American Journal of Emergency Medicine 37 (2019) 478–481

Contents lists available at ScienceDirect

American Journal of Emergency Medicine

journal homepage: www.elsevier.com/locate/ajem

Original Contribution

Emergency medicine physicians' ability to predict hospital admission at the time of triage☆

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ARTICLE INFO

Article history:
Received 17 May 2018
Accepted 11 June 2018

Keywords:
Triage
Hospital admission
Prediction
Patient flow

ABSTRACT

Background: We seek to determine if experienced emergency medicine physicians can accurately predict the likelihood of admission for patients at the time of triage. Such predictions, if proven to be accurate, could decrease the time spent in the ED for patients who will ultimately be admitted by hastening downstream workflow.
Methods: This is a prospective cohort study of experienced physicians at a large urban hospital. Physicians were asked to predict the likelihood of admission for patients based only on information available in the EMR at the time of triage. Physicians also predicted the service to which the patients would be admitted. Physicians provided a confidence level of their prediction. Measures of predictive accuracy were calculated, including sensitivity, specificity, and area under the receiver operating characteristic curve.
Results: 35 physicians evaluated 398 patient charts and made predictions. Sensitivity of determining admission for the entire cohort was 51.8%. The specificity was 89.1%. For those predictions made with a confidence level of >90%, sensitivity was 61.5% and specificity was 95.7%. Among physicians correctly predicting admission, the admitting service was predicted accurately 88.6% of the time.
Conclusion: Physicians performed poorly at predicting which patients would be admitted at the time of triage, even when they were confident in their predictions. Conversely, physicians accurately predicted who would be discharged. Physicians predicted with reasonable accuracy the service to which patients were ultimately admitted. More research and operational assessment needs to be performed to determine if these predictions can help improve ED efficiency.

1. Introduction

1.1. Background and rationale

A consistent frustration for ED providers and patients alike is the frequent long wait times associated with ED visits. This is particularly pronounced in patients who are awaiting admission. Longer wait times have been shown to lead to decreased patient satisfaction, operational inefficiency, and worse outcomes for those patients who are ultimately admitted [1-3].

Most EDs request admission for a patient only when the patient's evaluation suggests a certainty of admission [4, 5]. However, in contrast to healthcare provider systems, manufacturing industry often improves flow by utilizing predicted demand to start production early rather than waiting for orders to be placed first [5]. In the healthcare setting, the availability of inpatient beds is argued to be the single most important cause of delayed ED flow [5]. Predicting demand for these beds and anticipated staffing needs can significantly improve flow [2, 6-9]. An increase in anticipated admissions can be addressed with increasing nursing staff, opening up more bed units, and implementing a "surge" protocol.

To date, several research efforts have attempted to predict admissions from the ED more efficiently. Multiple efforts have been evaluated to predict admissions in the pre-hospital setting and at triage. However, in evaluating triage nurses and paramedics using clinical judgment to predict admission, multiple studies have concluded that these providers are unable to predict admission with sufficient accuracy [1, 2, 5].

Admission prediction using logistic regression models has proven to be more accurate than clinical judgment alone [2, 5]. Attempts to predict admission with natural language processing via neural network modeling also demonstrated impressive accuracy [10]. Unfortunately,

☆ **Reprints:** Reprints not available.
Grant: HealthPartners Institute Resident Research Grant.
Meetings: None.
Conflicts of interest: None.
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https://doi.org/10.1016/j.ajem.2018.06.023
0735-6757/

while some of these objective methods are more accurate than clinical judgment alone, they have been difficult to adopt due to the complexity associated with applying these methods [2].

In an effort to utilize a simpler prediction for admission, the Pediatric Risk of Admission Score II (PRISAII), which is a simple scoring system that does not require any modeling, was tested against triage nurse predictions and found to be inferior to the subjective predictions of triage nurses [6]. This suggests simpler methods are also not sufficient.

1.2. Objectives

The goal of this research is to determine if experienced EM physicians can accurately predict ED patient admission at the time of triage. A secondary goal is to determine if physicians can accurately predict to which service these patients will be admitted.

To our knowledge, no research exists in determining if emergency physicians can predict admission of patients at the time of triage using clinical judgment coupled with information available at the time of triage without seeing the patient or any ED work-up. We chose this method (rather than having the physician physically see the patient) primarily because it fit in our preexisting workflow. At our hospital, we have a bed hub model with a central multidisciplinary group (triage physician, case manager, nurse, patient flow coordinator) that oversees and facilitates all hospital admissions. If a member of this group could predict admissions, then they could expedite downstream work such as increasing inpatient nurse or physician staff or activate a surge workflow to increase urgency of discharges.

