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Real-time prediction of patient disposition and the impact of reporter confidence on mid-level triage accuracies – An Israeli observational study

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Abstract

Aim: The Emergency Department (ED) is the first port-of-call for most patients receiving hospital care and as such acts as a gatekeeper to the wards, driving patient flow through the hospital. ED overcrowding is a well-researched field, negatively affecting patient outcome, staff wellbeing and hospital reputation. An accurate, real time model capable of predicting ED overcrowding has obvious merit in a world becoming increasingly computational, although the complicated dynamics of the department have hindered international efforts to design such a model. Triage nurses' assessments have been shown to be accurate predictors of patient disposition and could, therefore, be useful input for overcrowding and patient flow models.

Methods: In this study we assess the prediction capabilities of triage nurses in a Level 1 urban Israeli hospital. ED settings included both acute and ambulatory wings. Nurses were asked to predict admission or discharge for each patient over a 3-month period, as well as exact admission destination. Prediction confidence was used as an optimization variable.

Result: Triage nurses accurately predicted admission outcome for 77% of patients in the acute wing, rising to 88% when their prediction certainty was high. Accuracies were higher still for patients in the ambulatory wing. In particular, negative predictive values for admission were highly accurate at 90%, irrespective of area or certainty levels.

Conclusion: Nurses prediction of disposition should be considered for input for real time ED models.

Article Summary

Strengths and Limitations:

- In comparison to previous research in this field, this observational study was conducted on a large cohort of patients, very few of whom were excluded from analysis, thus strengthening the reliability of the results.
- To our knowledge, this is the first study of its kind conducted in Israel, whose emergency department operates somewhat differently to those of Western Europe and the US. The fact that the data supports that of previous studies from these territories is reassuring.
- Results suggest that triage nurses are indeed capable of accurately predicting patient disposition in general. Furthermore, using the CTAS as a triage tool, we were able to identify subsections of patients for whom prediction accuracy was very high and those for whom it was less so, meaning predictions can effectively be graded on their relative likelihood of being correct.
- The scope of this study did not include observing patient specific characteristics other than which general department was responsible for their primary care. We are therefore unable to draw conclusions on prediction accuracy on a disease or presentation specific level (i.e. chest pain/ ACS).
- It is our belief that despite prediction accuracies being high in this study, they are not accurate enough in their raw form to directly influence ED management. We do propose, however, that such predictions could be effectively used as part of a more holistic real-time, machine learning ED analysis tool as a cheap and quick input metric.

Introduction

Overcrowding in the Emergency Department (ED) is such a common phenomenon that in many hospitals it is seen to be the routine working environment. Such strain on staff and resources has an impact on the ability of staff to adequately provide medical services and, therefore, the quality of patient care and their hospital experience. Multiple previous studies have shown that ED overcrowding has a negative effect on many outcomes including, but not limited to: patient mortality and waiting times[1], door to needle time in patients suspected of having acute myocardial infract[1][2], pain management[3] and delays in antibiotic administration[4]. Additionally, overcrowding has been found to be a major factor in staff burnout[5].

Naturally, overcrowding is, therefore, a common topic of internal auditing and research publications. In Israel, a national survey conducted in 2018 revealed that EDs on average operated at 104% capacity, with an average length of stay of 3.0 hours[6]. The Tel Aviv Sourasky Medical Center (TASMC) ED, the locale for this study, is a particularly busy inner-city hospital, with a length of stay of attending patients of3.3 hours on average, increasing for those requiring admission (51% staying over 5 hours)[6].

Improvement in real-time analysis and computational models of ED overcrowding are expected to facilitate better provision of medical treatment and allocation of resources, thus improving patient outcome in the ED, as well as in the admitting departments[3][1] There are many tools designed for retrospective analysis of ED disposition prediction and overcrowding[7]. Several studies have shown that tools combining objective

[1] Door to needle time is the elapsed time between the arrival of a patient with acute MI to the hospital and the start of coronary arteries catheterization. It is generally accepted that sub 90 minutes provides optimal outcomes.

metrics with triage nurses' disposition predictions are able to produce good patient admission prediction as early as at time of triage[8]. In recent years, there have been attempts to construct real-time overcrowding models, often using triage scores and bed availability as inputs[9][10]. Examples include The National Emergency Department Overcrowding Scale (NEDOCS), The Emergency Department Work Index (EDWIN) and The Risk Management, Economic Sustainability, and Actuarial Science Development in Indonesia (READI)[2][10]. No study has, as of yet, compared the efficacy of these tools.

In TASMC's ED, similar to other large medical centers in Israel, nurses triage patients using the Canadian Triage and Acuity Scale (CTAS) method, a model combining subjective metrics such as presenting complaint and severity of pain with objective metrics such as vital signs, evidence of bleeding, rash etc.[11]. CTAS level ranges from 1 to 5 and represents the urgency in which patients require medical review. 1 correlates to patients in the resuscitation area who require immediate review, whereas 5 represents non urgent cases with the lowest priority for review. In the United States, for comparison, The Emergency Severity Index (ESI) triage method is the most commonly used.

Many studies have shown that triage nurses are able to predict disposition with a high degree of accuracy, based on their experience and the limited information available to them at the time of triage. However this has never been assessed in Israel. For example, Danette et al published a study in which triage nurses were able to predict admission with 71.5% sensitivity and discharge with 88.0% specificity[12]. The negative predictive value (NPV) for discharge was also particularly high, at 90%. Predictions were most accurate for young patients and for patients with a low (level 1) or high (level 4-5) ESI score[12]. Another study looking at overall disposition predictions demonstrated similar results (sensitivity 75.6%, specificity 84.5%)[13]. Importantly, when nurses were asked to assign a level of confidence to their predictions, a high degree of certainty correlated with improved accuracy of disposition prediction (sensitivity 83.6%, specificity 93.1%, NPV 95%)[13]. However, a similar study from the UK was unable to demonstrate good accuracy of triage disposition predictions (sensitivity and specificity 68% and 85% respectively)[14].

In addition to triage nurse predictions, several studies have looked into the possibility that objective metrics can predict patient disposition. A 2009 retrospective study examined the cases of 1100 patients in 6 medical centers, excluding trauma, psychiatric and OBGYN patients. That study used a variant automatic prediction model available during triage: age over 60, chest pain, shortness of breath, dizziness, weakness or syncope, history of cancer, history of diabetes. Each variant was ascribed a weight (total combined score 0 to 14). When the total score was above 4 (34% of cases), the likelihood of admission was 77%, and when the score was above 5 (29% of cases), the likelihood rose to 80%.[15]

Another study attempted to build a prediction model based on data that is routinely collected during the triage process. This retrospective study included approximately 300,000 ED case files. Of these cases, 60% were used to train the model and 40% were used to validate it. The data used as input for training included demographic characteristics (age, sex, ethnicity), recent (<3 months) hospital admissions or ED visits, method of arrival, patient acuity category and the presence of chronic illness (e.g. diabetes, hypertension, dyslipidemia). The variables that were found to be significant for hospitalization prediction were age, method of arrival and patient acuity category[16].

