Study objective: Emergency department (ED) waiting times can affect patient satisfaction and quality of care. We develop and validate a model that predicts an individual patient's median and 95th percentile waiting time by using only data available at triage.

Methods: From the existing ED information system, we extracted date and time of triage completion, start time of emergency physician consultation, and patient acuity category (1=most urgent, 3=least urgent). Quantile regression was applied for model development and parameter estimation by using visits from January 2011. We assessed absolute prediction error, defined as the median difference between the 50th percentile (median) predicted waiting time and actual waiting time, and the proportion of underestimated prediction, defined as the percentage of patients whose actual waiting time exceeded the 95th percentile prediction. The model was validated retrospectively with June 2010 data and prospectively with data from April to June 2011 after integration with the existing ED information system.

Results: The derivation set included 13,200 ED visits; 903 (6.8%) were patient acuity category 1, 5,530 (41.9%) were patient acuity category 2, and 6,767 (51.3%) were patient acuity category 3. The median and 95th percentile waiting times were 17 and 57 minutes for patient acuity category 2 and 21 and 89 minutes for patient acuity category 3, respectively. The final model used predictors of patient acuity category, patient queue sizes, and flow rates only. In the retrospective validation, 5.9% of patient acuity category 2 and 5.4% of category 3 waiting times were underestimated. The median absolute prediction error was 11.9 minutes (interquantile range [IQR] 5.9 to 22.1 minutes) for patient acuity category 2 and 15.7 minutes (IQR 7.5 to 30.1 minutes) for category 3. In prospective validation, 4.3% of patient acuity category 2 and 5.8% of category 3 waiting times were underestimated. The median absolute prediction error was 9.2 minutes (IQR 4.4 to 15.1 minutes) for patient acuity category 2 and 12.9 minutes (IQR 6.5 to 22.5 minutes) for category 3.

Conclusion: Using only a few data elements available at triage, the model predicts individual patients' waiting time with good accuracy. [Ann Emerg Med. 2012;60:299-308.]

Please see page 300 for the Editor's Capsule Summary of this article.

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INTRODUCTION

Long waiting times in the emergency department (ED) are common in Singapore and in many developed and developing counties.[1-10] This problem may not be easily resolved because of the complexity of causes, limited resources, and unpredictable surges in demand.

Studies on customer psychology in waiting situations[11-17] reported that real-time prediction of waiting time improved patient satisfaction and service quality, especially when queues were unclear to customers. Many studies show that ED patient satisfaction is positively correlated with patients receiving more information and when patients' actual waiting time is shorter than the expected waiting time.[18-25] Real-time prediction of waiting times may also help clinicians prioritize patients, adjust work flow and operations when they are falling behind, and minimize the time spent on answering patients' queries on their waiting time.

Models have been developed to predict ED waiting time by using generalized linear model or queuing theory.[26-29] However, these models predicted mean waiting time. There are limitations associated with mean time prediction. Mean waiting time in the ED is highly skewed to the right because the mean prediction is easily biased by the outliers. Less than 50% but still a substantial percentage of patients' waiting times are underestimated by mean prediction. Point estimation is risky because of the great variation in waiting time.

Editor's Capsule Summary

What is already known on this topic

Satisfaction with emergency department (ED) care is higher when patients are provided an estimate of waiting time, but no predictive models for waiting time exist.

What question this study addressed

Can we use information available at triage to predict an individual's waiting time?

What this study adds to our knowledge

In a single ED, an accurate estimate of waiting time for each patient could be derived from the patient's acuity, the number of patients waiting to be seen, and the number of patients who began treatment in the past hour.

How this is relevant to clinical practice

If this model works as well in other EDs, it can be integrated into existing ED information systems to inform patients about the likely wait and alert providers to problems with patient flow.

This study aimed to develop a model for real-time prediction of expected waiting time from triage to consultation in the ED, using routinely available data. We aimed to predict a waiting time range of median (50th percentile) to 95th percentile instead of the point estimation of mean. The advantages of using this range of estimates are that it will show patients that waiting time in the ED is not fixed but a rough estimate, the median is more accurate than the mean because it is less affected by outliers, and the 95th percentile waiting time decreases the expectation of waiting patients and therefore may help shorten the perceived waiting time.

Quantile regression is a good tool for achieving the objectives because it models the relation between a set of predictor variables and specific percentiles (or quantiles) of the response variable and it specifies changes in the quantiles of the response. The quantile regression parameter estimates the change in a specified quantile of the response variable produced by a 1-unit change in the predictor variable.[30-32] Quantile regression is sometimes called order regression, and it is less sensitive to outliers compared with ordinary least square regressions.

