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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

Journal:	<i>BMJ Open</i>
Manuscript ID	bmjopen-2021-050026
Article Type:	Original research
Date Submitted by the Author:	08-Feb-2021
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Keywords:	Health policy < HEALTH SERVICES ADMINISTRATION & MANAGEMENT, ACCIDENT & EMERGENCY MEDICINE, HEALTH SERVICES ADMINISTRATION & MANAGEMENT

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7 2 reporter confidence on mid-level triage accuracies –
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11 3 An Israeli observational study
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46 46 **Key words:** Health policy, Screening, Public Health, Health systems evaluation,
47 47 Control strategies
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50 48
51 49 Word count: 3197
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2
3 53 **Abstract**
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6 54 **Aim:** The Emergency Department (ED) is the first port-of-call for most patients
7
8 55 receiving hospital care and as such acts as a gatekeeper to the wards, driving patient
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10 56 flow through the hospital. ED overcrowding is a well-researched field, negatively
11
12 57 affecting patient outcome, staff wellbeing and hospital reputation. An accurate, real
13
14 58 time model capable of predicting ED overcrowding has obvious merit in a world
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16 59 becoming increasingly computational, although the complicated dynamics of the
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18 60 department have hindered international efforts to design such a model. Triage nurses'
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20 61 assessments have been shown to be accurate predictors of patient disposition and
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22 62 could, therefore, be useful input for overcrowding and patient flow models.
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27 63 **Methods:** In this study we assess the prediction capabilities of triage nurses in a Level
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29 64 1 urban Israeli hospital. ED settings included both acute and ambulatory wings.
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31 65 Nurses were asked to predict admission or discharge for each patient over a 3-month
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33 66 period, as well as exact admission destination. Prediction confidence was used as an
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35 67 optimization variable.
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40 68 **Result:** Triage nurses accurately predicted admission outcome for 77% of patients in
41
42 69 the acute wing, rising to 88% when their prediction certainty was high. Accuracies were
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44 70 higher still for patients in the ambulatory wing. In particular, negative predictive values
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46 71 for admission were highly accurate at 90%, irrespective of area or certainty levels.
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49 72 **Conclusion:** Nurses prediction of disposition should be considered for input for real
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51 73 time ED models.
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3 76 **Article Summary**
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6 77 **Strengths and Limitations:**
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- 9 78 • In comparison to previous research in this field, this observational study was
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11 79 conducted on a large cohort of patients, very few of whom were excluded from
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13 80 analysis, thus strengthening the reliability of the results.
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16 81 • To our knowledge, this is the first study of its kind conducted in Israel, whose
17
18 82 emergency department operates somewhat differently to those of Western
19
20 83 Europe and the US. The fact that the data supports that of previous studies from
21
22 84 these territories is reassuring.
23
24
25 85 • Results suggest that triage nurses are indeed capable of accurately predicting
26
27 86 patient disposition in general. Furthermore, using the CTAS as a triage tool, we
28
29 87 were able to identify subsections of patients for whom prediction accuracy was
30
31 88 very high and those for whom it was less so, meaning predictions can effectively
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33 89 be graded on their relative likelihood of being correct.
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36 90 • The scope of this study did not include observing patient specific characteristics
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38 91 other than which general department was responsible for their primary care. We
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40 92 are therefore unable to draw conclusions on prediction accuracy on a disease or
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42 93 presentation specific level (i.e. chest pain/ ACS).
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45 94 • It is our belief that despite prediction accuracies being high in this study, they
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47 95 are not accurate enough in their raw form to directly influence ED management.
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49 96 We do propose, however, that such predictions could be effectively used as part
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51 97 of a more holistic real-time, machine learning ED analysis tool as a cheap and
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53 98 quick input metric.
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100 **Introduction**

101 Overcrowding in the Emergency Department (ED) is such a common phenomenon that
102 in many hospitals it is seen to be the routine working environment. Such strain on staff
103 and resources has an impact on the ability of staff to adequately provide medical
104 services and, therefore, the quality of patient care and their hospital experience.
105 Multiple previous studies have shown that ED overcrowding has a negative effect on
106 many outcomes including, but not limited to: patient mortality and waiting times[1],
107 door to needle time in patients suspected of having acute myocardial infarct¹[2], pain
108 management[3] and delays in antibiotic administration[4]. Additionally, overcrowding
109 has been found to be a major factor in staff burnout[5].

110 Naturally, overcrowding is, therefore, a common topic of internal auditing and research
111 publications. In Israel, a national survey conducted in 2018 revealed that EDs on
112 average operated at 104% capacity, with an average length of stay of 3.0 hours[6]. The
113 Tel Aviv Sourasky Medical Center (TASMC) ED, the locale for this study, is a
114 particularly busy inner-city hospital, with a length of stay of attending patients of 3.3
115 hours on average, increasing for those requiring admission (51% staying over 5
116 hours)[6].

117 Improvement in real-time analysis and computational models of ED overcrowding are
118 expected to facilitate better provision of medical treatment and allocation of resources,
119 thus improving patient outcome in the ED, as well as in the admitting departments[3][1]
120 There are many tools designed for retrospective analysis of ED disposition prediction
121 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.

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3 122 metrics with triage nurses' disposition predictions are able to produce good patient
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5 123 admission prediction as early as at time of triage[8]. In recent years, there have been
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7 124 attempts to construct real-time overcrowding models, often using triage scores and bed
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9 125 availability as inputs[9][10]. Examples include The National Emergency Department
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11 126 Overcrowding Scale (NEDOCS), The Emergency Department Work Index (EDWIN)
12
13 127 and The Risk Management, Economic Sustainability, and Actuarial Science
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15 128 Development in Indonesia (READI)²[10]. No study has, as of yet, compared the
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17 129 efficacy of these tools.

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22 130 In TASMC's ED, similar to other large medical centers in Israel, nurses triage patients
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24 131 using the Canadian Triage and Acuity Scale (CTAS) method, a model combining
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26 132 subjective metrics such as presenting complaint and severity of pain with objective
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28 133 metrics such as vital signs, evidence of bleeding, rash etc.[11]. CTAS level ranges from
29
30 134 1 to 5 and represents the urgency in which patients require medical review. 1 correlates
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32 135 to patients in the resuscitation area who require immediate review, whereas 5 represents
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34 136 non urgent cases with the lowest priority for review. In the United States, for
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36 137 comparison, The Emergency Severity Index (ESI) triage method is the most commonly
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38 138 used.

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43 139 Many studies have shown that triage nurses are able to predict disposition with a high
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45 140 degree of accuracy, based on their experience and the limited information available to
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47 141 them at the time of triage. However this has never been assessed in Israel. For example,
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49 142 Danette et al published a study in which triage nurses were able to predict admission
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51 143 with 71.5% sensitivity and discharge with 88.0% specificity[12]. The negative
52
53 144 predictive value (NPV) for discharge was also particularly high, at 90%. Predictions
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55 145 were most accurate for young patients and for patients with a low (level 1) or high (level
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57 146 4-5) ESI score[12]. Another study looking at overall disposition predictions

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3 147 demonstrated similar results (sensitivity 75.6%, specificity 84.5%)[13]. Importantly,
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5 148 when nurses were asked to assign a level of confidence to their predictions, a high
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8 149 degree of certainty correlated with improved accuracy of disposition prediction
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10 150 (sensitivity 83.6%, specificity 93.1%, NPV 95%)[13]. However, a similar study from
11
12 151 the UK was unable to demonstrate good accuracy of triage disposition predictions
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15 152 (sensitivity and specificity 68% and 85% respectively)[14].