2. Methods

2.1. Study design

This is a prospective cohort study utilizing a convenience sample of experienced board certified EM physicians and ED patients. It was approved by the hospital institutional review board.

2.2. Study setting and participants

This study was conducted between October 2016 and August 2017. The study took place in an ED at a large urban tertiary care teaching hospital with an annual census of 85,000. Data was collected in real time by research assistants in the ED. Any physician with at least five years of post-residency clinical experience was eligible to participate in the study. Physicians were given the option to opt out prior to the initiation of the study. Research assistants approached any qualifying physician on shift working in the ED and requested predictions for admission on patients seeking emergency care who had not yet been evaluated by any provider. These were patients waiting in triage as well as patients that had been brought by ambulance who had not been seen by a provider. Typically, nursing notes, vital signs and the EMR charts were available to be read and assessed.

A convenience sample of patients was chosen by research assistants. Eligible patients met the following inclusion criteria: age 18 and older and triaged as emergency severity index (ESI) category 2–5. Mental health patients, patients who required immediate care (ESI 1), patients who had already been seen by a provider and direct transfers from outside hospitals were not eligible.

2.3. Data collection and outcome measures

Physicians were required to provide a prediction for admission (yes or no), a prediction for the admitting service when applicable, and a level of confidence. Admission was defined as either inpatient admission or observational admission. The confidence level was obtained using a visual analog scale. After obtaining a prediction from a physician, research assistants would gather further information on patient characteristics utilizing the EMR. They would then also record patient admission or discharge. All data was collected and stored on a secure network drive. Unique patient identifiers were not collected.

The primary outcome measure was sensitivity and specificity of predictions for admission. This was also evaluated based on a confidence level. The secondary outcome measure was accuracy of predicting the admitting service.

2.4. Statistical methods

Relevant characteristics of the patient population under study were summarized using descriptive statistics. Comparisons by admission status were evaluated using Fisher's exact test (categorical variables) or Wilcoxon-Mann-Whitney tests (continuous variables). Measures of prediction accuracy included sensitivity (proportion of actual admissions predicted as admissions); specificity (proportion of discharges predicted as discharges); positive predictive value (proportion of admission predictions resulting in admission); and negative predictive value (proportion of discharge predictions resulting in discharge). Receiver operating characteristic (ROC) curves, and corresponding area under the ROC curve (AUC) estimates were generated using the 'pROC' package for R (v. 3.3.0). All other analyses were conducted using SAS (v. 9.4). A significance level of 0.05 was assumed throughout, and all *p*-values are two-sided.

3. Results

A total of 35 physicians participated in this study and made a total of 398 predictions (range, 1–50 predictions per physician). They predicted 78 admissions and 320 discharges. Ultimately, there were 313 actual discharges and 85 admissions, leading to an admission rate of 21.4%. Baseline characteristics of patients are described in Table 1. Admitted patients were older (57.1 vs 34.8), had a higher acuity ESI (2.7 vs 3.0), and were more likely to have been referred from clinic (22.3% vs 8.0%). Admitted patients had a significantly higher prevalence of diabetes and renal disease. All of these differences are anticipated due to correlation with more acute illness. There was no significant difference in gender, arrival mode, or presence of hypertension or heart disease. While there was a statistically significant difference in ESI scores, this is unlikely to be clinically relevant. The ESI distribution was as follows: ESI 2 (15.0%), ESI 3 (74.9%), ESI 4 (9.6%), and ESI 5 (0.5%).

Overall, physicians were able to make predictions on admission with a sensitivity of 51.8% and a specificity of 89.1%. The positive predictive value and negative predictive value were 56.4% and 87.2% respectively. At a physician confidence interval cutoff of 90%, physicians were able to

Table 1
Baseline characteristics of the study population, overall and by admission result.

Variable	Total predictions ($N = 392$)		Patient ultimately discharged ($N = 307$)		Patient ultimately admitted ($N = 85$)		P-value
Characteristics							
Mean age (SD)	47.2	±18.1	44.4	±17.0	57.1	±18.4	<0.001
Female gender (%)	236	(60.7)	183	(60.0)	53	(63.1)	0.705
ESI triage score (SD)	3.0	±0.5	3.0	±0.5	2.7	±0.5	<0.001
Arrival by EMS (%)	27	(7.0)	18	(5.9)	9	(10.8)	0.143
Referred from clinic (%)	43	(11.1)	24	(7.9)	19	(22.6)	0.001
Co-morbidities							
Hypertension (%)	84	(21.6)	61	(20.0)	23	(27.4)	0.177
Diabetes (%)	61	(15.7)	40	(13.1)	21	(25.0)	0.011
CAD or heart failure (%)	35	(9.0)	24	(7.9)	11	(13.1)	0.138
Renal disease (%)	20	(5.1)	11	(3.6)	9	(10.7)	0.021

Number missing: age, 3 (0.8%); gender, 3 (0.8%); ESI Triage Score, 4 (1.0%); arrival by EMS, 5 (1.3%); referred from clinic, 3 (0.8%); hypertension, 3 (0.8%); diabetes, 3 (0.8%); CAD or heart failure, 3 (0.8%); renal disease, 3 (0.8%).
All percentages are calculated among the non-missing.