The concept of combining triage predictions and admission prediction models was explored by Cameron et al in 2017. In their research they compared the prediction ability of triage nurses to that of a simple clinical tool, the Glasgow Admission Prediction Score (GAPS[2]). Their research demonstrated that, in most cases, GAPS was superior at predicting patient admission outcome over triage nurses (accuracy of 0.810 vs 0.759)[17]. The exception was in cases where nurses were very certain of their prediction, supporting previous findings[13]. The authors proposed a combination of both predictions. By allowing nurses "to veto" GAPS when they were certain of their predication, accuracy was improved to 0.892[17]. It is important to point out that GAPS is not an objective tool as it takes into account the triage level as determined by the triage nurse[8]. Riodan et al also acknowledged this in their 2017 publication examining patients with ESI level 3. They experimented with several variables including age, pulse, systolic blood pressure and pain in an attempt to build a regression model capable of predicting patient discharge[18].

As with other areas of medicine, there is growing interest in the field of artificial intelligence, in particular machine learning, to predict patient admission outcome at the triage level[19]. One such study found that a trained algorithm outperformed classical methods, especially when predicting outcomes for patients with moderate scores (i.e. CTAS level 3)[20][19]. This is a field that is expected to develop rapidly in the coming years. However, such tools are only as robust as the data that was used to train them,

Glasgow Admission Prediction Score [2] is a score based on age (a point is given for each decade) triage urgency level (20 points for level 1, 5 points for level 3); 10 points are given if the patient was referred by a doctor to the ED; 5 points are given if the patient was brought in by ambulance or was admitted in the last 12 months. The model also gives a point for each point received by the NEWS score (national early warning score – a score based on vital signs). This tool was found to by efficient in predicting admission[17].

meaning that at present it is necessary to continue to develop human approaches to data analysis.

Methods

In this single center, observational, retrospective study to determine the accuracy of nurse predictions relating to patient disposition and destination, data was gathered between the period of April 1st 2019 and June 30th 2019 in TASMC ED (a tertiary hospital) for all adult patients.

Ethical approval was sought and approved by a Helsinki committee, reference 0223-19.

All the nurses who took part in this study were graduates of the Emergency Medicine Nursing Course. No data was collected on the nurses themselves. The medical team blinded to the triage predictions to avoid bias.

The participating nurses were asked to fill out a questioner that was embedded in the ED's patient managing software. For each patient, the nurse provided disposition predictions (admission or discharge), exact admission destination prediction (where relevant) and level of certainty in the predication (high, medium, low).

Patient demographic data was also gathered (patients ID number, sex, age) as well as ED time of arrival and discharge from the ED (home vs admission), triage placement in the ambulatory wing vs acute ED wing, triage level (1-5) according to CTAS, vitals (BP, heart rate, oxygen saturation, respiratory rate, temperature) and pain level (according to Numeric pain Assessment Scale - NAS). Textual data regarding the reason of ED visit (i.e. presenting complaint) was also included.

Selection criteria included any patient visiting the ED and seen by the triage team in said period of time, excluding patients seen by the pediatric team.

Data was processed in order to calculate the sensitivity, specificity, PPV, NPV and accuracy of nurses' prediction, as well as the influence of various patient characteristics on these parameters.

This manuscript was prepared in accordance with the STROBE statement for improved reporting of outcomes from observational studies.

Results

Overall, in April through June 2019, data was gathered for 33,685 ED visits, 11,143 being referred to the ambulatory wing (33%) and 22,542 were seen in the acute department (67%). The average age of attendee was 51 years old. The male to female ratio was approximately 52:48. 6,566 cases (20%) had incomplete triage prediction forms and were excluded from the results, meaning a total of 27,119 questionnaires were processed for analysis – 19,146 (71%) acute and 7,973 (29%) ambulatory. No statistically significant difference regarding disposition was found between the group that had complete triage prediction forms and the group that was excluded.

In the ambulatory, wing discharge was predicted for 7,307 cases (92%), of which 6950 cases were discharged (total discharges – 7,304), meaning nurse predictions were over 95% accurate for this group. Hospital admission was predicted for 666 cases, of which only 312 were actually admitted (overall number of hospitalizations – 669), giving a lower accuracy of only 47%. Combined accuracy was 91%. Positive predictive value (PPV) and negative predictive value (NPV) were 95% and 46% respectively. For the purpose of this calculation, admission was defined as a positive test result and discharge negative. Sensitivity and specificity were 47% and 95% respectively (Chart 1).

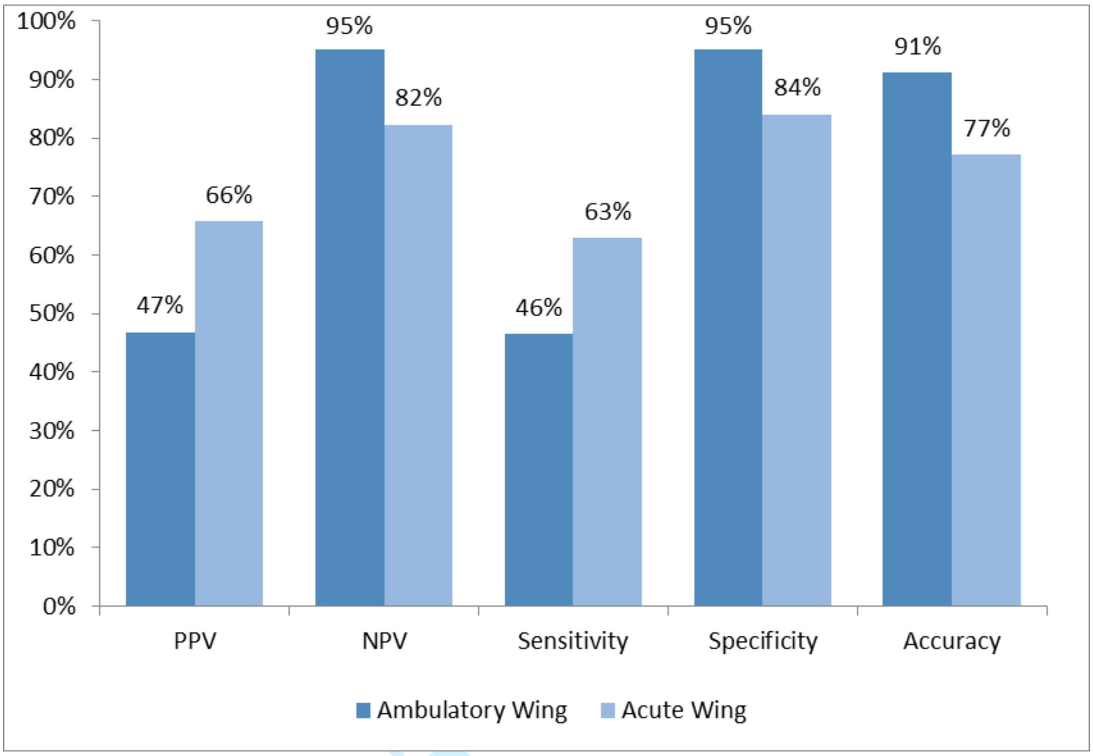

Chart 1: Triage Predictions According to Wing

In the acute wing, discharge was predicated for 13,145 cases, of which 10,816 were discharged (overall number of discharges 12,867), giving a prediction accuracy of 82%. Hospital admission was predicted for 6,001, of which 3,950 were actually admitted (overall number of admissions – 6,279), meaning, again, that a lower accuracy of 66% was observed for this group. Combined accuracy was 77%. PPV and NPV were 84% and 62% respectively Sensitivity was 63% and specificity was 84% (Chart 1).