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17
18 153 In addition to triage nurse predictions, several studies have looked into the possibility
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20 154 that objective metrics can predict patient disposition. A 2009 retrospective study
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22 155 examined the cases of 1100 patients in 6 medical centers, excluding trauma, psychiatric
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24 156 and OBGYN patients. That study used a variant automatic prediction model available
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27 157 during triage: age over 60, chest pain, shortness of breath, dizziness, weakness or
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29 158 syncope, history of cancer, history of diabetes. Each variant was ascribed a weight (total
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31 159 combined score 0 to 14). When the total score was above 4 (34% of cases), the
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33 160 likelihood of admission was 77%, and when the score was above 5 (29% of cases), the
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35 161 likelihood rose to 80%.[15]

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39 162 Another study attempted to build a prediction model based on data that is routinely
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41 163 collected during the triage process. This retrospective study included approximately
42
43 164 300,000 ED case files. Of these cases, 60% were used to train the model and 40% were
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45
46 165 used to validate it. The data used as input for training included demographic
47
48 166 characteristics (age, sex, ethnicity), recent (<3 months) hospital admissions or ED
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50 167 visits, method of arrival, patient acuity category and the presence of chronic illness (e.g.
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52 168 diabetes, hypertension, dyslipidemia). The variables that were found to be significant
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55 169 for hospitalization prediction were age, method of arrival and patient acuity
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57 170 category[16].
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3 171 The concept of combining triage predictions and admission prediction models was
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5 172 explored by Cameron et al in 2017. In their research they compared the prediction
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7 173 ability of triage nurses to that of a simple clinical tool, the Glasgow Admission
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9 174 Prediction Score (GAPS²). Their research demonstrated that, in most cases, GAPS was
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11 175 superior at predicting patient admission outcome over triage nurses (accuracy of 0.810
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13 176 vs 0.759)[17]. The exception was in cases where nurses were very certain of their
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15 177 prediction, supporting previous findings[13]. The authors proposed a combination of
16
17 178 both predictions. By allowing nurses "to veto" GAPS when they were certain of their
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19 179 prediction, accuracy was improved to 0.892[17]. It is important to point out that GAPS
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21 180 is not an objective tool as it takes into account the triage level as determined by the
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23 181 triage nurse[8]. Riodan et al also acknowledged this in their 2017 publication examining
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25 182 patients with ESI level 3. They experimented with several variables including age,
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27 183 pulse, systolic blood pressure and pain in an attempt to build a regression model capable
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29 184 of predicting patient discharge[18].

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36 185 As with other areas of medicine, there is growing interest in the field of artificial
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38 186 intelligence, in particular machine learning, to predict patient admission outcome at the
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40 187 triage level[19]. One such study found that a trained algorithm outperformed classical
41
42 188 methods, especially when predicting outcomes for patients with moderate scores (i.e.
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44 189 CTAS level 3)[20][19]. This is a field that is expected to develop rapidly in the coming
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46 190 years. However, such tools are only as robust as the data that was used to train them,
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Glasgow Admission Prediction Score² 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 be efficient in predicting admission[17].

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3 191 meaning that at present it is necessary to continue to develop human approaches to data
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5 192 analysis.
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8 193 **Methods**
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11 194 In this single center, observational, retrospective study to determine the accuracy of
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13 195 nurse predictions relating to patient disposition and destination, data was gathered
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15 196 between the period of April 1st 2019 and June 30th 2019 in TASMC ED (a tertiary
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17 197 hospital) for all adult patients.
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21 198 Ethical approval was sought and approved by a Helsinki committee, reference 0223-
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23 199 19.
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26 200 All the nurses who took part in this study were graduates of the Emergency Medicine
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28 201 Nursing Course. No data was collected on the nurses themselves. The medical team
29
30 202 blinded to the triage predictions to avoid bias.
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34 203 The participating nurses were asked to fill out a questioner that was embedded in the
35
36 204 ED's patient managing software. For each patient, the nurse provided disposition
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38 205 predictions (admission or discharge), exact admission destination prediction (where
39
40 206 relevant) and level of certainty in the predication (high, medium, low).
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44 207 Patient demographic data was also gathered (patients ID number, sex, age) as well as
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46 208 ED time of arrival and discharge from the ED (home vs admission), triage placement
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48 209 in the ambulatory wing vs acute ED wing, triage level (1-5) according to CTAS, vitals
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50 210 (BP, heart rate, oxygen saturation, respiratory rate, temperature) and pain level
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52 211 (according to Numeric pain Assessment Scale - NAS). Textual data regarding the
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54 212 reason of ED visit (i.e. presenting complaint) was also included.
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3 214 Selection criteria included any patient visiting the ED and seen by the triage team in
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5 215 said period of time, excluding patients seen by the pediatric team.
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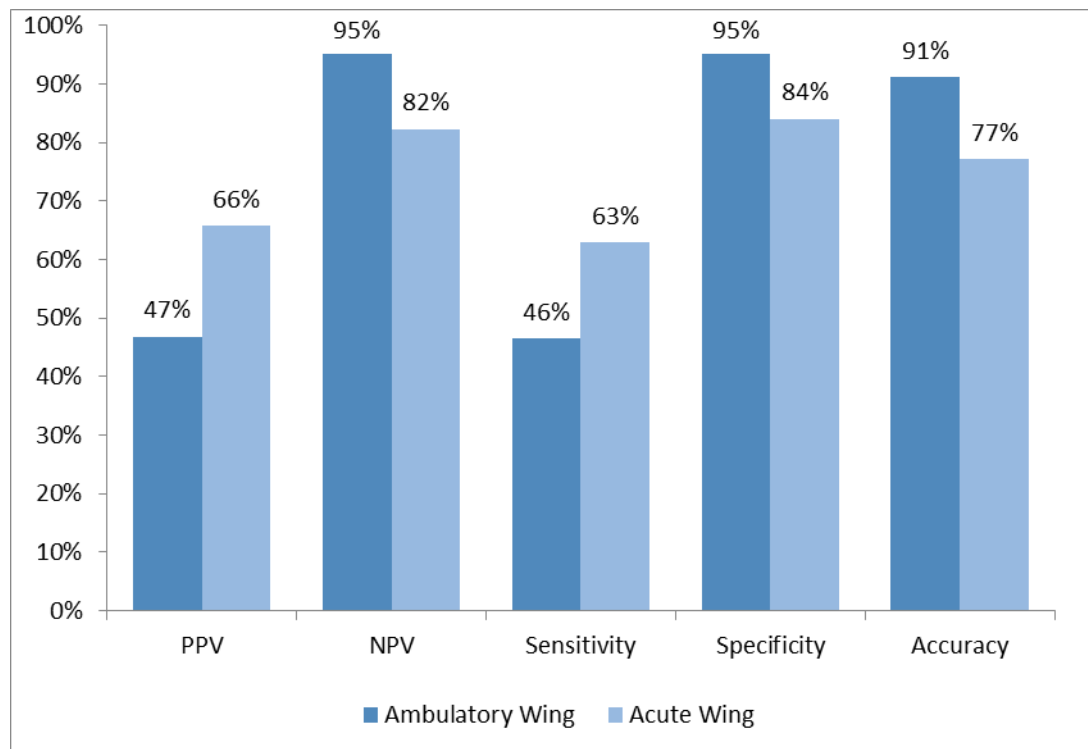
8 216 Data was processed in order to calculate the sensitivity, specificity, PPV, NPV and
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10 217 accuracy of nurses' prediction, as well as the influence of various patient characteristics
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12 218 on these parameters.
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16 219 This manuscript was prepared in accordance with the STROBE statement for improved
17
18 220 reporting of outcomes from observational studies.
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21 **Results**