Table 2
Prediction performance.

	Predictions overall	95% CI	Predictions at a 90% confidence level	95% CI
Sensitivity	51.8%	(40.7, 62.7)	61.5%	(40.6, 79.8)
Specificity	88.9%	(84.9, 92.2)	95.6%	(90.1, 98.6)
Positive predictive value	56.4%	(44.7, 67.6)	76.2%	(52.8, 91.8)
Negative predictive value	86.9%	(82.7, 90.5)	91.6%	(85.1, 95.9)

make predictions of admission with a sensitivity of 61.5% and a specificity of 95.7%. At this same level of confidence, the positive predictive value and negative predictive value were 76.2% and 91.7% respectively (Table 2). The ROC analysis of physician performance reveals an AUC of 0.705 (Fig. 1). Among predictions correctly predicting admission, the admitting service was predicted accurately 88.6% of the time.

4. Discussion

Physicians performed poorly in predicting when a patient would be admitted. Even when physicians were confident in their prediction, sensitivities of prediction increased only from 51.8% to 61.5%. This suggests physicians have poor insight in to the likelihood of admission prior to personally evaluating a patient. Conversely, physicians demonstrated a prediction specificity of 89.1% (95.7% when the confidence level was >90%). This demonstrates strong performance in predicting discharge. Furthermore, physicians were able to predict the service of admission at the time of triage with reasonable accuracy.

These findings are comparable to past studies of health care providers predicting admission prior to evaluation. In a prospective, observational study, Kosowsky evaluated how ED triage nurses were able to predict admission based on clinical judgment. The sensitivity and specificity of these predictions were 61.7% and 90.1% respectively [7]. Levine performed a prospective cross-sectional study that determined prediction accuracies in paramedics in the prehospital setting. Sensitivity and specificity was 68% and 96% [8]. Nurses and paramedics were likely able to perform better at predicting admission because they were able to physically see the patient as part of their assessment. We chose to not allow the physicians to see the patients because we were specifically curious if a provider sitting at a computer removed from the department could accurately perform the task. In addition, we chose not to perform the study retrospectively to prevent any possibility of the predicting physician seeing EMR data beyond the time of triage (such as provider notes, imaging or admission status).

Various analytical models have also been created and tested to predict patient admission early in their presentation to the Emergency Department. A model for admission in Singapore attained specificity of 76.9% and sensitivity of 77.6% when a certain cutoff was used [4]. The ROC curve for this data was 0.849. In the UK, modeling that used the

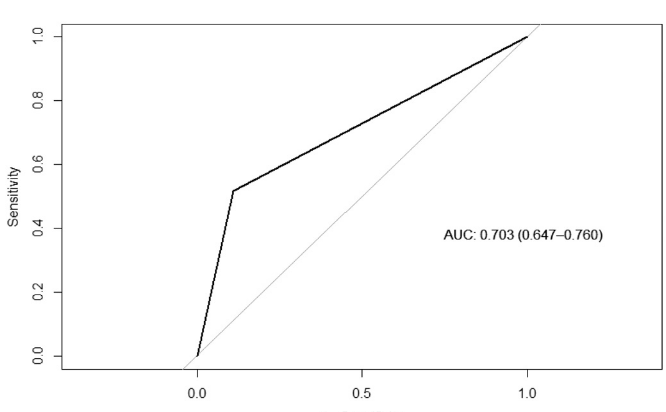

Fig. 1. ROC curve for accuracy of admission predictions.

Manchester Triaging System obtained a ROC curve of 0.8778 with a 78.0% sensitivity and 81.7% specificity when the curve was used as a binary predictor [2]. In Australia, a prediction model using the Australian Triage Score along with multiple other variables attained a ROC of 0.80 [1]. Zhang et al. generated a prediction model that incorporated natural language processing and was able to reach an UAC of 0.844 using logistic regression [10]. Compared to our study's AUC of 0.705, these analytics models hold great promise in operational application [4].