Nurses were not successful at accurately predict the eventual department of admission at the time of triage in both acute and ambulatory wing settings. The exception to this was for admissions to the Oncology department; however this was a very small cohort (Table 1).

	Acute Wing	Ambulatory Wing

	No. cases predicted to be admitted	Actual number of admitted cases	Accuracy of triage predictions %	No. cases predicted to be admitted	Actual number of admitted cases	Accuracy of triage predictions %
Surgery	687	275	40	41	3	7.3
Internal Medicine	3345	1833	54.8	230	75	32.6
Ophthalmology	15	1	6.7	11	4	36.4
Cardiology	295	121	41	4	1	25
Orthopedics	337	173	51.3	77	46	59.7
Oncology	9	2	22.2	1	1	100
ENT	97	24	24.7	60	15	25
Dermatology	79	25	31.6	109	53	48.6
Neurology	337	141	41.8	45	16	35.6
Urology	119	36	30.3	13	5	38.5
Neurosurgery	189	61	32.3	21	11	52.4

Table 1 : Deposition Prediction Accuracy by Wing

No significant difference was found regarding prediction accuracy between male and female patients in either wing. There was also no significant different in the accuracy of prediction for patients with normal vital signs (pulse, BP, oxygen saturation, temperature) compared to patients with abnormal vitals, remaining approximately 90% in the ambulatory wing and 76% in the acute wing. The exception to this was predictions in patients with abnormal temperatures in the ambulatory wing, which reduced prediction accuracy to 72%.

CTAS triage level had a significant influence on prediction accuracy (Chart 2).

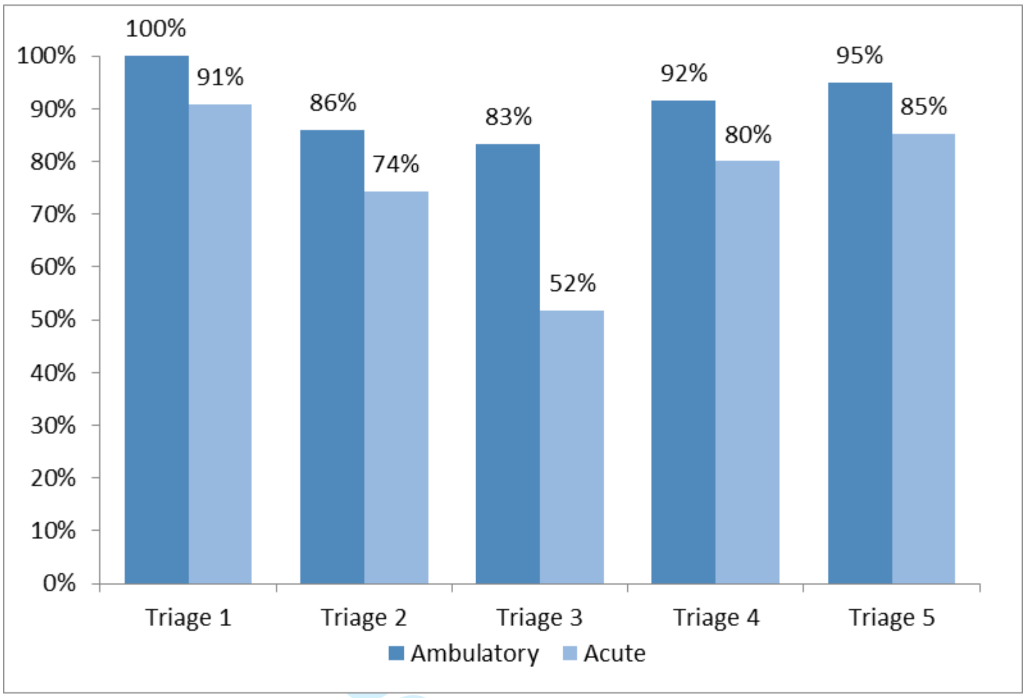

Chart 2: Effect of Triage Level on Prediction Accuracy

As expected, with mid-CTAS levels (specifically level 3) predictions were less accurate. In the ambulatory wings there was only one case of CTAS level 1 and less than 1% of cases were CTAS level 2. In comparison, 50% of cases were CTAS level 4.

In the acute wing, about 1% of patients were CTAS level 1. Most patients were CTAS level 3 and 4 (50% and 38% respectively). In this department, predictions regarding CTAS level 3 were particularly inaccurate.

The effect of nurses working shift on the accuracy of prediction was also evaluated. Nursing shift patterns in the ED were limited to morning (07:00-15:00), evening (15:00-23:00) and night (23:00-07:00). During the data collection period for this study the ambulatory wing closed at 23:00, therefore for this wing only morning and evening shifts were analyzed.

In the acute wings average prediction accuracy was 85% during the night shift, significantly better than the evening (78%) and morning (71%) shifts. The total number of cases recorded in this study was similar for the morning and evening shifts, however for the night shift the number of cases was 50% smaller. There was no significant difference in the proportion of cases recorded as CTAS level 1 and 2 between shifts, although a larger proportion of CTAS level 5 cases was seen during night shifts. For these patients, prediction accuracy was high and contributed to the overall higher accuracy level.

The degree of reporter certainty when making a prediction had a significant impact on accuracy (Chart 3). In the ambulatory wings, when a nurse stated that the prediction was made with high certainty, the accuracy of the prediction was over 96%. Most predictions in this wing were stated to be highly certain or moderately certain (5,235 and 2,541 accordingly), and only a minority were given with low certainty (458, approximately 5.5%).

In the acute wing a similar increase was observed for predictions reported as having a high degree of certainty - 88% accurate, compared to 77% for the wing as a whole. In this wing, prediction uncertainty was considerably higher (2,114, 11%), and the accuracy of these predictions was just 60% (compared to 70% in the ambulatory wing).

Importantly, CTAS level 3 cases with a high degree of reporter confidence were highly accurate (93% for ambulatory wing and 85% for acute wing), significantly greater than CTAS level 3 accuracies as a whole. It is important to point out that the likelihood of a high certainty prediction for triage level 3 cases is lower than average (Chart 3, Table 2a/ b).