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24 222 Overall, in April through June 2019, data was gathered for 33,685 ED visits, 11,143
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26 223 being referred to the ambulatory wing (33%) and 22,542 were seen in the acute
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28 224 department (67%). The average age of attendee was 51 years old. The male to female
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30 225 ratio was approximately 52:48. 6,566 cases (20%) had incomplete triage prediction
31
32 226 forms and were excluded from the results, meaning a total of 27,119 questionnaires
33
34 227 were processed for analysis – 19,146 (71%) acute and 7,973 (29%) ambulatory. No
35
36 228 statistically significant difference regarding disposition was found between the group
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38 229 that had complete triage prediction forms and the group that was excluded.
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43 230 In the ambulatory, wing discharge was predicted for 7,307 cases (92%), of which 6950
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45 231 cases were discharged (total discharges – 7,304), meaning nurse predictions were over
46
47 232 95% accurate for this group. Hospital admission was predicted for 666 cases, of which
48
49 233 only 312 were actually admitted (overall number of hospitalizations – 669), giving a
50
51 234 lower accuracy of only 47%. Combined accuracy was 91%. Positive predictive value
52
53 235 (PPV) and negative predictive value (NPV) were 95% and 46% respectively. For the
54
55 236 purpose of this calculation, admission was defined as a positive test result and discharge
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57 237 negative. Sensitivity and specificity were 47% and 95% respectively (Chart 1).
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Chart 1: Triage Predictions According to Wing

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

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

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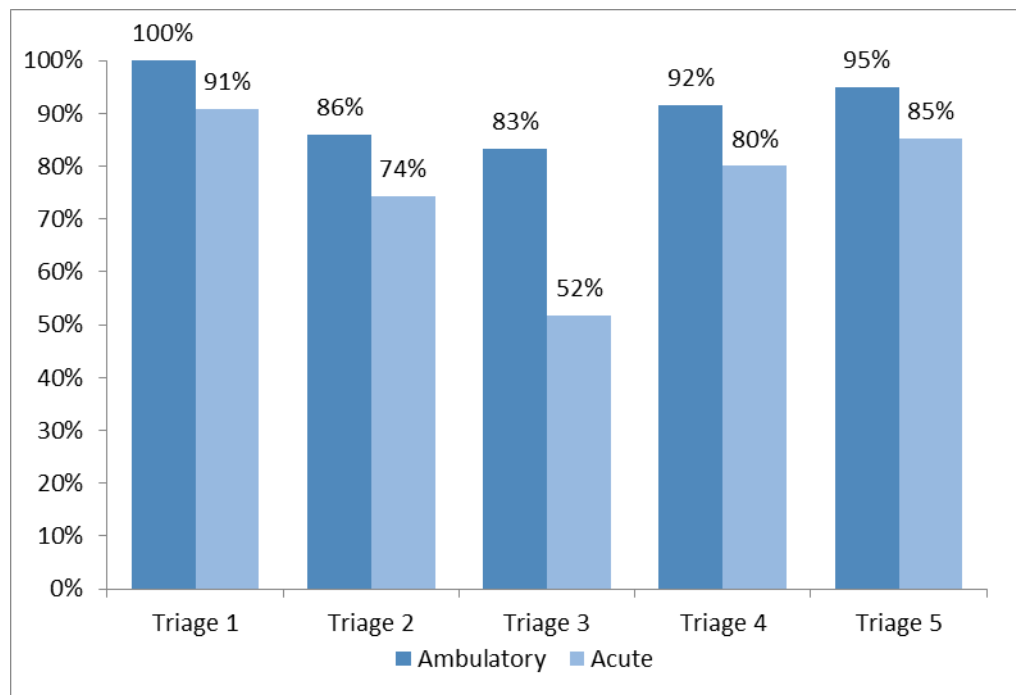
Acute Wing	Ambulatory Wing
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	No. cases predicted to be admitted	Actual number of admitted cases	Accuracy of triage predictions %	No. cases predicted to be admitted	Actual number of admitted cases	Accuracy of triage predictions %
Surgery	687	275	40	41	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

252 *Table 1 : Deposition Prediction Accuracy by Wing*

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

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



261

262 *Chart 2: Effect of Triage Level on Prediction Accuracy*

263 As expected, with mid-CTAS levels (specifically level 3) predictions were less
 264 accurate. In the ambulatory wings there was only one case of CTAS level 1 and less
 265 than 1% of cases were CTAS level 2. In comparison, 50% of cases were CTAS level 4.
 266 In the acute wing, about 1% of patients were CTAS level 1. Most patients were CTAS
 267 level 3 and 4 (50% and 38% respectively). In this department, predictions regarding
 268 CTAS level 3 were particularly inaccurate.

269

270 The effect of nurses working shift on the accuracy of prediction was also evaluated.
 271 Nursing shift patterns in the ED were limited to morning (07:00-15:00), evening (15:00-
 272 23:00) and night (23:00-07:00). During the data collection period for this study the
 273 ambulatory wing closed at 23:00, therefore for this wing only morning and evening
 274 shifts were analyzed.

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3 275 In the acute wings average prediction accuracy was 85% during the night shift,
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5 276 significantly better than the evening (78%) and morning (71%) shifts. The total number
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7
8 277 of cases recorded in this study was similar for the morning and evening shifts, however
9
10 278 for the night shift the number of cases was 50% smaller. There was no significant
11
12 279 difference in the proportion of cases recorded as CTAS level 1 and 2 between shifts,
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14 280 although a larger proportion of CTAS level 5 cases was seen during night shifts. For
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16 281 these patients, prediction accuracy was high and contributed to the overall higher
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19 282 accuracy level.
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22 283 The degree of reporter certainty when making a prediction had a significant impact on
23
24 284 accuracy (Chart 3). In the ambulatory wings, when a nurse stated that the prediction
25
26 285 was made with high certainty, the accuracy of the prediction was over 96%. Most
27
28 286 predictions in this wing were stated to be highly certain or moderately certain (5,235
29
30 287 and 2,541 accordingly), and only a minority were given with low certainty (458,
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32 288 approximately 5.5%).
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36 289 In the acute wing a similar increase was observed for predictions reported as having a
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38 290 high degree of certainty - 88% accurate, compared to 77% for the wing as a whole. In
39
40 291 this wing, prediction uncertainty was considerably higher (2,114, 11%), and the
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42 292 accuracy of these predictions was just 60% (compared to 70% in the ambulatory wing).
43
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46 293 Importantly, CTAS level 3 cases with a high degree of reporter confidence were highly
47
48 294 accurate (93% for ambulatory wing and 85% for acute wing), significantly greater than
49
50 295 CTAS level 3 accuracies as a whole. It is important to point out that the likelihood of a
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52 296 high certainty prediction for triage level 3 cases is lower than average (Chart 3, Table
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54 297 2a/ b).
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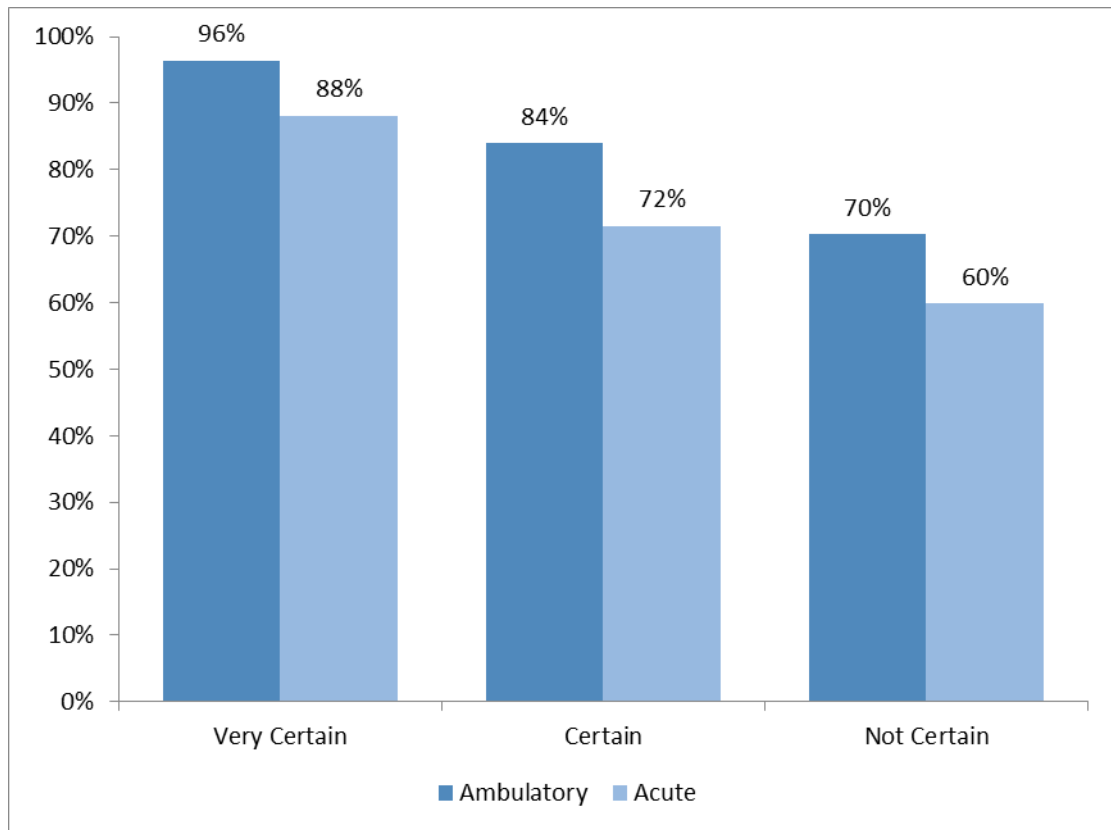


