Title: Can we predict which COVID-19 patients will need transfer to intensive care within 24 hours of floor admission?

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ABSTRACT

Background

Patients with COVID-19 can present to the emergency department (ED) at any point during the spectrum of illness, making it difficult to predict what level of care the patient will ultimately require. Admission to a ward bed, which is subsequently upgraded within hours to an intensive care unit (ICU) bed, represents an inability to appropriately predict the patient's course of illness. Predicting which patients will require ICU care within 24 hours would allow admissions to be managed more appropriately.

Methods

This was a retrospective study of adults admitted to a large healthcare system, including 14 hospitals across the state of Indiana. Included patients were aged ≥ 18 years, were admitted to the hospital from the ED, and had a positive PCR test for COVID-19. Patients directly admitted to the ICU or in whom the PCR test was obtained > 3 days after hospital admission were excluded. Extracted data points included demographics, comorbidities, ED vital signs, laboratory values, chest imaging results, and level of care on admission. The primary outcome was a combination of either death or transfer to ICU within 24 hours of admission to the hospital. Data analysis was performed by logistic regression modeling to determine a multivariable model of variables that could predict the primary outcome.

Results

Of the 542 included patients, 46 (10%) required transfer to ICU within 24 hours of admission. The final composite model, adjusted for age and admission location, included history of heart failure, initial oxygen saturation of <93%, plus either WBC > 6.4 or GFR < 46. The odds ratio for decompensation within 24 hours was 5.17 (CI 2.17-12.31) when all criteria were present. For patients without the above criteria, the odds ratio for ICU transfer was 0.20 (0.09 to 0.45).

Conclusions

Although our model did not perform well enough to stand alone as a decision guide, it highlights certain clinical features which are associated with increased risk of decompensation.

INTRODUCTION

SARS-CoV-2 is a novel coronavirus first identified in Wuhan, China in November of 2019, which has quickly spread globally, with the United States accounting for nearly a quarter of all cases.[1–3] As of the writing of this manuscript, cases have exploded exponentially in the United States after a brief period of stagnated growth.[4] Worldwide, the SARS-CoV-2 pandemic has killed hundreds of thousands of patients, with reported mortality ranging from 0.4% to 7%.[5] Those who are elderly or comorbid have the highest risk of death.[6,7]

While most patients have mild illness at onset, some are completely asymptomatic, and others eventually manifest severe symptoms requiring intensive care unit (ICU) hospitalization.[6–9] Factors such as rapid disease progression, variability in decisions by inpatient and ED providers, and ICU bed availabilities can all complicate the process of predicting what level of care will be required for these patients. However, admission to a non-ICU bed, which is subsequently upgraded within hours to an ICU level of care, can put undue strain on the inpatient teams, who have to admit the patient: spending substantial time gathering information and writing orders, only to have another (ICU) team have to repeat the entire process again just several hours later. Similarly, admission to an ICU bed, which is then downgraded to a medical bed within 24 hours, may be problematic especially when there are bed shortages. In addition, placing a COVID-19 patient into a room that they quickly leave requires an extensive decontamination process, and ultimately costs precious availability of an inpatient bed.

Predicting which patients are going to require ICU or ventilator support within 24 hours, would allow more appropriate allocation of resources from the onset of admission, improving patient care and eliminating repetitive work and freeing up space and providers to care for the many other patients who need it during this pandemic.

The primary objective of this study was to determine clinical variables associated with need for an upgrade to ICU care within 24 hours of admission to a non-ICU floor.

METHODS

This retrospective electronic medical record (EMR) review was approved as exempt research by the local institutional review (Indiana University) board.

Patients and Settings

Data collection took place across a large integrated healthcare system which includes 14 hospitals across the state of Indiana. Annual ED volume across the hospitals ranges from approximately 6,000 to 90,000, and the system sees over 400,000 combined ED patients per year.

Included patients were adults aged ≥ 18 years admitted to the hospital from the ED with a positive PCR test for COVID-19 that was drawn in the emergency department from March 1, 2020 – April 10, 2020. Patients with a PCR test drawn > 3 days after hospital admission were excluded, as they may have been infected in the hospital after being admitted. For this study, patients admitted directly to the ICU from the ED were also excluded. No further exclusion criteria were applied.