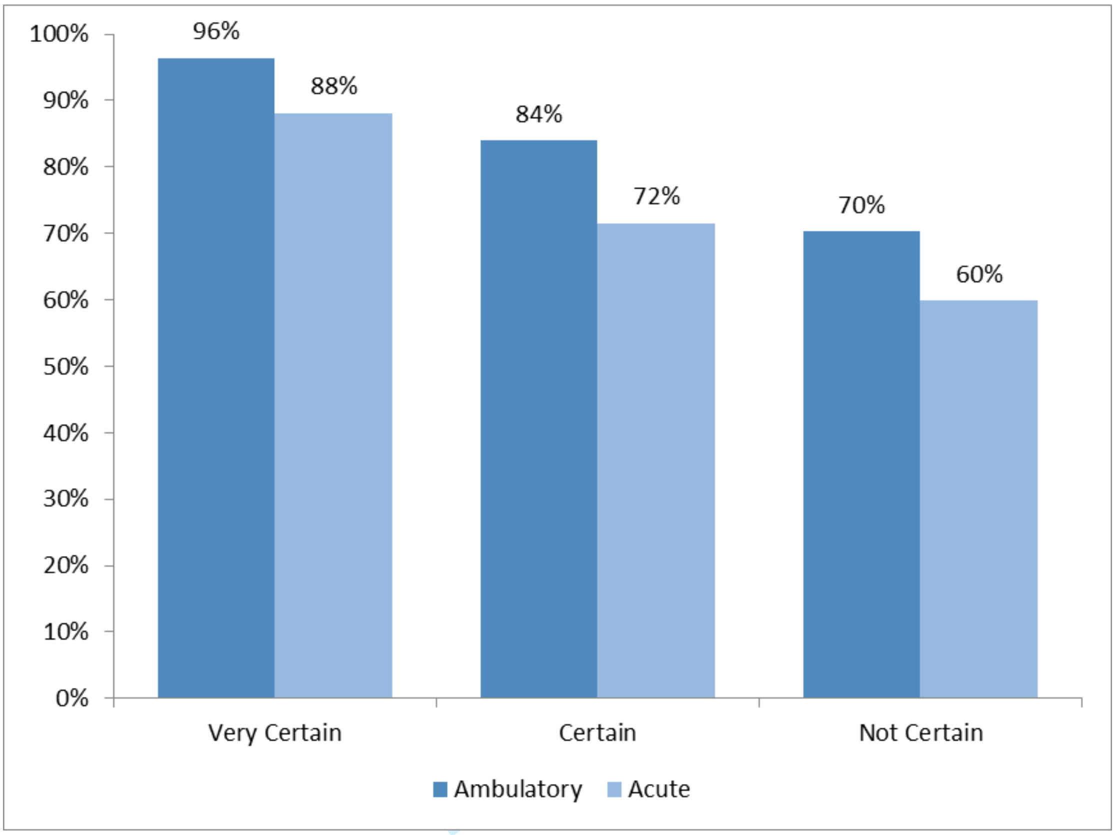

Chart 3: Effect of Prediction Certainty on Prediction Accuracy

Table 2a -Triage level 3, Ambulatory Wing						
			True Disposition			
Prediction	Certainty level	% Rate	Discharge	Hospitalization	Total	Accuracy %
Admission	Very Certain	29%	15	39	54	72%
	Somewhat Certain	52%	73	25	98	26%
	Not Certain	19%	32	4	36	11%
Total		100%	120	68	188	36%
Discharge	Very Certain	55%	806	27	833	97%
	Somewhat Certain	38%	524	57	581	90%
	Not Certain	7%	101	13	114	89%
Total		100%	1431	97	1528	94%
Grand Total			1551	165	1716	87%

Table 2b – Triage level 3, Acute Wing						
			True Disposition			
Prediction	Certainty level	% Rate	Discharge	Hospitalization	Total	Accuracy %
Discharge	Very Certain	34%	1747	255	2002	87%
	Somewhat Certain	53%	2422	691	3113	78%
	Not Certain	12%	498	223	721	69%
Total		100%	4667	1169	5836	80%
Admission	Very Certain	31%	210	910	1120	81%
	Somewhat Certain	56%	834	1154	1988	58%
	Not Certain	13%	248	205	453	45%
Total		100%	1292	2269	3561	64%
Grand Total			5959	3438	9397	74%

Table 2a/ 2b: Breakdown of Triage Level 3 Cases in Ambulatory and Acute wards and the Effect of Prediction Certainty

Discussion

The results of this study support the results of previous studies: trained triage nurses are able to accurately predict patient disposition during the triage process. At extremes of CTAS/ triage score (1 and 5) these predications were more accurate, as is to be expected. Additionally, reporter confidence is also positively correlated to prediction accuracy, potentially highlighting a particularly useful as well as easy metric to measure.

Regarding the lack of accuracy in predicted admission destination, it appears (through discussion with nurses who participated in the study) that the structure of the questionnaire itself may be the cause of the inaccuracy. However, patients are often prevented from being transferred to the most suitable ward by factors outside the control of the ED, such as bed availability. The subject of destination prediction and the varying limiting factors will be further evaluated in future studies.

Regarding the difference in the prediction accuracy between different shifts, it seems that the higher accuracy in the acute wing during night shifts may be in part due to a greater percentage of CTAS level 5 triage patients in the said wing during this shift, as ambulatory patients are seen there at night. As Level 5 cases were predicted with a greater degree of accuracy, this may explain the results.

Careful consideration was given to the analysis of CTAS level 3 patients in this study. These patients represent a substantial percentage of presentations to most EDs including our own. In general, reporters struggled to accurately predict disposition for this group. It was demonstrated, however, that when the triage nurse was certain of their prediction for this group, the accuracy of the prediction was high. This simple metric may therefore allow for accurate predictions for subset of level 3 patients.

An additional study, ongoing at the time of writing, will evaluate the ability of triage predictions to improve the accuracy of a machine learning algorithm designed to predict overcrowding and patient disposition, especially in areas which demonstrated poor accuracy (i.e. CTAS level 3).

This research demonstrated that, even at the point of triage, it is possible to predict discharge with a high degree of certainty for over 60% of ED patients. This group includes all ambulatory wing patients, patients at either extreme of triage level (1 and 5) and any patient for whom the triage nurse is certain of their prediction.

Limitations

The major disadvantage of the use of triage predictions as part of an overcrowding analysis tool is the added workload for already over worked nursing staff. It is our opinion that additional evidence of the effectiveness of this method is required before recommendations are made.

It is evident from the data concerning disposition predictions that they are, in general, not accurate enough in their raw form to greatly influence the management of the ED. However, it is our belief such data can be used as a part of a real-time ED overcrowding analysis tool, capable of assisting bed managers and improving patient flow as well as allowing for better allocation of resources.

Conclusion

Triage nurses are able to accurately predict disposition with a high degree of accuracy, particularly for patients with extremes of CTAS score. With the introduction of prediction confidence as a metric, accuracy increased for all predictions, including those made for middling CTAS scores. However, predictions for patient destination once admitted were not accurate. We believe that implementing these metrics into a machine learning overcrowding tool may improve overall performance and assist in maximising flow through the emergency department, thus decreasing length of stay.

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Footnotes

Ethics: Ethical approval was sought and approved by a Helsinki committee, reference 0223-19. The Helsinki committee waived the requirement for written informed consent.

Contributors: DT was involved with conceptualization, visualization, drafting the manuscript, reviewing and editing the manuscript; NS was involved with conceptualization, investigation, methodology, supervision, drafting the manuscript and reviewing and editing the manuscript; NNG was involved with data curation; YM was involved with data curation; DEF was involved with reviewing and editing the manuscript; SA was involved with project administration and software; AC was involved with project administration and visualization; MKS was involved with formal analysis; GP was involved with data curation and project administration.

DT, NS, NNG, YM, DEF, SA, AC, MKS and GP agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Real-time prediction of patient disposition and the impact of reporter confidence on mid-level triage accuracies – An observational study in Israel

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Real-time prediction of patient disposition and the impact of reporter confidence on mid-level triage accuracies – An observational study in Israel

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Abstract

Aim: The Emergency Department (ED) is the first port-of-call for most patients receiving hospital care and as such acts as a gatekeeper to the wards, directing patient flow through the hospital. ED overcrowding is a well-researched field, and negatively affects patient outcome, staff wellbeing and hospital reputation. An accurate, real time model capable of predicting ED overcrowding has obvious merit in a world becoming increasingly computational, although the complicated dynamics of the department have hindered international efforts to design such a model. Triage nurses' assessments have been shown to be accurate predictors of patient disposition and could, therefore, be useful input for overcrowding and patient flow models.