MATERIALS AND METHODS

Study Design

This is an observational study using routinely collected hospital data to develop a predictive model of individual patients' waiting time in the ED. The individual patient's waiting time is defined as the interval from triage end time to the physician's consultation start time, as recorded by the ED information system. The ethical review of the study was exempted by the hospital's Research Ethics Committee because there was no patient personal information extracted.

Setting

The study was conducted in the ED of a 1,200-bed tertiary care hospital in Singapore, which has approximately 400 ED patient visits per day. Because another new hospital, located 14 km away from the study hospital, started its operations in August 2010, the patient volume and waiting time in the study hospital's ED have significantly decreased. As a result, we performed both a retrospective validation with data before August 2010 and a prospective validation with data after the model was implemented in April 2011.

In the current practice in EDs in Singapore, patients on arrival are immediately triaged by nurses into different acuity categories. They then wait to see physicians, with their waiting times varying with patient acuity categories. For patient acuity category status, the Ministry of Health of Singapore[33] categorizes patients who require immediate resuscitation, are in cardiovascular collapse, or are in imminent danger of collapse as patient acuity category 1; patients with a major emergency or illness, who are nonambulatory, or who are having severe symptoms but not requiring resuscitation as patient acuity category 2; and patients with a minor emergency or ambulatory patients with mild to moderate symptoms as patient acuity category 3. Patients in acuity category 1 have the highest priority, followed by those in category 2 and then 3. In the study ED, the patients in acuity categories 1 and 2 are cared for by one team of physicians, whereas patients in acuity category 3 are managed by another team. The physicians in the 2 teams are not fixed and they can interchange if necessary.

At the end of triage, the nurse clicks a button to transfer the patient to the next service point in the ED. The triage end time is then automatically recorded by the ED information system. The consultation start time is also automatically recorded when the physician clicks the button to call a patient for consultation.

Data Collection and Processing

Data for derivation and validation were extracted from the existing ED information system, which is a "homegrown" online transaction system tailored for routine care and patient services in the ED and is used for patient registration, triage, consultation, medication prescription, and payment. Data from January 2011 were used to develop the model. Because of the opening of a second hospital in August 2010, visits in January 2011 were not as numerous as before. Therefore, we also performed a retrospective validation against data from an arbitrarily chosen month before August 2010 to test the robustness and generalizability of the model and also to test whether the model could reasonably handle unpredicted surges in patient volume. There were nearly 20% more patient visits in the retrospective validation data than in the derivation. The model was also prospectively validated with data from April to June 2011. Variables extracted were the date, the end time of triage, the start time of consultation, and patient acuity category for every patient visit. For patient acuity categories 1 to 3, the sizes of patient queues at the triage end time and the patient flow rates of queues in the preceding hour were counted from the data.

The size of patient queue is the number of patients who are currently waiting for the physicians' call for consultation at triage end time. Using the patient's triage end time as the reference time, the queue size for that patient is the number of patients whose triage ended before the reference time and whose consultation started after the reference time. The flow rate is the number of patients called by physicians for consultation in the proceeding hour of the triage end time. Using the patient's triage end time as the reference time, the flow rate for that patient is the number of patients whose consultation started within the hour before the reference time. The sizes of patient queues and the flow rates are specific to the patient acuity category. Only patients of specific patient acuity category should be counted in calculating the 2 predictors of that patient acuity category.

The waiting time was first log-transformed to ensure that the predicted waiting times would be nonnegative. The log transformation was used to guarantee a nonnegative value to the predicted waiting time. But log transformation might not be necessary because median and 95th percentile waiting times can hardly be negative. And even if it occurs, the negative prediction values can be reset as 0. Nevertheless log-transformation does not change the overall performance of the model because quantile regression has the property of monotone equivariance, which does not hold for mean regression.[30-32] For a monotone transform, like log() or exp(), a conditional p*th* quantile of log(y) or exp(y) is the log or exp of the conditional p*th* quantile of Y:

$$Q^{(p)}(\log(Y|X) = \log(Q^{(p)}(Y|X)); \text{ and } Q^{(p)}(Y|X) = e^{Q^{(p)}(\log Y|X)}.$$

But in ordinary least square regression,

$$E(\log(Y|X) \neq \log(E(Y|X)); \text{ and } E(Y|X) \neq e^{E(\log Y|X)}.$$

Quantile regression was then applied to estimate the 50th and 95th percentile waiting time (log-transformed) for patients in acuity categories 2 and 3, respectively. Patients in acuity category 1 are immediately treated; therefore, no prediction is needed. A bootstrap resampling method was used to estimate the SEMs of the B coefficients, with 500 replicates (Stata BSQREQ was used for model development).[34]

All potential predictors associated with the waiting time from triage to consultation entered the model as independent variables, which were the sizes of patient acuity categories 1, 2, and 3 queues; the patient flow rates of patient acuity categories 1, 2, and 3 queues; day of the week; and time of day (derived from triage end time).