Chart 3: Effect of Prediction Certainty on Prediction Accuracy

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Table 2a - Triage level 3, Ambulatory Wing

Prediction	Certainty level	% Rate	True Disposition		Total	Accuracy %
			Discharge	Hospitalization		
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

Prediction	Certainty level	% Rate	True Disposition		Total	Accuracy %
			Discharge	Hospitalization		
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%

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

330 **Discussion**

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

337 Regarding the lack of accuracy in predicted admission destination, it appears (through
 338 discussion with nurses who participated in the study) that the structure of the
 339 questionnaire itself may be the cause of the inaccuracy. However, patients are often

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3 340 prevented from being transferred to the most suitable ward by factors outside the control
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5 341 of the ED, such as bed availability. The subject of destination prediction and the varying
6
7 342 limiting factors will be further evaluated in future studies.
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11 343 Regarding the difference in the prediction accuracy between different shifts, it seems
12
13 344 that the higher accuracy in the acute wing during night shifts may be in part due to a
14
15 345 greater percentage of CTAS level 5 triage patients in the said wing during this shift, as
16
17 346 ambulatory patients are seen there at night. As Level 5 cases were predicted with a
18
19 347 greater degree of accuracy, this may explain the results.
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23 348 Careful consideration was given to the analysis of CTAS level 3 patients in this study.
24
25 349 These patients represent a substantial percentage of presentations to most EDs including
26
27 350 our own. In general, reporters struggled to accurately predict disposition for this group.
28
29 351 It was demonstrated, however, that when the triage nurse was certain of their prediction
30
31 352 for this group, the accuracy of the prediction was high. This simple metric may therefore
32
33 353 allow for accurate predictions for subset of level 3 patients.
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35
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37 354 An additional study, ongoing at the time of writing, will evaluate the ability of triage
38
39 355 predictions to improve the accuracy of a machine learning algorithm designed to predict
40
41 356 overcrowding and patient disposition, especially in areas which demonstrated poor
42
43 357 accuracy (i.e. CTAS level 3).
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47 358 This research demonstrated that, even at the point of triage, it is possible to predict
48
49 359 discharge with a high degree of certainty for over 60% of ED patients. This group
50
51 360 includes all ambulatory wing patients, patients at either extreme of triage level (1 and
52
53 361 5) and any patient for whom the triage nurse is certain of their prediction.
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1
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3 364 **Limitations**
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6 365 The major disadvantage of the use of triage predictions as part of an overcrowding
7
8 366 analysis tool is the added workload for already over worked nursing staff. It is our
9
10 367 opinion that additional evidence of the effectiveness of this method is required before
11
12 368 recommendations are made.
13
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15

16 369 It is evident from the data concerning disposition predictions that they are, in general,
17
18 370 not accurate enough in their raw form to greatly influence the management of the ED.
19
20 371 However, it is our belief such data can be used as a part of a real-time ED overcrowding
21
22 372 analysis tool, capable of assisting bed managers and improving patient flow as well as
23
24 373 allowing for better allocation of resources.
25
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27

28 374 **Conclusion**
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30

31 375 Triage nurses are able to accurately predict disposition with a high degree of accuracy,
32
33 376 particularly for patients with extremes of CTAS score. With the introduction of
34
35 377 prediction confidence as a metric, accuracy increased for all predictions, including
36
37 378 those made for middling CTAS scores. However, predictions for patient destination
38
39 379 once admitted were not accurate. We believe that implementing these metrics into a
40
41 380 machine learning overcrowding tool may improve overall performance and assist in
42
43 381 maximising flow through the emergency department, thus decreasing length of stay.
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458 **Footnotes**

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

461 **Contributors:** DT was involved with conceptualization, visualization, drafting the
462 manuscript, reviewing and editing the manuscript; NS was involved with
463 conceptualization, investigation, methodology, supervision, drafting the manuscript
464 and reviewing and editing the manuscript; NNG was involved with data curation; YM
465 was involved with data curation; DEF was involved with reviewing and editing the
466 manuscript; SA was involved with project administration and software; AC was
467 involved with project administration and visualization; MKS was involved with formal
468 analysis; GP was involved with data curation and project administration.

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

472 **Funding:** This trial received no specific grant from any funding agency in the public,
473 commercial, or not-for-profit sectors.

474 **Competing Interests:** The authors declare that they have no competing interests.

475 **Patient and public involvement statement:** Patients or the public were not involved
476 in the design, or conduct, or reporting, or dissemination plans of our research.

477 **Patient consent for publication:** Not required.

478 **Data availability statement:** All data relevant to the study are included in the article
479 or uploaded as supplementary information.