Methods: In this study we assess the prediction capabilities of triage nurses in a Level 1 urban hospital in central Israeli. ED settings included both acute and ambulatory wings. Nurses were asked to predict admission or discharge for each patient over a 3-month period, as well as exact admission destination. Prediction confidence was used as an optimization variable.

Result: Triage nurses accurately predicted whether the patient would be admitted or discharged in 77% of patients in the acute wing, rising to 88% when their prediction certainty was high. Accuracies were higher still for patients in the ambulatory wing. In particular, negative predictive values for admission were highly accurate at 90%, irrespective of area or certainty levels.

Conclusion: Nurses prediction of disposition should be considered for input for real time ED models.

Article Summary

Strengths and Limitations:

- This study was conducted on a large cohort of patients, very few of whom were excluded from analysis, thus strengthening the reliability of the results.
- To our knowledge, this is the first study of its kind conducted in Israel, and the fact that the data supports that of previous studies from other regions is reassuring.
- The study was limited to data collected from one ED in one institution in Israel, and did not take into account the nurses' experience or educational background, limiting both its internal and external validity.
- We are unable to draw conclusions on prediction accuracy related to specific diseases or presentation (i.e. chest pain/ ACS) as this was beyond the scope of our study.
- We believe that the results of the study indicate that predictions could be effectively used as part of a more holistic real-time, machine learning ED analysis tool as an accurate, cost efficient and quick input metric.

Introduction

Overcrowding in the Emergency Department (ED) has become such a common phenomenon that it is become a routine working environment in many hospitals. The strain on staff and hospital resources has an impact on the ability to provide adequate medical services and directly correlates with the quality of patient care and overall hospital experience. Multiple studies have demonstrated that ED overcrowding has a negative effect on many outcomes including patient mortality and waiting times [1], door to needle time in patients suspected of having acute myocardial infract[1][2], pain management [3] and delays in antibiotic administration [4]. Additionally, overcrowding is a major contributing factor in staff burnout [5].

Overcrowding is, therefore, a frequent topic of internal auditing and research publications. In Israel, a national survey conducted in 2018 revealed that EDs on average operated at 104% capacity, with an average length of stay of 3.0 hours [6]. The Tel Aviv Sourasky Medical Center (TASMC) ED, the location of this study, is a particularly busy inner-city hospital, with a patient length of stay of.3 hours on average, and even higher for those requiring admission (51% staying over 5 hours) [6].

Improvement in real-time analysis and computational models of ED overcrowding are expected to facilitate better provision of medical treatment and allocation of resources, thus improving patient outcome in the ED, as well as in the admitting hospital departments [3][1] There are many tools designed for retrospective analysis of ED disposition prediction and overcrowding [7]. Several studies have shown that tools combining objective metrics with triage nurses' disposition predictions are able to

[1] Door to needle time is the elapsed time between the arrival of a patient with acute MI to the hospital and the start of coronary arteries catheterization. It is generally accepted that sub 90 minutes provides optimal outcomes.

produce good patient admission prediction as early as at time of triage [8]. In recent years, there have been attempts to construct real-time overcrowding models, often using triage scores and bed availability as inputs [9][10]. Examples include The National Emergency Department Overcrowding Scale (NEDOCS), the Emergency Department Work Index (EDWIN) and the Risk Management, Economic Sustainability, and Actuarial Science Development in Indonesia (READI)[2] [10]. No study has, as of yet, compared the efficacy of these tools.

In TASMC's ED nurses triage patients using the Canadian Triage and Acuity Scale (CTAS), a model combining subjective metrics such as presenting complaint and severity of pain with objective metrics such as vital signs, evidence of bleeding, presence of rash etc. [11]. CTAS levels range from 1 to 5 and indicate the urgency in which patients require medical attention. A score of 1 indicates patient who require immediate attention in the resuscitation bay, whereas 5 indicates nonurgent cases with the lowest priority. In the United States, for comparison, the Emergency Severity Index (ESI) triage method is the most commonly used.

Many studies have demonstrated that triage nurses are able to predict patient disposition with a high degree of accuracy, based on their experience and the limited information available to them at the time of triage. For example, Danette et al published a study in which triage nurses were able to predict admission with 71.5% sensitivity and discharge with 88.0% specificity [12]. The negative predictive value (NPV) for discharge was also particularly high at 90%. Predictions were most accurate for young patients and for patients with a low (level 1) or high (level 4-5) ESI score [12]. Another study looking at overall disposition predictions demonstrated similar results (sensitivity 75.6%, specificity 84.5%) [13]. Importantly, when nurses were asked to assign a level of confidence to their predictions, a high degree of certainty correlated with improved accuracy of disposition prediction (sensitivity 83.6%, specificity 93.1%, NPV 95%) [13]. However, a similar study from the UK was unable to demonstrate high accuracy of triage disposition predictions (sensitivity and specificity 68% and 85% respectively) [14]. The accuracy of nurse triage in Israel has never been assessed in.

In addition to triage nurse predictions, several studies have explored the possibility of utilizing objective metrics to predict patient disposition. A 2009 retrospective study examined 1100 patient cases in 6 medical centers, excluding trauma, psychiatric and OBGYN patients. That study used a variant automatic prediction model available during triage: age over 60, chest pain, shortness of breath, dizziness, weakness or syncope, history of cancer, history of diabetes. Each variant was ascribed a weight with a total combined score of 0 to 14. When the total score was above 4 (34% of cases), the likelihood of admission was 77%, and when the score was above 5 (29% of cases), the likelihood rose to 80%.[15]

Another study attempted to build a prediction model based on data that is routinely collected during triage. This retrospective study included approximately 300,000 ED case files. Of these cases, 60% were used to train the model and 40% were used to validate it. The data used as input for training included demographic characteristics (age, sex, ethnicity), recent (<3 months) hospital admissions or ED visits, method of arrival, patient acuity category and the presence of chronic illness (e.g. diabetes, hypertension, dyslipidemia). The variables that were found to be significant for hospitalization prediction were age, method of arrival and patient acuity category [16].

The concept of combining triage predictions and admission prediction models was explored by Cameron et al in 2017. In their research they compared the prediction ability of triage nurses to that of a simple clinical tool, the Glasgow Admission

Prediction Score (GAPS[2]). Their research demonstrated that in most cases, GAPS was superior at predicting patient admission outcome over triage nurses (accuracy of 0.810 vs 0.759) [17]. The exception was in cases where nurses were very with their prediction, supporting previous findings [13]. The authors proposed a combination of both triage and admission prediction models. By allowing nurses to overrule GAPS when they were certain of their predication, overall accuracy was improved to 0.892 [17]. It is important to note that GAPS is not an objective tool as it takes into account the triage level as determined by the triage nurse [8]. Riodan et al acknowledged this in their 2017 publication examining patients with ESI level 3. They experimented with several variables including age, pulse, systolic blood pressure and pain in an attempt to build a regression model capable of predicting patient discharge [18].