The selection of the candidate predictors was based on queuing theory, literature review, and practical consideration. According to queuing theory, the waiting time of a first-come, first-serve queue is solely decided by the demand (number of patients waiting to be treated by physicians in the ED scenario) and supply (number of physicians on duty in the ED scenario).[35,36] The queues in the ED are not purely in accordance to a first-come, first-serve basis. A patient's waiting time may be affected by his or her severity. But the majority of the patients in the same acuity level should follow the rule of first-come, first-serve. Additionally, the queues in this ED are not isolated. Clinicians can move among different queues, and they may serve 1 or more queues concurrently, depending on the real-time needs. Therefore, for the prediction of patient acuity category 2 waiting time, not only the patient acuity category 2 queue size and flow rate but also the patient acuity categories 1 and 3 queue sizes and flow rates were included as a candidate predictor; as was the case for patient acuity category 3 prediction.

Time of day and day of week were also included as candidate predictors because they satisfied the criteria of being the confounders: because demand is different at different times and days of the week, they were likely to be correlated with both the queue sizes and flow rates and the waiting times, and they were not in the causal pathway from the queue sizes and flow rates to the waiting times.

Bootstrap resampling was applied to give an unbiased estimation of the P values. Considering the large sample size and few candidate predictors, $P<.05$ was used for selecting important predictors. A model developed from the derivation data was then applied to the 2 validation data sets for assessing the fitness and generalizability of the model.

The absolute prediction errors and the proportion of underestimated prediction were used to assess the model. The absolute prediction error was defined as the absolute difference between the actual waiting time and the predicted median waiting time. The proportion of underestimated prediction was defined as number of underestimated waiting times divided by the number of total predicted waiting times. A patient's waiting time was underestimated if his or her predicted 95th percentile waiting time was less than actual waiting time. A 5% underestimated prediction was expected because the 95th percentile waiting time was used as the upper limit.

The predictive model was implemented in the ED in April 2011 by using the equations with the coefficients estimated from the quantile regression, using the Patient Information Board system, a stand-alone information system with a personal computer and a few liquid crystal displayers. The system was developed to track patients' movement in the ED, as requested by patients and their accompanying family members. The computational program running on the back-end computer in the Patient Information Board system in real time extracts patients' data (start and end times at each service point) from the existing ED information system, tracks the flow rates and queue sizes, and calculates the predicted waiting times for patients. The ED information system was not modified for implementing the system. All the elements required for the

Table 1. The statistics of the actual waiting times.*

	Derivation Data		Retrospective Validation Data		Prospective Validation Data	
Percentile	**PAC 2**	**PAC 3**	**PAC 2**	**PAC 3**	**PAC 2**	**PAC 3**
5	2	3	4	7	2	4
25	8	9	15	22	10	14
50	17	21	28	45	18	29
75	30	41	47	79	31	54
95	57	89	80	130	57	105
Minimum	0	0	0	0	0	0
Maximum	232	311	221	240	212	325
Mean	22	30	33	54	23	39
SD	18	29	24	40	18	34
Total visits, N	5,530	6,767	6,172	7,991	16,680	19,643

PAC, Patient acuity category.
*Data are reported in minutes.

waiting time prediction model were readily available from the existing ED information system.

At the end of triaging, the predicted waiting times for patients are displayed on the liquid crystal displayer and are refreshed every 5 minutes. Every time the data refreshed, the predicted waiting times decrease by 5 minutes. The predicted patients' waiting times are not recalculated by changes in flow because of the following consideration: (1) the models were developed to predict only the waiting time from the end of triage to the start of consultation, and it might not be applicable for predicting the remaining waiting time during waiting; (2) we hypothesized that the flow rates do not change significantly while the patients are waiting, and the change in waiting time is mainly driven by the shortening of queue sizes; and (3) the remaining waiting time can be roughly estimated as the predicted waiting time minus the time already passed.

If a patient has not been attended to by the time his or her predicted upper limit waiting time is reached, the system will trigger an alert and the predicted waiting time will be displayed in red. When the nurses on duty notice the alerts, they will immediately investigate the problem and help facilitate the patient flow in the ED.

All statistical analyses and model development were conducted with Stata (version 11; StataCorp, College Station, TX).