Data Collection

Data was abstracted using a standardized form and was entered into REDCap,[10] a secure data collection instrument. Data included days from symptom onset to ED presentation, basic demographics such as age and gender, comorbidities, ED vital signs, laboratory values including culture results, chest imaging results, and level of care upon admission [medical/surgical ward vs. progressive care unit (PCU): a "step down" level of care that is higher acuity than medical/surgical ward but lower acuity than intensive care.] Level of care was defined based on the computerized order entered by the admitting hospitalist team. Chest imaging results were labeled as either "clear," "single lobe infiltrates," "multi-lobar infiltrates," or "clear x-ray with involvement on CT only." Vital signs extracted were the first blood pressure, heart rate, oxygen saturation, temperature, and respiratory rate recorded in the ED record. The last values recorded while the patient was still in the ED for blood pressure, heart rate, oxygen saturation, and respiratory rate were also extracted. If an ambulatory oxygen saturation was documented in the EMR, it was extracted and recorded separately. Comorbidities were based on chart review of the ED note, admission note, and any clinic or primary care notes available in the EMR. The presence or absence of the following comorbidities was recorded for each patient: smoking, obesity, hypertension, diabetes, hyperlipidemia, heart failure, previous ischemic heart disease, active cancer, dialysis dependent renal disease, chronic obstructive pulmonary disease (COPD), asthma, current chemotherapy, human immunodeficiency virus (HIV), history of organ transplantation, and current use of immunosuppressants.

Most data, including basic demographics such as age and gender, ED vital signs, laboratory values, level of care upon admission (medical/surgical ward vs progressive care unit), were automatically extracted via an EMR data pull. Some data points, such as radiology reports, comorbidities, and patient outcomes (including patient death or intubation) were manually abstracted by trained physician researchers or a trained research assistant. As most of the data points were automatically pulled from the EMR, there was no interobserver variability calculated.

Outcomes

The primary outcome was a combination of either death or transfer to ICU within 24 hours of admission to the hospital. The time of ICU transfer was based on either transfer orders or timing of a physician note stating the patient would be transferred to the ICU, whichever came first. A note indicating an ICU transfer that did not subsequently occur was not counted as an event. Secondary outcomes were death within 24 hours, death prior to hospital discharge, intubation within 24 hours, and intubation at any time during hospitalization.

Statistical Analysis

Data are described using means (with standard deviation), median (with interquartile range), or proportions (with 95% confidence interval), where appropriate; normality assumption was checked using the Shapiro-Wilk test. Given that limiting analysis to patients with complete data (complete case analysis) can lead to bias in study results[11], multiple imputation (MI) was performed. Variables where missingness was ≤ 30% were imputed under the assumption that they were missing at random (MAR). Data were determined to have an arbitrary missingness pattern and therefore the fully conditional specification approach was used, with linear regression used to impute continuous variables and logistic regression used for categorical variables. Cut-points for continuous predictor variables were determined using Youden's J statistic; to meet the distributional assumptions of the imputation model, right-skewed continuous data were log-transformed prior to imputation, then back-transformed prior to determination of the optimal cut-point. Auxiliary variables for the imputation model were selected where correlation (Pearson's r) with imputed variables was ≥ 0.4, or where aggregate values (or proportions) were significantly different between those with complete versus missing data on bivariate analysis (e.g., significantly different age between those with versus without missing values for imputed variable X).The number of imputations was set to the maximum percent of missing data (m=30), with 100 burn-in iterations before the first imputation step and 25 iterations between successive steps, which achieved

>95% relative efficiency for all imputed variables. Convergence of the imputation models was assessed by visual inspection of trace plots. In the final model, imputed variables (number imputed, percent missing) were: troponin (n=116, 21.40%), procalcitonin (n=162, 29.89%), total leukocyte count (n=2, 0.37%), lymphocyte count (n=22, 4.06%), GFR (n=9, 1.66%), plus cut-points for each. Auxiliary variables included aspartate aminotransferase (AST), age, respiratory rate, initial ED oxygen saturation, CO_2, death or intubation during hospitalization, obesity, history of heart failure (HF), ischemic heart disease, diabetes mellitus, or chronic obstructive pulmonary disease (COPD); the dependent variable for the primary outcome (ICU transfer within 24 hours) was also included.