BMJ Open

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

Journal:	<i>BMJ Open</i>
Manuscript ID	bmjopen-2021-050026.R1
Article Type:	Original research
Date Submitted by the Author:	13-Sep-2021
Complete List of Authors:	Trotzky, Daniel; Shamir Medical Center, Department of Emergency Medicine Shopen, Noaa; Tel Aviv Sourasky Medical Center, Deptment og Emergency Medicine Mosery, Jonathan; Yitzhak Shamir Medical Center Assaf Harofeh Negri Galam , Neta; Tel Aviv Sourasky Medical Center, Department of Emergency Medicine Mimran, Yizhaq; Tel Aviv Sourasky Medical Center, Department of Emergency Medicine Fordham, Daniel; Yitzhak Shamir Medical Center Assaf Harofeh, Department of Emergency Medicine Avisar, Shiran; Yitzhak Shamir Medical Center Assaf Harofeh, Department of Emergency Medicine Cohen, Aya; Yitzhak Shamir Medical Center Assaf Harofeh, Department of Emergency Medicine Katz Shalhav, Malka ; Tel Aviv Sourasky Medical Center, Department of Emergency Medicine Pachys, Gal; Yitzhak Shamir Medical Center Assaf Harofeh, Department of Emergency Medicine
Primary Subject Heading:	Emergency medicine
Secondary Subject Heading:	Medical management
Keywords:	Health policy < HEALTH SERVICES ADMINISTRATION & MANAGEMENT, ACCIDENT & EMERGENCY MEDICINE, HEALTH SERVICES ADMINISTRATION & MANAGEMENT

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7 2 reporter confidence on mid-level triage accuracies –
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11 3 An observational study in Israel
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53
54 49 **Key words:** Health policy, Screening, Public Health, Health systems evaluation,
55 50 Control strategies
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57 51 Word count: 3444
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1
2
3 **Abstract**
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6 **Aim:** The Emergency Department (ED) is the first port-of-call for most patients
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8 receiving hospital care and as such acts as a gatekeeper to the wards, directing patient
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10 flow through the hospital. ED overcrowding is a well-researched field, and negatively
11
12 affects patient outcome, staff wellbeing and hospital reputation. An accurate, real time
13
14 model capable of predicting ED overcrowding has obvious merit in a world becoming
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16 increasingly computational, although the complicated dynamics of the department
17
18 have hindered international efforts to design such a model. Triage nurses' assessments
19
20 have been shown to be accurate predictors of patient disposition and could, therefore,
21
22 be useful input for overcrowding and patient flow models.
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27 **Methods:** In this study we assess the prediction capabilities of triage nurses in a Level
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29 1 urban hospital in central Israeli. ED settings included both acute and ambulatory
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31 wings. Nurses were asked to predict admission or discharge for each patient over a 3-
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33 month period, as well as exact admission destination. Prediction confidence was used
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35 as an optimization variable.
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40 **Result:** Triage nurses accurately predicted whether the patient would be admitted or
41
42 discharged in 77% of patients in the acute wing, rising to 88% when their prediction
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44 certainty was high. Accuracies were higher still for patients in the ambulatory wing. In
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46 particular, negative predictive values for admission were highly accurate at 90%,
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48 irrespective of area or certainty levels.
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52 **Conclusion:** Nurses prediction of disposition should be considered for input for real
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54 time ED models.
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3 77 **Article Summary**
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6 78 **Strengths and Limitations:**
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- 9 79 • This study was conducted on a large cohort of patients, very few of whom were
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11 80 excluded from analysis, thus strengthening the reliability of the results.
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14 81 • To our knowledge, this is the first study of its kind conducted in Israel, and the
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16 82 fact that the data supports that of previous studies from other regions is
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18 83 reassuring.
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21 84 • The study was limited to data collected from one ED in one institution in Israel,
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23 85 and did not take into account the nurses' experience or educational background,
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25 86 limiting both its internal and external validity.
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28 87 • We are unable to draw conclusions on prediction accuracy related to specific
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30 88 diseases or presentation (i.e. chest pain/ ACS) as this was beyond the scope of
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32 89 our study.
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35 90 • We believe that the results of the study indicate that predictions could be
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37 91 effectively used as part of a more holistic real-time, machine learning ED
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39 92 analysis tool as an accurate, cost efficient and quick input metric.
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95 **Introduction**

96 Overcrowding in the Emergency Department (ED) has become such a common
97 phenomenon that it is become a routine working environment in many hospitals. The
98 strain on staff and hospital resources has an impact on the ability to provide adequate
99 medical services and directly correlates with the quality of patient care and overall
100 hospital experience. Multiple studies have demonstrated that ED overcrowding has a
101 negative effect on many outcomes including patient mortality and waiting times [1],
102 door to needle time in patients suspected of having acute myocardial infarct¹[2], pain
103 management [3] and delays in antibiotic administration [4]. Additionally, overcrowding
104 is a major contributing factor in staff burnout [5].

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

111 Improvement in real-time analysis and computational models of ED overcrowding are
112 expected to facilitate better provision of medical treatment and allocation of resources,
113 thus improving patient outcome in the ED, as well as in the admitting hospital
114 departments [3][1] There are many tools designed for retrospective analysis of ED
115 disposition prediction and overcrowding [7]. Several studies have shown that tools
116 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.

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3 117 produce good patient admission prediction as early as at time of triage [8]. In recent
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5 118 years, there have been attempts to construct real-time overcrowding models, often using
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7 119 triage scores and bed availability as inputs [9][10]. Examples include The National
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9 120 Emergency Department Overcrowding Scale (NEDOCS), the Emergency Department
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11 121 Work Index (EDWIN) and the Risk Management, Economic Sustainability, and
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13 122 Actuarial Science Development in Indonesia (READI)² [10]. No study has, as of yet,
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15 123 compared the efficacy of these tools.
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19
20 124 In TASMC's ED nurses triage patients using the Canadian Triage and Acuity Scale
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22 125 (CTAS), a model combining subjective metrics such as presenting complaint and
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24 126 severity of pain with objective metrics such as vital signs, evidence of bleeding,
25
26 127 presence of rash etc. [11]. CTAS levels range from 1 to 5 and indicate the urgency in
27
28 128 which patients require medical attention. A score of 1 indicates patient who require
29
30 129 immediate attention in the resuscitation bay, whereas 5 indicates nonurgent cases with
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32 130 the lowest priority. In the United States, for comparison, the Emergency Severity Index
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34 131 (ESI) triage method is the most commonly used.
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39 132 Many studies have demonstrated that triage nurses are able to predict patient disposition
40
41 133 with a high degree of accuracy, based on their experience and the limited information
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43 134 available to them at the time of triage. For example, Danette et al published a study in
44
45 135 which triage nurses were able to predict admission with 71.5% sensitivity and discharge
46
47 136 with 88.0% specificity [12]. The negative predictive value (NPV) for discharge was
48
49 137 also particularly high at 90%. Predictions were most accurate for young patients and
50
51 138 for patients with a low (level 1) or high (level 4-5) ESI score [12]. Another study
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53 139 looking at overall disposition predictions demonstrated similar results (sensitivity
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55 140 75.6%, specificity 84.5%) [13]. Importantly, when nurses were asked to assign a level
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57 141 of confidence to their predictions, a high degree of certainty correlated with improved
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3 142 accuracy of disposition prediction (sensitivity 83.6%, specificity 93.1%, NPV 95%)
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5 143 [13]. However, a similar study from the UK was unable to demonstrate high accuracy
6
7 144 of triage disposition predictions (sensitivity and specificity 68% and 85% respectively)
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9 145 [14]. The accuracy of nurse triage in Israel has never been assessed in.

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13 146 In addition to triage nurse predictions, several studies have explored the possibility of
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15 147 utilizing objective metrics to predict patient disposition. A 2009 retrospective study
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17 148 examined 1100 patient cases in 6 medical centers, excluding trauma, psychiatric and
18
19 149 OBGYN patients. That study used a variant automatic prediction model available
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21 150 during triage: age over 60, chest pain, shortness of breath, dizziness, weakness or
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23 151 syncope, history of cancer, history of diabetes. Each variant was ascribed a weight with
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25 152 a total combined score of 0 to 14. When the total score was above 4 (34% of cases), the
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27 153 likelihood of admission was 77%, and when the score was above 5 (29% of cases), the
28
29 154 likelihood rose to 80%.[15]

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34 155 Another study attempted to build a prediction model based on data that is routinely
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36 156 collected during triage. This retrospective study included approximately 300,000 ED
37
38 157 case files. Of these cases, 60% were used to train the model and 40% were used to
39
40 158 validate it. The data used as input for training included demographic characteristics
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42 159 (age, sex, ethnicity), recent (<3 months) hospital admissions or ED visits, method of
43
44 160 arrival, patient acuity category and the presence of chronic illness (e.g. diabetes,
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46 161 hypertension, dyslipidemia). The variables that were found to be significant for
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48 162 hospitalization prediction were age, method of arrival and patient acuity category [16].