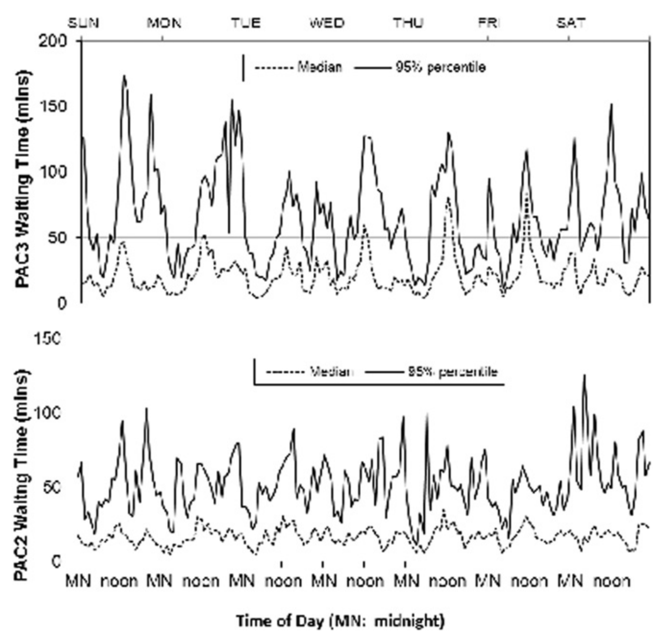

Figure 1. The distribution of the actual waiting times by day of week and time of day. PAC 3 actual waiting time (top) and PAC 2 actual waiting time (bottom).

RESULTS

There were 13,200 ED visits in January 2011. Among them, 903 (6.8%) were patient acuity category 1, 5,530 (41.9%) were patient acuity category 2, and 6,767 (51.3%) were patient acuity category 3 cases. The median and 95th percentile waiting times were 17 and 58 minutes for patient acuity category 2 and 21 and 89 minutes for patient acuity category 3, respectively. Table 1 shows the statistics of the waiting times for both the derivation and the validation data sets.

Figures 1 and 2 showed the crude correlation between waiting time and the predictors. The waiting time varied with the day of week and the time of day. The median waiting time for patient acuity category 2 was relatively stable, whereas patient acuity category 3 median waiting time had greater variation. The 95th percentile waiting time had greater variation than the median (Figure 1). The waiting time was also correlated with the flow rates and the queue sizes, but the relationships were not linear. As the queue size increased, the waiting time tended to be longer, whereas as the flow rate increased, the direction of change in the waiting time was not evident (Figure 2).

In the final model for the patient acuity category 2 median waiting time prediction, the predictors were patient acuity categories 2 and 3 queue sizes, as well as the patient acuity category 2 flow rate. The predictors for patient acuity category 3 median waiting time were patient acuity category 1 to 3 queue

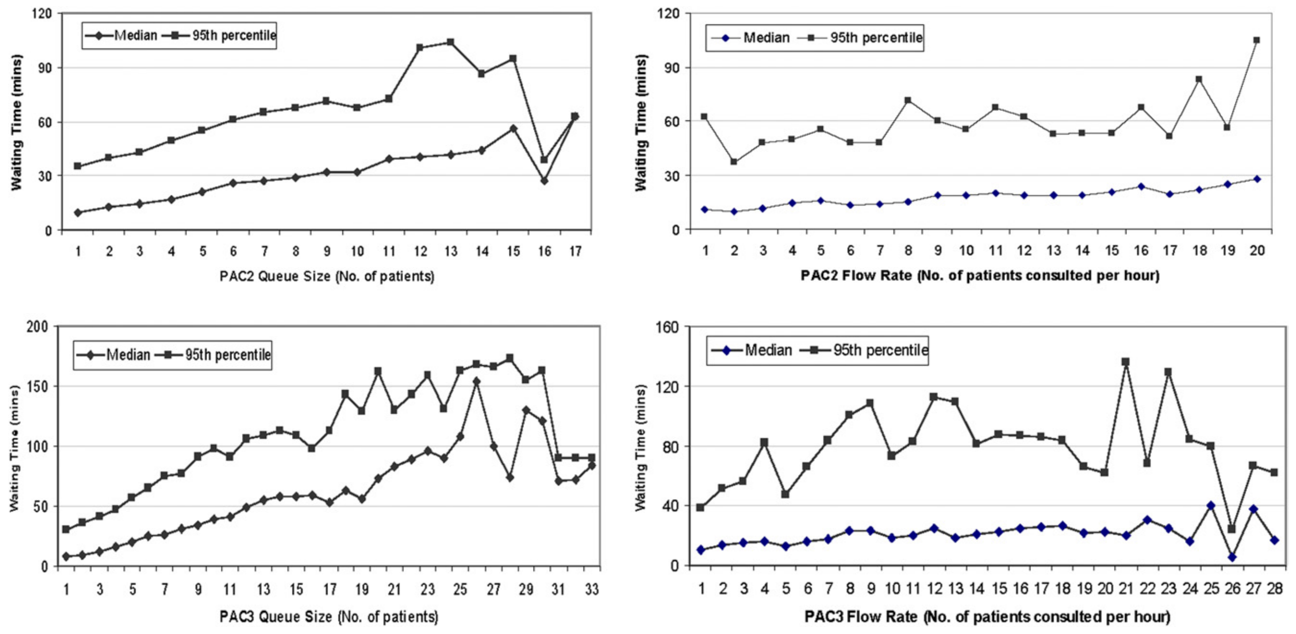

Figure 2. The correlation between the actual waiting time and the flow rate and queue size. The PAC 2 waiting time and the PAC 2 queue size (top left); the PAC 2 waiting time and the PAC 2 flow rate (top right); the PAC 3 waiting time and the PAC 3 queue size (bottom left); the PAC 2 waiting time; and the PAC 2 flow rate (bottom right).