As with many areas of medicine, there is growing interest in the field of artificial intelligence, in particular machine learning, to predict patient admission outcome at the triage level [19]. One such study found that a trained algorithm outperformed classical methods, especially when predicting outcomes for patients with moderate scores (i.e. CTAS level 3) [20][19]. This is a field that is expected to develop rapidly in the coming years. Another interesting study by Tahayori et al. analyzed the use of natural language processing (NLP) to predict the disposition of patients [21]. The algorithm developed was applied to ED triage notes with a relatively high level of accuracy. Such tools are only as robust as the algorithm developed and the data that was input and used to train

Glasgow Admission Prediction Score [2] is a score based on age (a point is given for each decade) triage urgency level (20 points for level 1, 5 points for level 3); 10 points are given if the patient was referred by a doctor to the ED; 5 points are given if the patient was brought in by ambulance or was admitted in the last 12 months. The model also gives a point for each point received by the NEWS score (national early warning score – a score based on vital signs). This tool was found to by efficient in predicting admission [17].

them, so at present it is necessary to continue to develop human approaches to data analysis.

Methods

This is a single center, observational, retrospective study to determine the accuracy of nurse predictions of patient disposition and destination. Data was gathered between the period of April 1st 2019 and June 30th 2019 in TASMC ED,a tertiary hospital in central Israel, for all adult patients.

Ethical approval was sought and approved by the Tel-Aviv Sourasky Medical Center Helsinki committee reference 0223-19.

All the nurses who took part in this study were graduates of the Emergency Medicine Nursing Course. No data was collected on the nurses themselves. The medical team was blinded to the nurses' triage predictions to avoid bias.

The participating nurses were asked to fill out a questionnaire that was embedded in the ED's patient managing software. The nurses were aware of the study and completed the questionnaire in a short period of time with no interference with their work. For each patient, the nurse provided disposition predictions (admission or discharge), exact admission destination prediction (where relevant) and level of certainty in the predication (high, medium, low).

Patient demographic data was gathered (patients ID number, sex, age) as well as time of arrival and discharge from the ED (home vs admission), triage placement in the ambulatory wing or acute ED wing, triage level (1-5) according to CTAS, vitals (BP, heart rate, oxygen saturation, respiratory rate, temperature) and pain level (according to Numeric pain Assessment Scale - NAS). Textual data regarding the reason of ED visit (i.e. presenting complaint) was also included. Selection criteria included any patient visiting the ED and seen by the triage team in said period of time, excluding patients seen by the pediatric team.

Data was processed in order to calculate the sensitivity, specificity, PPV, NPV and accuracy of nurses' prediction, as well as the influence of various patient characteristics on these parameters.

This manuscript was prepared in accordance with the STROBE statement for improved reporting of outcomes from observational studies.

Results

Between April and June 2019, data was gathered from 33,685 ED visits, of which 11,143 were referred to the ambulatory wing (33%) and 22,542 to the acute department (67%). The average patient age was 51 years old. The male to female ratio was approximately 52:48. A total of 6,566 cases (20%) had incomplete triage prediction forms and were excluded from the results. A total of 27,119 questionnaires were included in the analysis – 19,146 (71%) acute and 7,973 (29%) ambulatory. No statistically significant difference regarding disposition was found between the group that had complete triage prediction forms and the group that was excluded.

In the ambulatory wing of the ED, discharge was predicted in 7,307 cases (92%), of which 6,950 cases were actually discharged. For this group, the accuracy of nurse predictions was high with 95% accuracy rate. Nurses predicted hospital admission in 666 cases, of which only 312 were actually admitted. Here the nurses' predictive accuracy was much lower at 47%. Combined accuracy was 91%. Positive predictive value (PPV) and negative predictive value (NPV) were 95% and 46% respectively. For the purpose of this calculation, admission was defined as a positive test result and discharge negative. Sensitivity and specificity were 47% and 95% respectively (Figure 1).

In the acute wing of the ED, discharge was predicted in 13,145 cases, of which 10,816 were actually discharged (overall number of discharges 12,867), with a prediction accuracy of 82%. Hospital admission was predicted in 6,001 cases, of which 3,950 were actually admitted (overall number of admissions – 6,279), with a lower accuracy of 66%. Combined accuracy was 77%. PPV and NPV were 84% and 62%, respectively. Sensitivity was 63% and specificity was 84% (Figure 1).

Nurses did not demonstrate a high level of accuracy in predicting the receiving admission department in the hospital at the time of triage for both acute and ambulatory wing settings. The exception to this was for admissions to the Oncology department; however, this was a very small cohort (Table 1).

	Acute Wing			Ambulatory Wing		
	No. cases predicted to be admitted	Actual number of admitted cases	Accuracy of triage predictions %	No. cases predicted to be admitted	Actual number of admitted cases	Accuracy of triage predictions %
Surgery	687	275	40	41	3	7.3
Internal Medicine	3345	1833	54.8	230	75	32.6
Ophthalmology	15	1	6.7	11	4	36.4
Cardiology	295	121	41	4	1	25
Orthopedics	337	173	51.3	77	46	59.7
Oncology	9	2	22.2	1	1	100
ENT	97	24	24.7	60	15	25

Dermatology	79	25	31.6	109	53	48.6
Neurology	337	141	41.8	45	16	35.6
Urology	119	36	30.3	13	5	38.5
Neurosurgery	189	61	32.3	21	11	52.4

Table 1 : Disposition Prediction Accuracy by Wing

No significant difference was found in prediction accuracy between male and female patients in either wing. There was also no significant different in the prediction accuracy for patients with normal vital signs (pulse, BP, oxygen saturation, temperature) compared to patients with abnormal vitals, remaining approximately 90% in the ambulatory wing and 76% in the acute wing. The exception to this was predictions in patients with abnormal temperatures in the ambulatory wing, which reduced prediction accuracy to 72%.

CTAS triage level had a significant influence on prediction accuracy (Figure 2).

As expected, with mid-CTAS levels (specifically level 3) predictions were less accurate. In the ambulatory wings there was only one case of CTAS level 1 and less than 1% of cases were CTAS level 2. In comparison, 50% of cases were CTAS level 4.

In the acute wing, about 1% of patients were CTAS level 1. Most patients were CTAS level 3 and 4 (50% and 38% respectively). In this department, predictions in cases with a CTAS level 3 were particularly inaccurate.

The impact of the time of nurses' working shift on the accuracy of prediction was also evaluated. Nurse shifts in the ED were divided into the morning (07:00-15:00), evening (15:00-23:00) and night (23:00-07:00). During the data collection period for this study the ambulatory wing closed at 23:00, therefore only morning and evening shifts were analyzed there.

In the acute wing, average prediction accuracy was 85% during the night shift, significantly better than the evening (78%) and morning (71%) shifts. The total number of cases recorded in this study was similar for the morning and evening shifts, however for the night shift the number of cases was 50% smaller. There was no significant difference in the proportion of cases recorded as CTAS level 1 and 2 between shifts, although a larger proportion of CTAS level 5 cases was seen during night shifts. For these patients, prediction accuracy was high and contributed to the overall higher accuracy level.

The degree of reporter certainty when making a prediction had a significant impact on accuracy (Figure 3). In the ambulatory wings, when a nurse stated that the prediction was made with high certainty, the accuracy of the prediction was over 96%. Most predictions in this wing were stated to be highly certain or moderately certain (5,235 and 2,541 accordingly), and only a minority were given with low certainty (458, approximately 5.5%).