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53 163 The concept of combining triage predictions and admission prediction models was
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55 164 explored by Cameron et al in 2017. In their research they compared the prediction
56
57 165 ability of triage nurses to that of a simple clinical tool, the Glasgow Admission

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3 166 Prediction Score (GAPS²). Their research demonstrated that in most cases, GAPS was
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5 167 superior at predicting patient admission outcome over triage nurses (accuracy of 0.810
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7 168 vs 0.759) [17]. The exception was in cases where nurses were very with their prediction,
8
9 169 supporting previous findings [13]. The authors proposed a combination of both triage
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11 170 and admission prediction models. By allowing nurses to overrule GAPS when they
12
13 171 were certain of their predication, overall accuracy was improved to 0.892 [17]. It is
14
15 172 important to note that GAPS is not an objective tool as it takes into account the triage
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17 173 level as determined by the triage nurse [8]. Riodan et al acknowledged this in their 2017
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19 174 publication examining patients with ESI level 3. They experimented with several
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21 175 variables including age, pulse, systolic blood pressure and pain in an attempt to build a
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23 176 regression model capable of predicting patient discharge [18].
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29 177 As with many areas of medicine, there is growing interest in the field of artificial
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31 178 intelligence, in particular machine learning, to predict patient admission outcome at the
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33 179 triage level [19]. One such study found that a trained algorithm outperformed classical
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35 180 methods, especially when predicting outcomes for patients with moderate scores (i.e.
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37 181 CTAS level 3) [20][19]. This is a field that is expected to develop rapidly in the coming
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39 182 years. Another interesting study by Tahayori et al. analyzed the use of natural language
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41 183 processing (NLP) to predict the disposition of patients [21]. The algorithm developed
42
43 184 was applied to ED triage notes with a relatively high level of accuracy. Such tools are
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45 185 only as robust as the algorithm developed and the data that was input and used to train
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Glasgow Admission Prediction Score² 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 be efficient in predicting admission [17].

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3 186 them, so at present it is necessary to continue to develop human approaches to data
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5 187 analysis.
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8 188 **Methods**
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11 189 This is a single center, observational, retrospective study to determine the accuracy of
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13 190 nurse predictions of patient disposition and destination. Data was gathered between the
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15 191 period of April 1st 2019 and June 30th 2019 in TASMC ED, a tertiary hospital in central
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17 192 Israel, for all adult patients.
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21 193 Ethical approval was sought and approved by the Tel-Aviv Sourasky Medical Center
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23 194 Helsinki committee reference 0223-19.
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26 195 All the nurses who took part in this study were graduates of the Emergency Medicine
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28 196 Nursing Course. No data was collected on the nurses themselves. The medical team
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30 197 was blinded to the nurses' triage predictions to avoid bias.
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34 198 The participating nurses were asked to fill out a questionnaire that was embedded in the
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36 199 ED's patient managing software. The nurses were aware of the study and completed
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38 200 the questionnaire in a short period of time with no interference with their work. For
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40 201 each patient, the nurse provided disposition predictions (admission or discharge), exact
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42 202 admission destination prediction (where relevant) and level of certainty in the
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44 203 predication (high, medium, low).
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48 204 Patient demographic data was gathered (patients ID number, sex, age) as well as time
49
50 205 of arrival and discharge from the ED (home vs admission), triage placement in the
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52 206 ambulatory wing or acute ED wing, triage level (1-5) according to CTAS, vitals (BP,
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54 207 heart rate, oxygen saturation, respiratory rate, temperature) and pain level (according to
55
56 208 Numeric pain Assessment Scale - NAS). Textual data regarding the reason of ED visit
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58 209 (i.e. presenting complaint) was also included. Selection criteria included any patient
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3 210 visiting the ED and seen by the triage team in said period of time, excluding patients
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5 211 seen by the pediatric team.
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8 212 Data was processed in order to calculate the sensitivity, specificity, PPV, NPV and
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10 213 accuracy of nurses' prediction, as well as the influence of various patient characteristics
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12 214 on these parameters.
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16 215 This manuscript was prepared in accordance with the STROBE statement for improved
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18 216 reporting of outcomes from observational studies.
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20

21 217 **Results**

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24 218 Between April and June 2019, data was gathered from 33,685 ED visits, of which
25
26 219 11,143 were referred to the ambulatory wing (33%) and 22,542 to the acute department
27
28 220 (67%). The average patient age was 51 years old. The male to female ratio was
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30 221 approximately 52:48. A total of 6,566 cases (20%) had incomplete triage prediction
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32 222 forms and were excluded from the results. A total of 27,119 questionnaires were
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34 223 included in the analysis – 19,146 (71%) acute and 7,973 (29%) ambulatory. No
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36 224 statistically significant difference regarding disposition was found between the group
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38 225 that had complete triage prediction forms and the group that was excluded.
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43 226 In the ambulatory wing of the ED, discharge was predicted in 7,307 cases (92%), of
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45 227 which 6,950 cases were actually discharged. For this group, the accuracy of nurse
46
47 228 predictions was high with 95% accuracy rate. Nurses predicted hospital admission in
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49 229 666 cases, of which only 312 were actually admitted. Here the nurses' predictive
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51 230 accuracy was much lower at 47%. Combined accuracy was 91%. Positive predictive
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53 231 value (PPV) and negative predictive value (NPV) were 95% and 46% respectively. For
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55 232 the purpose of this calculation, admission was defined as a positive test result and
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233 discharge negative. Sensitivity and specificity were 47% and 95% respectively (Figure
234 1).

235 In the acute wing of the ED, discharge was predicted in 13,145 cases, of which 10,816
236 were actually discharged (overall number of discharges 12,867), with a prediction
237 accuracy of 82%. Hospital admission was predicted in 6,001 cases, of which 3,950 were
238 actually admitted (overall number of admissions – 6,279), with a lower accuracy of
239 66%. Combined accuracy was 77%. PPV and NPV were 84% and 62%, respectively.
240 Sensitivity was 63% and specificity was 84% (Figure 1).

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

245

246

	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

247 *Table 1 : Disposition Prediction Accuracy by Wing*

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

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

256

257 As expected, with mid-CTAS levels (specifically level 3) predictions were less
 258 accurate. In the ambulatory wings there was only one case of CTAS level 1 and less
 259 than 1% of cases were CTAS level 2. In comparison, 50% of cases were CTAS level 4.
 260 In the acute wing, about 1% of patients were CTAS level 1. Most patients were CTAS
 261 level 3 and 4 (50% and 38% respectively). In this department, predictions in cases with
 262 a CTAS level 3 were particularly inaccurate.