Table 2. The adjusted association between the predictors and the median waiting time.*[†]

	50th Percentile Log (PAC 2 Waiting Time)		50th Percentile Log (PAC 3 Waiting Time)	
Predictors	**B Coefficient**	**95% Confidence Interval**	**B Coefficient**	**95% Confidence Interval**
PAC 1 queue	—	—	0.071	0.217 to 0.121
PAC 2 queue	0.092	0.083 to 0.101	0.059	0.051 to 0.067
PAC 3 queue	0.019	0.014 to 0.024	0.070	0.066 to 0.074
PAC 2 flow rate	−0.009	−0.015 to −0.002	−0.010	−0.016 to −0.004
PAC 3 flow rate	—	—	−0.010	−0.014 to −0.006
Constant	2.587	2.568 to 2.689	2.912	2.866 to 2.959

*Equation for PAC 2 median waiting time: Y=exp(2.587+0.092×[PAC 2 queue size]+0.019×[PAC 3 queue size]–0.009×[PAC 2 flow rate]). Equation for PAC 3 median waiting time: Y=exp(2.912+0.071×[PAC 1 queue size]+0.059×[PAC 2 queue size]+0.070×[PAC 3 queue size]–0.010×[PAC 2 flow rate]–0.010×[PAC 3 flow rate]).
[†]Dashes indicate that, if the predictor was not identified in the model, its coefficients were left blank.

sizes and patient acuity categories 2 and 3 flow rates. After controlling for other confounders, patient acuity category 1 flow rate was not significant for category 2 or 3 waiting time prediction. The longer the queue size, the longer the waiting time. The faster the patient flow rate, the shorter the waiting time. Because of the log-transformation, with every 1-number increase in patient acuity category 2 queue size, the median waiting time for that category was expected to increase by 9.2%; with every 1-number increase in patient acuity category 2 flow rate, the median waiting time for that category was expected to decrease by 0.9% (Table 2).

In the final model for patient acuity category 2 95th percentile waiting time prediction, the predictors were patient acuity categories 1 to 3 queue sizes, the category 2 flow rate, and the day of the week. The significant predictors for 95th percentile patient acuity category 3 waiting time were categories 2 and 3 queue sizes and flow rate and the day of the week. Fridays had shorter patient acuity category 2 waiting time. Tuesdays and Fridays had shorter patient acuity category 3 waiting time. The longer the queue size, the longer the waiting time. The faster the patient flow rate, the shorter the waiting time. With every 1-number increase in patient acuity category 2 queue size, the 95th percentile waiting time for that category was expected to increase by 5.7%; with every 1-number increase in patient acuity category 2 flow rate, the 95th percentile waiting time for that category was expected to decrease by 1.1% (Table 3).

As would be expected, there were approximately 5% of patients whose 95th percentile waiting times were underestimated. In the derivation data set, 4.3% of waiting times for patients in acuity category 2 and 3.6% for those in acuity category 3 were underestimated. In the retrospective validation data set, 5.9% of waiting times for patients in acuity category 2 and 5.4% for those in category 3 were underestimated, whereas in the prospective validation data set,

Table 3. The adjusted association between the predictors and the 95th percentile waiting time.*[†]

	95th Percentile Log (PAC 2 Waiting Time)		95th Percentile Log (PAC 3 Waiting Time)	
Predictors	B Coefficient	95% Confidence Interval	B Coefficient	95% Confidence Interval
Day of week				
Monday	−0.072	−0.206 to 0.062	−0.057	−0.157 to 0.043
Tuesday	−0.004	−0.139 to 0.132	−0.191	−0.282 to −0.099
Wednesday	0.105	−0.045 to 0.256	−0.024	−0.132 to 0.085
Thursday	0.030	−0.108 to 0.167	−0.057	−0.140 to 0.026
Friday	−0.088	−0.234 to −0.060	−0.108	−0.212 to −0.004
Saturday	0.118	−0.041 to 0.277	0.074	−0.034 to 0.181
PAC 1 queue	0.099	0.020 to 0.177	—	—
PAC 2 queue	0.057	0.043 to 0.070	0.059	0.048 to 0.070
PAC 3 queue	0.019	0.012 to 0.026	0.052	0.045 to 0.058
PAC 2 flow rate	−0.011	−0.021 to −0.001	—	—
PAC 3 flow rate	—	—	−0.010	−0.016 to −0.004
Constant	3.698	3.567 to 3.838	3.828	3.727 to 3.928