After completion of the imputation model, logistic regression (LR) was used to assess univariate association between clinical and laboratory variables and the primary outcome; those with a p-value <0.2 were retained for further consideration in a multivariable (MV) model. An events-per-variable ratio of ~ 10:1 was used to guard against model over-fitting. The final MV model was selected by comparing Akaikie's Information Criteria, area under the receiver operating characteristic curve (AUC), and results of the Hosmer-Lemeshow test. Multi-collinearity between continuous variables was assessed with variance inflation factor. After selection of the final MV model, results from the 30 imputed data sets were combined and analyzed to determine the pooled parameter estimates with standard errors. Permutations of components of the final MV model were then explored for "collapse" into a single composite variable (i.e., A and B and C) for use as a clinical decision aid, with final selection of components and performance performed as previously described. Finally, age (given the importance attributed to this factor by clinicians when making admission decisions) and disposition location (our data set included patients admitted to both the floor and PCU and thus adjustment accounts for potential differences in odds of ultimately needing ICU level care between these groups) were added as covariates to the composite variable model to assess its independent association with the primary outcome. That is, the association of the composite variable with the primary outcome, regardless of patient age or location of disposition from the ED.

Sensitivity Analyses

For the imputation models, to test the MAR assumption, 10 addition MI models, with 30 imputations each, were created under the assumption of missing not at random. The first 5 multiplied the continuous variables by a scale factor of 0.5-0.9, in steps of 0.1. The next 5 were created using only 1 class of completely-observed categorical variables (heart failure=yes, COPD=yes, diabetes mellitus=no, in-hospital death=no, in-hospital intubation=yes). LR models, with the same variables as used in the main analyses, were then constructed, with pooled effects analyzed as previously described. A change in the direction of effect for any of the pooled parameter estimates was taken as evidence of violation of the

MAR assumption. To assess for bias in the MI models, complete case analysis was performed for each of the final LR models used in the main analysis; change in the direction of effect for any of the parameter estimates was taken as evidence of bias. A significance level of 0.05 was set for all comparisons. Statistical analysis was performed using SAS version 9.4 (SAS Institute, Cary, NC).

RESULTS:

Of 751 patents with PCR confirmed COVID-19, 542 were initially admitted, 86 of whom were admitted directly to the ICU and were excluded from this study. Among the 456 included patients, the average age was 62.8 and 50.2% were female. Table 1 provides further demographic information. Decompensation requiring ICU care within 24 hours occurred in 46 (10%) patients, of whom 29 (63.0%) were intubated within 24 hours of admission. No patients died within 24 hours. By the end of hospitalization, 4 (8.7%) had required hemofiltration for new onset renal failure, 33 (71.8%) had undergone intubation, and 9 (19.6%) died.

For fully-observed variables (Table 2), on univariate LR, the following factors were associated with increased odds of the primary outcome with a p-value ≤ 0.2: PCU admission (odds ratio [OR] 5.52, CI 2.93-10.45), history of HF (OR 2.20 , CI 1.02-4.72), multi-focal findings on chest radiography (OR 2.74, CI 1.19-6.27), initial respiratory rate (OR 1.10, CI 1.03-1.14), initial ED oxygen saturation <93% (OR 4.87, CI 2.41-9.87), last ED respiratory rate (OR 1.10,CI 1.04-1.16), and receiving non-rebreather (NRB) mask or greater supplemental oxygen upon ED presentation (OR 6.18, CI 2.09-18.28), and Hispanic versus Caucasian race (OR 2.76, CI 1.07-7.11). Reduced odds of the primary outcome with a p-value ≤ 0.2 were found for initial ED oxygen saturation (OR 0.88, CI 0.82-0.93, per 1 unit increase), last form of supplemental oxygen of NRB or more (OR 0.25, CI 0.12-0.51), and female versus male biologic sex (OR 0.40, CI 0.21-0.77). For imputed variables, elevated white blood cell count (OR 3.09, CI 1.58-6.04) was associated with decompensation, while higher lymphocyte count (OR 0.59, CI 0.30-1.15), and higher glomerular filtration rate (OR 0.33, CI 0.13-0.86) were associated with a decreased probability of decompensation with a p-value ≤ 0.2. Percent missingness for imputed variables was 0.37% (n=2) for WBC, 4.06% (n=22) for lymphocyte count, and 1.66% (n=9) for GFR. Notably, age, date or week of ED visit, and duration of symptoms were not associated with the primary outcome.

The final multivariable (MV) model included disposition location: ward versus PCU (OR 4.17, CI 2.12-8.33), history of HF (OR 2.54, CI 1.01-6.39), WBC count (OR 1.14, CI 1.03-1.26, per 1 unit increase), initial ED oxygen saturation (OR 1.14, CI 1.08-1.22, per 1 unit decrease), and GFR ≤ 46 (OR 6.63, CI 2.03-21.64) (Model 1 in Table 3). AUC for this model was 0.84 (standard error (SE) 0.03, CI

0.78-0.89). No significant interactions were found amongst final variables or other clinically plausible (i.e., “by meaning”) scenarios and thus none were included in the final model.