263 The impact of the time of nurses' working shift on the accuracy of prediction was also
 264 evaluated. Nurse shifts in the ED were divided into the morning (07:00-15:00), evening
 265 (15:00-23:00) and night (23:00-07:00). During the data collection period for this study

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3 266 the ambulatory wing closed at 23:00, therefore only morning and evening shifts were
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5 267 analyzed there.
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8 268 In the acute wing, average prediction accuracy was 85% during the night shift,
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10 269 significantly better than the evening (78%) and morning (71%) shifts. The total number
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12 270 of cases recorded in this study was similar for the morning and evening shifts, however
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14 271 for the night shift the number of cases was 50% smaller. There was no significant
15
16 272 difference in the proportion of cases recorded as CTAS level 1 and 2 between shifts,
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18 273 although a larger proportion of CTAS level 5 cases was seen during night shifts. For
19
20 274 these patients, prediction accuracy was high and contributed to the overall higher
21
22 275 accuracy level.
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27 276 The degree of reporter certainty when making a prediction had a significant impact on
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29 277 accuracy (Figure 3). In the ambulatory wings, when a nurse stated that the prediction
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31 278 was made with high certainty, the accuracy of the prediction was over 96%. Most
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33 279 predictions in this wing were stated to be highly certain or moderately certain (5,235
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35 280 and 2,541 accordingly), and only a minority were given with low certainty (458,
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37 281 approximately 5.5%).
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42 282 In the acute wing a similar increase was observed for predictions reported as having a
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44 283 high degree of certainty - 88% accurate, compared to 77% for the wing as a whole. In
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46 284 this wing, prediction uncertainty was considerably higher (2,114, 11%), and the
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48 285 accuracy of these predictions was just 60% (compared to 70% in the ambulatory wing).
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52 286 Importantly, CTAS level 3 cases with a high degree of reporter confidence were highly
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54 287 accurate (93% for ambulatory wing and 85% for acute wing), significantly greater than
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56 288 CTAS level 3 accuracies as a whole. It is important to point out that the likelihood of a
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289 high certainty prediction for triage level 3 cases is lower than average (Figure 3, Table
290 2a / b).

Table 2a -Triage level 3, Ambulatory Wing

Prediction	Certainty level	% Rate	True Disposition		Total	Accuracy %
			Discharge	Hospitalization		
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

Prediction	Certainty level	% Rate	True Disposition		Total	Accuracy %
			Discharge	Hospitalization		
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%

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

293 **Discussion**

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

1
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3 301 ED and reducing wait times. This system could be supplemented by machine learning
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5 302 and NLP, such as that presented in Tahayori et al. to assist in early identification of
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7 303 patients who require hospitalization and provide early notice to admitting hospital
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9 304 departments.

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13 305 After a discussion with nurses who participated in the study, the structure of the
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15 306 questionnaire itself may be the cause of the inaccuracy in predicted admission
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17 307 destination. However, patients are not always admitted to the most suitable ward due to
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19 308 factors outside the control of the ED, such as bed availability. The subject of destination
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21 309 prediction and the varying limiting factors will be further evaluated in future studies.

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25 310 Regarding the difference in the prediction accuracy between different shifts, it seems
26
27 311 that the higher accuracy in the acute wing during night shifts may be in part due to a
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29 312 greater percentage of CTAS level 5 triage patients in that wing during this shift, as
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31 313 ambulatory patients are also seen there at night. As Level 5 cases were predicted with
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33 314 a greater degree of accuracy, this may explain the results.

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37 315 Careful consideration was given to the analysis of CTAS level 3 patients in this study.
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39 316 These patients represent a substantial percentage of presentations to the ED. In general,
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41 317 reporters struggled to accurately predict disposition for this group. It was demonstrated,
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43 318 however, that when the triage nurse was confident in their prediction for this group, the
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45 319 accuracy was also high. This metric may therefore allow for accurate predictions for
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47 320 subset of level 3 patients.

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51 321 An additional study, ongoing at the time of writing, will evaluate the ability of triage
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53 322 predictions to improve the accuracy of a machine learning algorithm designed to predict
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55 323 overcrowding and patient disposition, especially in areas which demonstrated poor
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57 324 accuracy (i.e. CTAS level 3).

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3 325 This research demonstrated that it is possible to predict future discharge with a high
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5 326 degree of certainty for over 60% of ED patients even as early as initial triage. This
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8 327 group includes all ambulatory wing patients, patients at either extreme end of triage
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10 328 severity level (1 and 5) and any patient for whom the triage nurse is certain of their
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12 329 prediction.

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18 331 **Limitations**

21 332 The major disadvantage of the use of triage predictions as part of an overcrowding
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23 333 analysis tool is the added workload for nursing staff. It is our opinion that additional
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26 334 evidence of the effectiveness of this method is required before recommendations are
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28 335 made.

31 336 It is evident from the data concerning disposition predictions that they are, in general,
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33 337 not accurate enough in their raw form to greatly influence the management of the ED.
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36 338 However, it is our belief that such data can be used as a part of a real-time ED
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38 339 overcrowding analysis tool, capable of assisting bed managers and improving patient
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40 340 flow as well as allowing for better allocation of resources.

43 341 **Conclusion**

46 342 Triage nurses are able to accurately predict disposition with a high degree of accuracy,
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48 343 particularly for patients with on either extreme end of the CTAS score. With the
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51 344 introduction of prediction confidence as a metric, accuracy increased for all predictions,
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53 345 including those made for patients with middle-range CTAS scores. However,
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55 346 predictions for patient destination once admitted were not accurate. We believe that
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58 347 implementing these metrics into a machine learning overcrowding tool may improve
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3 348 overall performance and assist in maximising flow through the emergency department,
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6 349 thus decreasing length of stay.
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For peer review only

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43 Figure legends:
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46 422 Figure 1: Triage Predictions According to Wing
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49 423 Figure 2: Effect of Triage Level on Prediction Accuracy
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51 424 Figure 3: Effect of Prediction Certainty on Prediction Accuracy
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15 431 **Footnotes**

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19 432 **Ethics:** Ethical approval was sought and approved by a Helsinki committee, reference 0223-
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21 433 19. The Helsinki committee waived the requirement for written informed consent.
22
23

24 434 **Contributors:** DT was involved with conceptualization, visualization, drafting the
25
26 435 manuscript, reviewing and editing the manuscript; NS was involved with
27
28 436 conceptualization, investigation, methodology, supervision, drafting the manuscript
29
30 437 and reviewing and editing the manuscript; JM was involved with reviewing and editing
31
32 438 the manuscript; NNG was involved with data curation; YM was involved with data
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34 439 curation; DEF was involved with reviewing and editing the manuscript; SA was
35
36 440 involved with project administration and software; AC was involved with project
37
38 441 administration and visualization; MKS was involved with formal analysis; GP was
39
40 442 involved with data curation and project administration.
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45 443 DT, NS, JM, NNG, YM, DEF, SA, AC, MKS and GP agreed to be accountable for all
46
47 444 aspects of the work in ensuring that questions related to the accuracy or integrity of any
48
49 445 part of the work are appropriately investigated and resolved.
50
51

52
53 446 **Funding:** This trial received no specific grant from any funding agency in the public,
54
55 447 commercial, or not-for-profit sectors.
56
57

58 448 **Competing Interests:** The authors declare that they have no competing interests.
59
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3 449 **Patient and public involvement statement:** Patients or the public were not involved
4
5 450 in the design, or conduct, or reporting, or dissemination plans of our research.
6
7

8 451 **Patient consent for publication:** Not required.
9

10
11 452 **Data availability statement:** All data used in this study was collected from the
12
13 453 emergency department of Tel Aviv Sourasky Medical Center. Data summaries are
14
15 454 available in the study itself. Deidentified raw data may be available upon request from
16
17 455 the Noaa Shopen (2nd author) - email: noashopen@gmail.com
18
19