*Equation for PAC 2 95th percentile waiting time: Y=exp(3.698+0.099×[PAC 1 queue size]+0.057×[PAC 2 queue size]+0.019×[PAC 3 queue size]–0.011×[PAC 2 flow rate]–0.072×[Monday]–0.004×[Tuesday]+0.105×[Wednesday]+0.03×[Thursday]–0.088×[Friday]+0.118×[Saturday]). Equation for PAC 3 95th percentile waiting time: Y=exp(3.828+0.059×[PAC 2 queue size]+0.052×[PAC 3 queue size]–0.010×[PAC 3 flow rate]–0.057×[Monday]–0.191×[Tuesday]–0.024×[Wednesday]–0.057×[Thursday]–0.108×[Friday]+0.074×[Saturday]).
[†]Dashes indicate that, if the predictor was not identified in the model, its coefficients were left blank.

the proportions were 4.3% for patient acuity category 2 and 5.8% for category 3.

The scatterplots of the predicted median waiting times against the actual waiting times in the 3 data sets are shown (Figure 3). As expected, there were approximately 50% of patients whose predicted median waiting times were less than the actual waiting time. The predicted median waiting time has much smaller variation than the actual waiting time. In the derivation data, the mean and median of the absolute prediction errors were 11.7 and 9.2 minutes, respectively, for patient acuity category 2 waiting time, whereas they were 15.5 and 11.9 minutes, respectively, for patient acuity category 3 waiting time. The interquantile range (IQR) of the prediction error was 10.2 minutes (IQR 4.6 to 14.8 minutes) for patient acuity category 2 and 12.0 minutes (IQR 6.2 to 18.2 minutes) for patient acuity category 3. In the retrospective validation data, the mean and median of the absolute prediction errors were 16.7 and 11.9 minutes, respectively, for patient acuity category 2 waiting time, whereas they were 23.4 and 15.7 minutes, respectively, for patient acuity category 3 waiting time. The IQRs of the prediction error for patient acuity categories 2 and 3 were 16.2 minutes (IQR 5.9 to 22.1 minutes) and 22.6 minutes (IQR 7.5 to 30.1 minutes), respectively. In the prospective validation data, the mean and median of the absolute prediction error were 11.9 and 9.2 minutes, respectively, for patient acuity category 2 waiting time and 18.9 and 12.9 minutes, respectively, for patient acuity category 3 waiting time. The IQRs of the prediction error for patient acuity categories 2 and 3 were 10.7 minutes (IQR 4.4 to 15.1 minutes) and 16.0 minutes (IQR 6.5 to 22.5 minutes), respectively (Table 4*A*).

In addition, the mean, median, IQR, and 25th and 75th percentiles of the absolute difference between the actual waiting time and the predicted 95th percentile waiting time are shown in Table 4*B*. In the derivation data, the mean absolute difference between the predicted 95th percentile time and the actual waiting time was 31.9 minutes for patient acuity category 2 and 41.5 minutes for category 3, 35.9 minutes for patient acuity category 2 and 60.3 minutes for category 3 in the retrospective validation data, and 32.5 minutes for patient acuity category 2 and 37.1 minutes for category 3 in the prospective validation data.

LIMITATIONS

There are some limitations to this study. First, the selection of predictors was mainly based on queuing theory. Patient clinical characteristics may also affect waiting time, such as vital signs, the presenting complaints of bleeding, altered mental status, or severe pain. Their influence on waiting time for patients at the same acuity level is not clear. Patient acuity level was decided by triage nurses according to many factors, including vital signs and presenting complaints, which may make clinical parameters no more important for predicting waiting times at the same patient acuity category. According to the validation performance, the model is robust for application. Second, the model may not be directly applicable to other EDs because of the following: (1) patient acuity category is a local parameter defined by Ministry of Health of Singapore; (2) the waiting time is greatly affected by the operations in the ED; and (3) the effects (regression coefficients) of queue sizes and flow rates on the waiting time might be different in settings with different patient volumes or different waiting time distributions. However, the proposed novel modeling