In the acute wing a similar increase was observed for predictions reported as having a high degree of certainty - 88% accurate, compared to 77% for the wing as a whole. In this wing, prediction uncertainty was considerably higher (2,114, 11%), and the accuracy of these predictions was just 60% (compared to 70% in the ambulatory wing).

Importantly, CTAS level 3 cases with a high degree of reporter confidence were highly accurate (93% for ambulatory wing and 85% for acute wing), significantly greater than CTAS level 3 accuracies as a whole. It is important to point out that the likelihood of a high certainty prediction for triage level 3 cases is lower than average (Figure 3, Table 2a / b).

Table 2a -Triage level 3, Ambulatory Wing

			True Disposition			
Prediction	Certainty level	% Rate	Discharge	Hospitalization	Total	Accuracy %
Admission	Very Certain	29%	15	39	54	72%
	Somewhat Certain	52%	73	25	98	26%
	Not Certain	19%	32	4	36	11%
Total		100%	120	68	188	36%
Discharge	Very Certain	55%	806	27	833	97%
	Somewhat Certain	38%	524	57	581	90%
	Not Certain	7%	101	13	114	89%
Total		100%	1431	97	1528	94%
Grand Total			1551	165	1716	87%

Table 2b – Triage level 3, Acute Wing

			True Disposition			
Prediction	Certainty level	% Rate	Discharge	Hospitalization	Total	Accuracy %
Discharge	Very Certain	34%	1747	255	2002	87%
	Somewhat Certain	53%	2422	691	3113	78%
	Not Certain	12%	498	223	721	69%
Total		100%	4667	1169	5836	80%
Admission	Very Certain	31%	210	910	1120	81%
	Somewhat Certain	56%	834	1154	1988	58%
	Not Certain	13%	248	205	453	45%
Total		100%	1292	2269	3561	64%
Grand Total			5959	3438	9397	74%

Table 2a / 2b: Breakdown of Triage Level 3 Cases in Ambulatory and Acute wards and the Effect of Prediction Certainty

Discussion

The results of this study support the results of previous studies, namely that trained triage nurses can accurately predict patient disposition during the triage process. At the extremes of CTAS/ triage score (1 and 5) these predications were more accurate, as is to be expected. Additionally, reporter confidence is also positively correlated to prediction accuracy, potentially highlighting a particularly useful as well as easy metric to measure. We anticipate that the model we presented can be serve as an important tool in predicting patient disposition from triage, thereby improving patient flow in the

ED and reducing wait times. This sytem could be supplemented by machine learning and NLP, such as that presented in Tahayori et al. to assist in early identification of patients who require hospitalization and provide early notice to admitting hospital departments.

After a discussion with nurses who participated in the study, the structure of the questionnaire itself may be the cause of the inaccuracy in predicted admission destination. However, patients are not always admitted to the most suitable ward due to factors outside the control of the ED, such as bed availability. The subject of destination prediction and the varying limiting factors will be further evaluated in future studies.

Regarding the difference in the prediction accuracy between different shifts, it seems that the higher accuracy in the acute wing during night shifts may be in part due to a greater percentage of CTAS level 5 triage patients in that wing during this shift, as ambulatory patients are also seen there at night. As Level 5 cases were predicted with a greater degree of accuracy, this may explain the results.

Careful consideration was given to the analysis of CTAS level 3 patients in this study. These patients represent a substantial percentage of presentations to the ED. In general, reporters struggled to accurately predict disposition for this group. It was demonstrated, however, that when the triage nurse was confident in their prediction for this group, the accuracy was also high. This metric may therefore allow for accurate predictions for subset of level 3 patients.

An additional study, ongoing at the time of writing, will evaluate the ability of triage predictions to improve the accuracy of a machine learning algorithm designed to predict overcrowding and patient disposition, especially in areas which demonstrated poor accuracy (i.e. CTAS level 3).

This research demonstrated that it is possible to predict future discharge with a high degree of certainty for over 60% of ED patients even as early as initial triage. This group includes all ambulatory wing patients, patients at either extreme end of triage severity level (1 and 5) and any patient for whom the triage nurse is certain of their prediction.

Limitations

The major disadvantage of the use of triage predictions as part of an overcrowding analysis tool is the added workload for nursing staff. It is our opinion that additional evidence of the effectiveness of this method is required before recommendations are made.

It is evident from the data concerning disposition predictions that they are, in general, not accurate enough in their raw form to greatly influence the management of the ED. However, it is our belief that such data can be used as a part of a real-time ED overcrowding analysis tool, capable of assisting bed managers and improving patient flow as well as allowing for better allocation of resources.

Conclusion

Triage nurses are able to accurately predict disposition with a high degree of accuracy, particularly for patients with on either extreme end of the CTAS score. With the introduction of prediction confidence as a metric, accuracy increased for all predictions, including those made for patients with middle-range CTAS scores. However, predictions for patient destination once admitted were not accurate. We believe that implementing these metrics into a machine learning overcrowding tool may improve overall performance and assist in maximising flow through the emergency department, thus decreasing length of stay.

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Figure legends:

Figure 1: Triage Predictions According to Wing

Figure 2: Effect of Triage Level on Prediction Accuracy

Figure 3: Effect of Prediction Certainty on Prediction Accuracy

Footnotes

Ethics: Ethical approval was sought and approved by a Helsinki committee, reference 0223-19. The Helsinki committee waived the requirement for written informed consent.

Contributors: DT was involved with conceptualization, visualization, drafting the manuscript, reviewing and editing the manuscript; NS was involved with conceptualization, investigation, methodology, supervision, drafting the manuscript and reviewing and editing the manuscript; JM was involved with reviewing and editing the manuscript; NNG was involved with data curation; YM was involved with data curation; DEF was involved with reviewing and editing the manuscript; SA was involved with project administration and software; AC was involved with project administration and visualization; MKS was involved with formal analysis; GP was involved with data curation and project administration.

DT, NS, JM, NNG, YM, DEF, SA, AC, MKS and GP agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Data availability statement: All data used in this study was collected from the emergency department of Tel Aviv Sourasky Medical Center. Data summaries are available in the study itself. Deidentified raw data may be available upon request from the Noaa Shopen (2nd author) - email: noashopen@gmail.com

Reuse will be permitted in the event of collaborative efforts with appropriate accreditation where applicable.