We derived a composite outcome variable using factors from the final MV model that would be available to EPs at the time of disposition location decision (Model 2a/2b in Table 3). GFR and WBC were dichotomized at a cut-point determined by Youden’s J statistic (46 and 6.4, respectively). Initial ED oxygen saturation was dichotomized at 93%, which was felt to be more clinically useful than the Youden’s cut-point of 82%, and remained a statistically significant discriminator of the primary outcome.

We ultimately derived a set of criteria and evaluated the utility of the instrument to identify either the highest risk or lowest risk patients. For the composite of history of HF, plus initial oxygen saturation of <93%, plus either WBC > 6.4 or GFR < 46 (Model 2a in Table 3), the OR of ICU transfer was 5.43 (CI 1.74-16.99), AUC 0.54 (SE 0.02, CI 0.50-0.59) Only 14 patients (3.07%) were classified as high risk by this model. of whom 5 (35.7%) ultimately needed transfer to the ICU within 24 hours. Sensitivity for the model was 0.11 (CI 0.02-0.20), specificity was 0.98 (CI 0.96-0.99) with a positive predictive value of 0.36 (CI 0.11-0.61). After adjusting for age and admission location (ward versus PCU), the composite variable had an OR for the primary outcome of 5.26 (CI 1.45-19.10) with an AUC of 0.76 (SE 0.04, CI 0.68-0.83) (Model 3a in Table 3).

We additionally assessed whether patients without the high risk criteria could safely be considered “low risk” (Model 2b in Table 3). The low risk cohort of patients were thus those with no history of HF, initial oxygen saturation of ≥93%, plus either WBC ≤ 6.4 or GFR ≥46. The OR for ICU transfer in this group of patients was 0.20 (CI 0.09- 0.46) with an AUC of 0.66 (SE 0.03, CI 0.60-0.72) (Model 2b in Table 3). After adjusting for age and admission location (ward versus PCU), this composite variable had an OR for the primary outcome of 0.21 (CI 0.09-0.49) with an AUC of 0.81 (SE 0.03, CI 0.75-0.86) (Model 3b in Table 3). Of 202 patients (44.3%) who were classified as low risk by this model, 7 (3.5%) decompensated within 24 hours. Of the remaining 254 patients that were not qualified as low risk, 39 (15.4%%) were transferred to the ICU within 24 hours. Sensitivity was 0.85 (CI 0.74-0.95) and specificity was 0.48 (CI 0.43-0.52). Positive predictive value was 0.16 (CI 0.11-0.20) and negative predictive value was 0.96 (CI 0.94-0.99). Results of the sensitivity analyses were not different from results of the imputed data set and therefore only the latter are presented.

DISCUSSION:

Patients with COVID-19 can present to the ED at any point during the spectrum of illness, making it difficult to determine which patients will decompensate after admission. Studies have demonstrated that risk factors such as obesity, old age, coronary artery disease have been correlated with poorer outcomes, but these outcomes are not specific to any particular timeframe, particularly in reference to hospital presentation.[7,12,13] A recent study demonstrated that those with higher respiratory rates, lower pulse oximeter readings, and higher oxygen requirements could help predict which admitted patients would develop respiratory decompensation within 24 hours. However, there has been limited data on predictive models that can assist the crucial disposition decision: floor or ICU?[14,15]

In this retrospective study, we found that approximately 10% of COVID-19 patients admitted to the floor subsequently decompensated and required ICU transfer, which is similar to previous studies.[16] Our approach to modeling the primary outcome occurred in several steps. We first derived a model to optimize AUC; this model contained both continuous and categorical variables [including disposition location (ward versus PCU) as a variable] (Model 1 in Table 3). While a model of this type is informative, application at the bedside can be difficult, and therefore we created a dichotomous decision aid model (Model 2 in Table 3). Disposition location was excluded from this model since this information is not available to the ED clinician. However, because our data were compiled after admission (to detect occurrence of the primary outcome) we created a final model that adjusted for disposition location in order to understand the independent association of our decision aid with ICU transfer (Model 3 in Table 3). Age was also included as a covariate in this model "by meaning" as it often influences disposition decisions by ED clinicians.