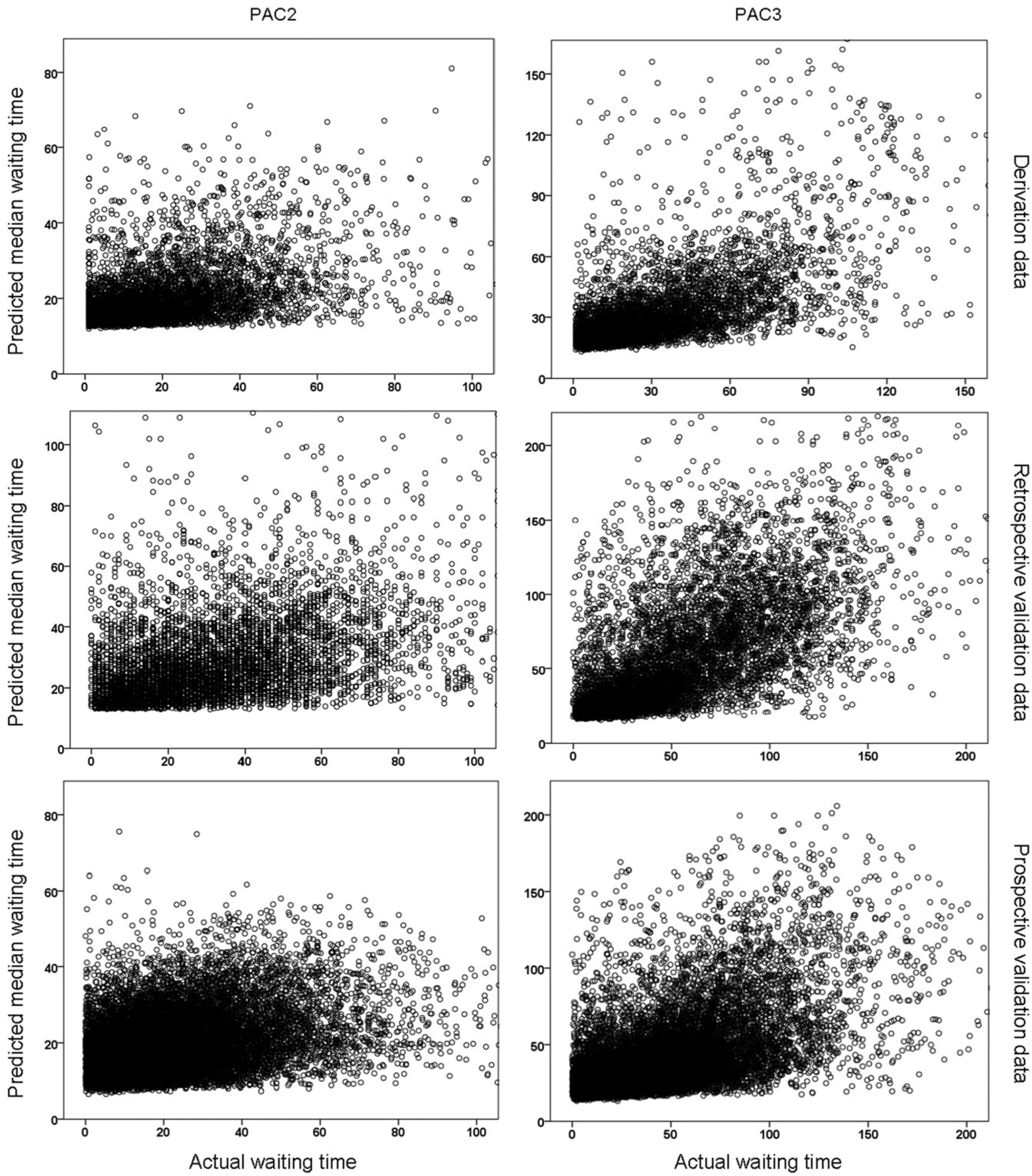

Figure 3. Scatterplots of the predicted median waiting times against actual waiting times (unit=minutes). The PAC 2 waiting time in derivation data (top left); the PAC 3 waiting time in derivation data (top right); the PAC 2 waiting time in retrospective validation data (middle left); the PAC 3 waiting time in retrospective validation data (middle right); the PAC 2 waiting time in prospective validation data (bottom left); and the PAC 3 waiting time in prospective validation data (bottom right).

Table 4. *A*, Absolute prediction errors: predicted median against actual waiting time.*

Statistics	Derivation Data (January 2011)		Retrospective Validation Data (June 2010)		Prospective Validation Data (April–June 2011)	
	PAC 2	PAC 3	PAC 2	PAC 3	PAC 2	PAC 3
Mean	11.7	15.5	16.7	23.4	11.9	18.5
Median	9.2	11.9	11.9	15.7	9.2	12.9
25th percentile	4.6	6.2	5.9	7.5	4.4	6.5
75th percentile	14.8	18.2	22.1	30.1	15.1	22.5
IQR	10.2	12.0	16.2	22.6	10.7	16.0
B, Absolute difference: predicted 95th percentile against actual waiting time.*						
Mean	31.9	41.5	35.9	60.3	32.5	37.1
Median	32.4	38.2	33.9	40.4	32.0	32.4
25th percentile	22.7	28.0	21.1	31.0	21.5	19.7
75th percentile	40.4	48.6	46.9	56.6	41.7	47.1
IQR	17.7	20.6	25.8	25.6	20.2	27.4

*Data are reported in minutes.

approach for waiting time prediction may still be useful for other EDs.