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21 456 Reuse will be permitted in the event of collaborative efforts with appropriate
22
23 457 accreditation where applicable.
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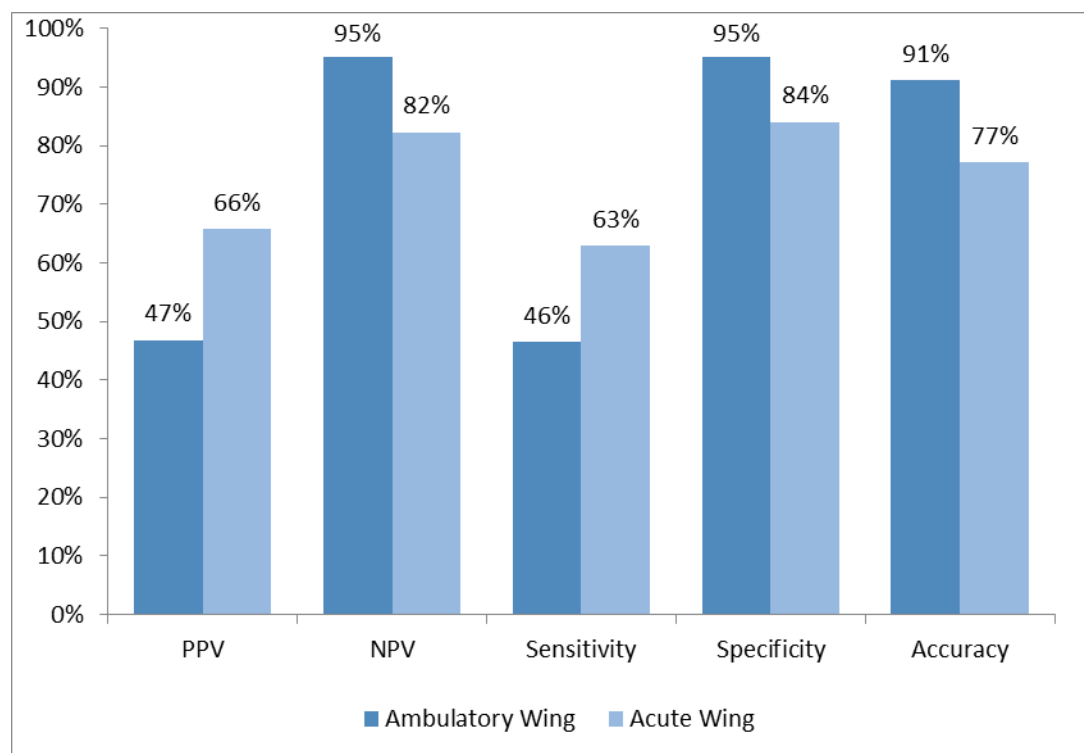


Figure 1: Triage Predictions According to Wing

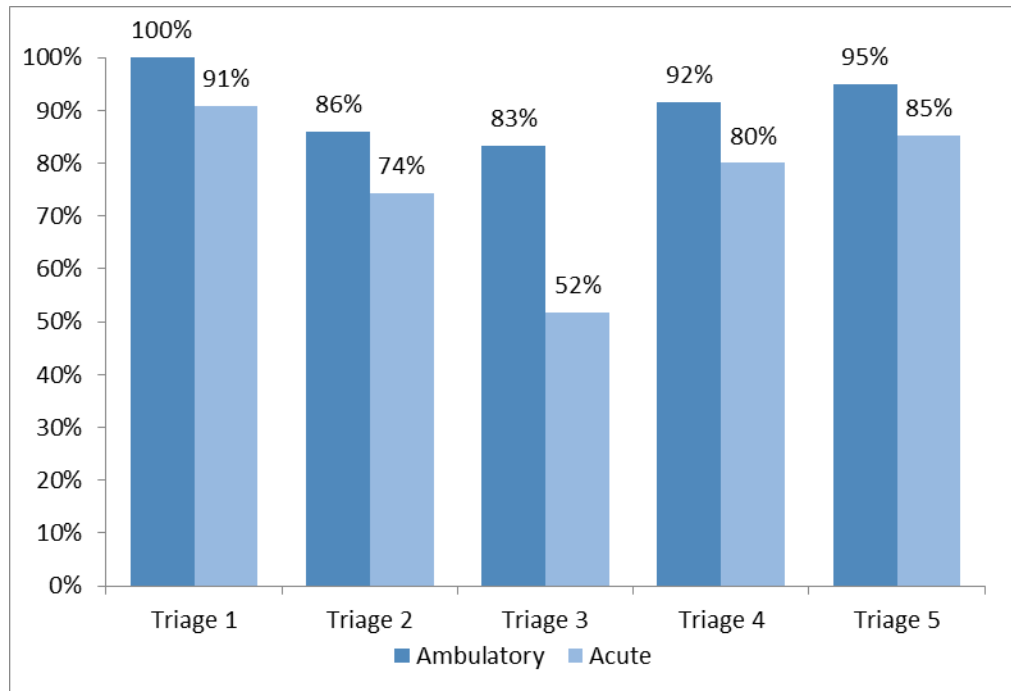


Figure 2: Effect of Triage Level on Prediction Accuracy

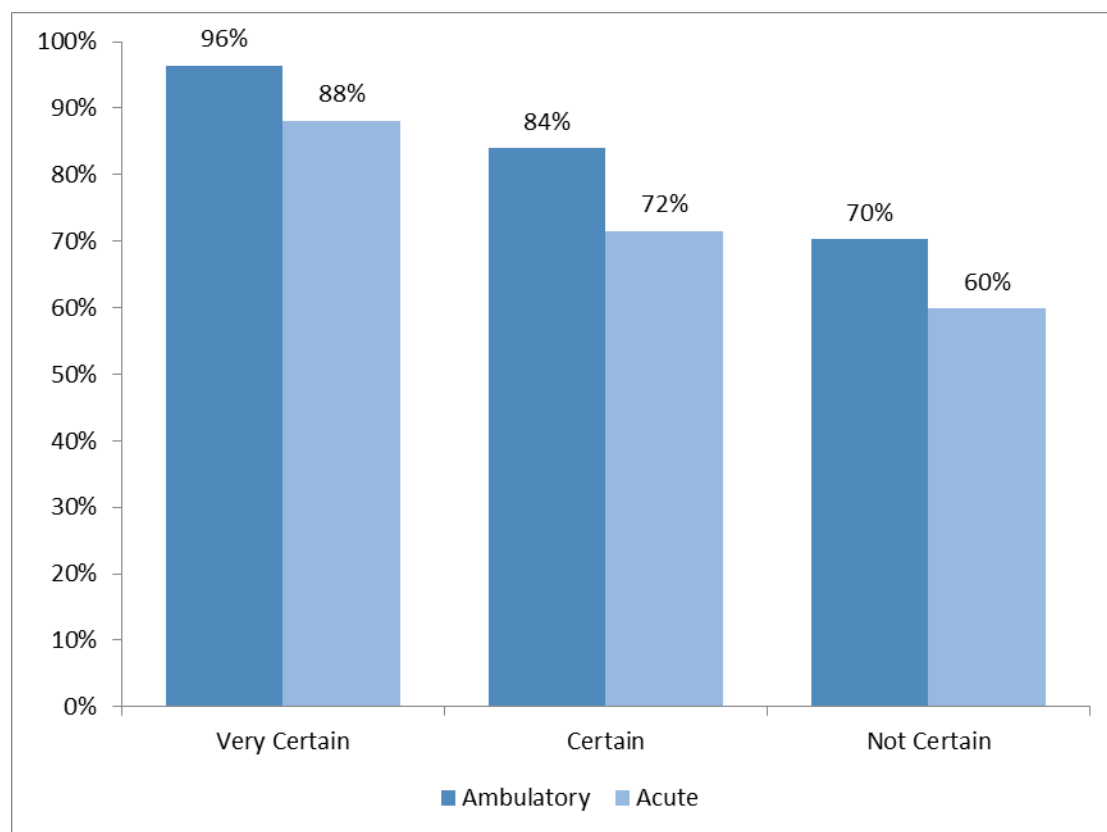


Figure 3: Effect of Prediction Certainty on Prediction Accuracy