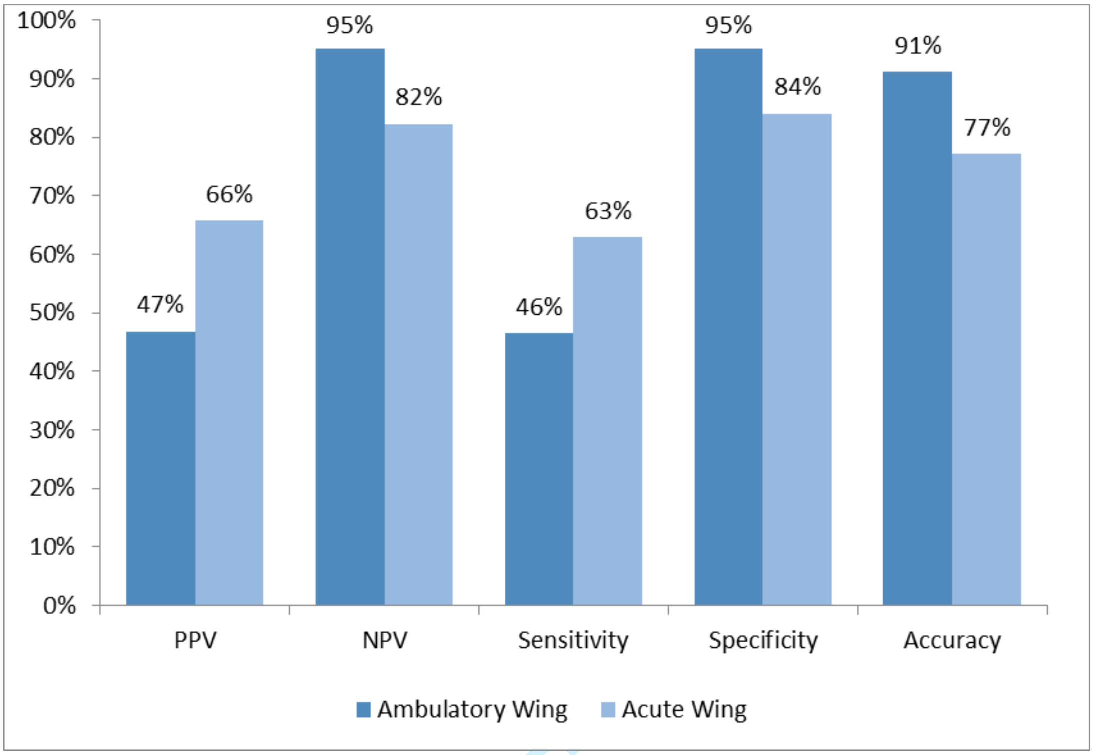

Figure 1: Triage Predictions According to Wing

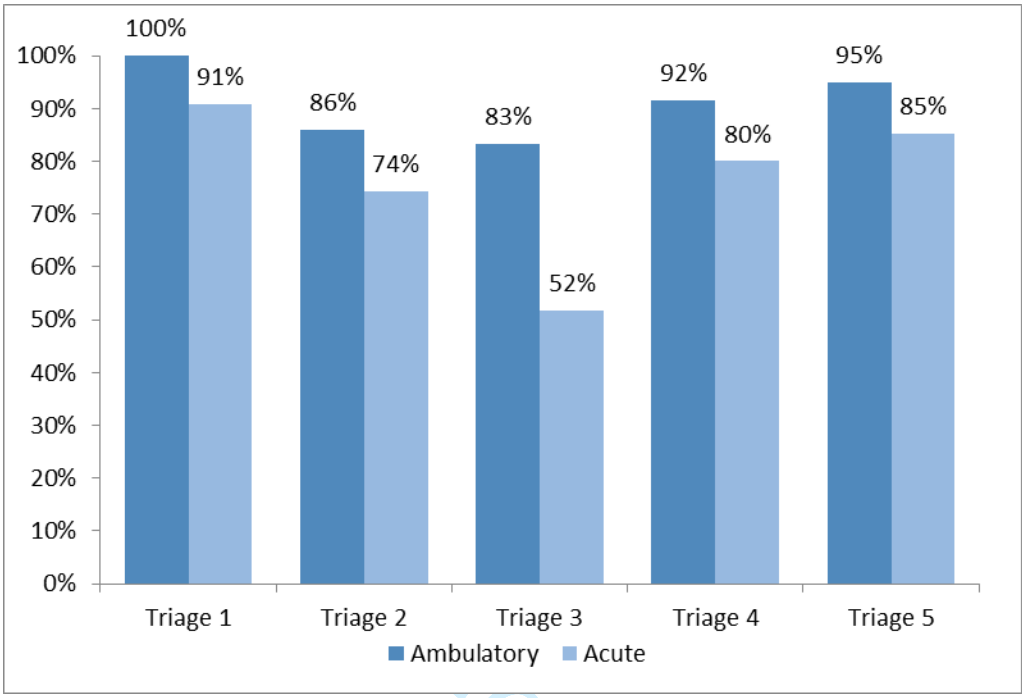

Figure 2: Effect of Triage Level on Prediction Accuracy

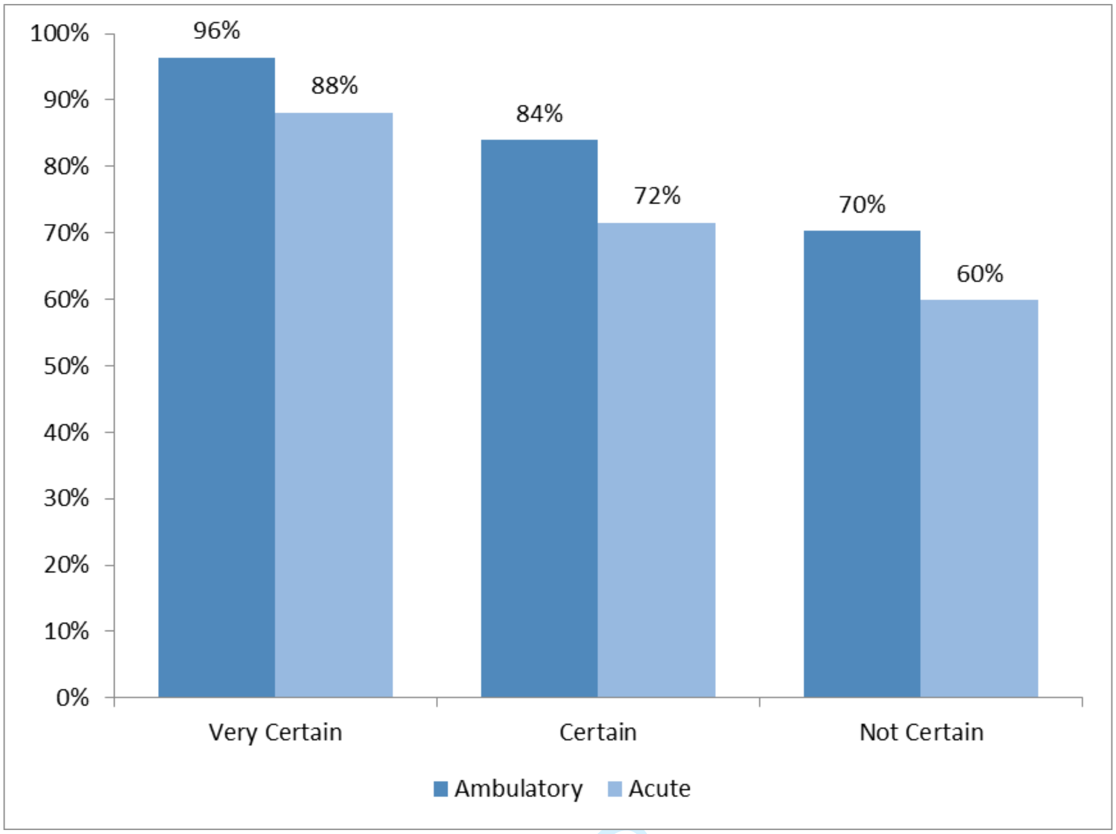

Figure 3: Effect of Prediction Certainty on Prediction Accuracy