DISCUSSION

In this study, we have evaluated the use of scant clinical information extracted from the existing ED information system to predict an individual patient's waiting time in the ED. The developed model is represented by equations, with the important predictors identified and their corresponding coefficients estimated by quantile regression. The model can be feasibly integrated into the existing ED information system for real-time waiting time prediction. It could help alert clinicians and administrators in the ED to a growing predicted waiting time or when patients fail to be seen within the predicted period. According to the good prediction accuracy and the sparse clinical information used, the developed model could be a good decision support tool for clinicians and administrators in the ED.

The data from January 2011 were used for model development. Singapore is a tropical country; therefore, a seasonal effect is not evident. The samples size of 1 month is large enough for model development. The good prediction performance of the model on the 2 validation data sets showed that it might work well for a wide range of patient attendance volumes.

The waiting time was mainly predicted by queue sizes and patient flow rates, and after controlling for these, day of the week and time of day were not significant predictors of median waiting time. Day of the week slightly affected the 95th percentile waiting time. It might be that, because median waiting time represented the central tendency and therefore was less sensitive to daily variation in patient volume and ED operations, patient acuity category 2 or 3 waiting times were not only affected by their own queue size but also the queue sizes of other patient acuity categories in the ED because physicians attending to the patients cross over different queues, depending on patients' needs. Compared with patients in acuity category 3, category 2 patients have higher priority in the ED because of the severity of their complaints. The median waiting time for patient acuity category 2 was less affected by variations in other factors compared with that for patient acuity category 3. The variance in the 95th percentile waiting time of patient acuity category 3 might be too large, and therefore the variance explained by the patient acuity category 1 queue size and category 2 flow rate became negligible. The importance of the predictors depended greatly on the operations in the ED. If physicians for patient acuity categories 2 and 3 queues are strictly separated, category 3's waiting time might not be affected by category 2's queue size and flow rate.

To our knowledge, there was only 1 peer-reviewed study on ED waiting time and its associated factors using regression analysis, which was conducted by a group from Johns Hopkins University.[37,38] However, the key drivers of waiting time were not included in their model, such as the number of physicians on duty and number of patients waiting to be seen. In their study, the median difference between the predicted (50th percentile) and the actual waiting time was 20 minutes (IQR= –17 to 47 minutes). About 43% of predicted waiting times were within 30 minutes of the actual times. The performance of our prediction model was better. The median of the absolute prediction error for all patients in our study was shorter by 16 minutes. More than 75% of predicted waiting times were within 22.5 minutes of the actual times by our prediction model.

In this study, we used patient flow rates instead of the number of physicians on duty because flow rates not only measure the differences in staff numbers but also the variation in physicians' seniority and expertise, which cannot be directly measured. The flow rates were defined as the number of patients who have been attended to in the last hour on account of the large patient volume in the study ED.

There might be autocorrelation among patients' waiting times: the waiting time of patient n may be correlated with that of patient $n+1$. But after accounting for the macro-level parameters such as the queue sizes and flow rates, the autocorrelation is negligible. On the other hand, autocorrelation, if present, would not affect the estimation of regression coefficients, but rather the estimation of coefficients' variances. Therefore, it should not be an issue as long as the models are used for prediction.

The percentile for the predicted upper limit of the waiting time was chosen as a compromise between a good service quality and an acceptable waiting time by ED patients. Although using the 99th percentile waiting time as the predicted upper limit can ensure that approximately 99% of waiting times are within the predicted upper limit, it could be too long to be accepted by patients. About 10% of patients' waiting times exceed the predicted upper limit if the 90th percentile is used, which may not indicate a good service quality. The predicted upper limit was shorter than 1 hour for most patient acuity category 2 patients and shorter than 2 hours for most category 3 patients in this study. On the other hand, one of the key performance indicators for EDs set by the Ministry of Health of Singapore is that the 95th percentile waiting times for patient acuity categories 2 and 3 be within 85 minutes and 110 minutes, respectively. Therefore, using the 95th percentile waiting time as the upper limit in this study also helps ED clinicians and managers monitor the performance indicator. If a substantial percentage of predicted upper limits exceeds the Ministry of Health standards, this will trigger an immediate action to facilitate patient flow in the ED.

Most studies suggested that providing patients with expected waiting time improved patient satisfaction in the ED.[21-25] However, the effect is not universal. The study by the Johns Hopkins's group[38] showed no improvement on patient satisfaction. Well-designed studies need to be conducted to evaluate the true effect of the waiting time prediction model on patient satisfaction in the study ED.

We have developed and validated a model for real-time waiting time prediction in the ED at triage. The model predicts the range of median to 95th percentile waiting time for every patient, and it is able to achieve good prediction accuracy with little clinical information. It could be an inexpensive way to improve service quality and patient satisfaction in the ED.

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