Further research needs to be performed to determine if physicians can predict admissions at the time of triage with reasonable accuracy. We suggest further evaluating physician predictions using a randomized sample of ED patients. To obtain a more representative sample, next steps may include a retrospective attempt at predictions via review of the electronic medical record data with appropriate data filters and limitations applied. It would also be relevant to determine if physicians can accurately predict admission after first evaluating the patient but prior to reviewing results of any labs or imaging. We have recently instituted a provider in triage (PIT) and we anticipate performing a similar study with the PIT making predictions after briefly seeing the patient alongside the triage nurse. If such predictions prove to be more accurate, they also have the potential to improve ED flow.

Limitations

This was a single center study in which predictions were achieved with a convenience sample of physicians and patients. As such, the data does not represent a random sample of all experienced physicians in this ED. Ultimately, there was a wide range in the number of predictions that individual physicians made. This certainly could skew the data if any of the physicians that made a large number of predictions were particularly adept at the task. Physicians were also able to decline participation on a case by case basis, perhaps because of busy times in the departments or discomfort in making a prediction. Either of these situations could have introduced bias. For safety reasons, we never forced a physician to make predictions as all of these physicians were working clinically. We did not want to unnecessarily disrupt their patient care.

Although physicians typically did not initially know if they would be treating a patient who they were predicting on, such a patient could ultimately have been bedded in their patient care area. Given the size of our ED and number of providers working at a given time, this was likely a rare occurrence. This is also a potential source of bias as these physicians could be compelled to comply with their predictions.

Patient selection for predictions was performed by research assistants based on an ad hoc quota. This introduced subjectivity in the selection process in terms of the ESI level, the timing of a presenting patient, and the provider available to make a prediction. Research assistants could have chosen more difficult predictions to stimulate interest, thereby falsely lowering the accuracy of admission by excluding the more obvious cases. Research assistants were also probably less likely to request predictions when the emergency department was overly busy or when certain staff were on shift.

We did not have enough patients in any given ESI group to perform subgroup analysis at this level. It would be interesting to focus on the patients with ESI 3 and 4 as these likely represent the challenging 'grey zone' where admission or discharge is less certain.

Conclusion

In an effort to predict admissions from the ED at the time of triage, physicians performed poorly. Physicians did perform well at predicting discharge and determining the service of admission. Many opportunities exist to determine if physicians' prediction performance can be improved to contribute to ED efficiency.

References

[1] Kim Susan W, Li Jordan Y, Hakendorf Paul, Teubner David Jo, Ben-Tovim David I, Thompson Campbell H. Predicting admission of patients by their presentation to the emergency department. Emerg Med Australas Emergency Medicine Australasia 2014;26(4):361–7.
[2] Cameron Allan, Rodgers Kenneth, Ireland Alastair, Jamdar Ravi, Mckay Gerard A. A simple tool to predict admission at the time of triage. Emergency Medicine Journal Emerg Med J 2014;32(3):174–9.
[3] Ackroyd-Stolarz S, Read Guernsey J, Mackinnon NJ, et al. The association between a prolonged stay in the emergency department and adverse events in older patients admitted to hospital: a retrospective cohort study. BMJ Qual Saf 2011;20(7):564–9.
[4] Sun Yan, Heng Bee Hoon, Tay Seow Yian, Seow Eillyne. Predicting hospital admissions at emergency department triage using routine administrative data. Acad Emerg Med 2011;18(8):844–50.
[5] Peck Jordan S, Benneyan James C, Nightingale Deborah J, Gaehde Stephan A. Predicting emergency department inpatient admissions to improve same-day patient flow. Acad Emerg Med 2012;19(9) n. pag. 8h.
[6] Bradman Kate, Borland Meredith, Pascoe Elaine. Predicting patient disposition in a paediatric emergency department. J Paediatr Child Health 2012;50(10) (n. pag).
[7] Kosowsky Joshua M, Shindel Stuart, Liu Tiepu, Hamilton Catherine, Pancioli Arthur M. Can emergency department triage nurses predict Patients' dispositions? Am J Emerg Med 2001;19(1):10–4 [Web].
[8] Levine Saul D, Colwell Christopher B, Pons Peter T, Gravitz Craig, Haukoos Jason S, Mcvaney Kevin E. How well do paramedics predict admission to the hospital? A prospective study. J Emerg Med 2006;31(1):1–5.
[9] Zlotnik Alexander, et al. Building a decision support system for inpatient admission prediction with the Manchester triage system and administrative check-in variables. CIN: Computers, Informatics, Nursing 2016;34(5):224–30.
[10] Zhang X, et al. Prediction of emergency department hospital admission based on natural language processing and neural networks. Methods Inf Med 2017;56.5: 377–89.