We chose to adjust for age rather than including it in the decision aid to prevent the loss of signal associated with dichotomizing a continuous variable. Other risk factors associated with increased odds of the primary outcome but not retained due to significance included bilateral findings on chest radiography, initial and last documented ED respiratory rate, and requiring supplemental oxygen upon ED presentation. Interestingly, our study differs from prior literature that link co-morbidities such as type 2 diabetes, coronary artery disease, or obesity with increased illness severity.[12,17,18] We found that these risk factors (specifically, hypertension, hyperlipidemia, COPD, smoking history, obesity, coronary artery disease and length of disease) were not significant for predicting who would need critical care within 24 hrs. Notably, these factors have previously been shown to be related to final disease severity such as mortality, but in our study were not helpful in predicting 24-hour decompensation.

Our final composite (dichotomous) decision aid to identify "high-risk" patients consisted of history of heart failure, initial oxygen saturation of <93%, WBC >6.4 or GFR <46, and was associated with an OR of 5.43 predicting ICU transfer, with a high specificity of 0.98 and low sensitivity of 0.11. Although this rule was highly specific, very few patients met the criteria for high risk and there was a high occurrence of false positive making its clinical utility doubtful.

We also assessed the ability of the instrument to identify those at lowest risk: those patients with no history of heart failure, initial oxygen saturation of ≥93%, and WBC ≤6.4 or GFR ≥46. Sensitivity for this model was 0.85 and specificity was 0.48, with a negative predictive value of 0.96. This aid could potentially have value at the bedside as providers could be reassured that patients meeting these criteria have low risk of needing an ICU bed within 24 hours of admission.

While very few patients who are deemed low risk by this model decompensated within 24 hours, specificity was quite low, so failure to qualify as "low risk" should not automatically be interpreted as "high risk," or prompt an ICU admission. Discriminatory performance increased after adjusting for age and disposition location, meaning that use of our decision aid in the ED, regardless of patient age, would result in 81% being correctly classified. We believe that with a sensitivity of 85%, this low-risk decision model can be combined with clinical gestalt to streamline decision-making in the ED by identifying which patients are low risk for decompensating within 24 hours and thus can be safely admitted to a floor bed. Patients who fail to qualify as low risk by our model, require further clinical judgement to aid in the disposition location in order to prevent over-triage to the ICU.

There are multiple future implications from this study. External validation of the tool, as well as comparison to clinician judgement alone would help address this question more completely. A larger patient population would allow new studies to look at which risk factors could predict mortality within 24 hours. There may also be value in assessing whether disposition destinations (ICU vs non-ICU) change over time, as experience with COVID-19 continues to grow, or as hospitals fluctuate in their capacity to provide ICU care. Lastly, models such as ours can potentially be used to help direct which patients would require certain treatments to improve outcomes.

LIMITATIONS:

There were several important limitations in our study. The most prominent limitation in our study is that the best fit model we could design appears to have limited clinical utility. We initially strived to find a specific model that could help determine which patients were at high risk of needing an ICU bed within 24 hours of admission. Our model (2a/3a in Table 3) was highly specific but had such low sensitivity and identified so few patients as high risk that it would have a limited role at the bedside.

We reversed the criteria to try to identify low risk patients (2b/3b in Table 3) for decompensation. The utility of this version was more promising, with higher sensitivity and moderate specificity and a negative predictive value of 0.96. However, like many clinical decision rules, both versions neglect clinical gestalt.[19] Further, similar to many other COVID-19 specific decision rules, our model had different "high-risk" variables from other models published. For example, the quick COVID-19 Severity

Index found a correlation with respiratory rate while the COVID-GRAM critical illness risk score includes such variables as cancer history and direct bilirubin.[16,20] These models (including our own) may have different clinical/laboratory variables because of inherent differences between patient populations as well as statistical methodology. Because of these limitations, we suggest that when using these models, clinicians also add their clinical judgment when making disposition decisions.

Second, we only included those patients with a documented positive COVID-19 rapid PCR test. This could have resulted in exclusion of patients who presented with COVID-19 like symptoms but never had a test drawn prior to admission, although this is unlikely because the system was testing nearly all admissions during this time period. Because of the variable reported sensitivity of the PCR test (70%-83%),[21,22] we more likely could have excluded patients who had a false negative COVID-19 test but either never got a repeat COVID-19 test or had one that was performed ≥ 3 days after admission. We assume these cases are rare as most patients who had a negative test and had severe COVID-19 like symptoms frequently had repeat testing ordered by their admitting provider to confirm the diagnosis, and almost no patients were excluded for a positive test ≥ 3 days from admission.

As this was during the beginning of the pandemic, our facilities (like many other facilities across the United States) did not have rapid tests and results typically took 24-48 hours to come back. ED physicians, therefore, would not have known the COVID-19 status of the patient while making their admission decision. However, during this time, the clinical suspicion for COVID-19 patients was very high and we assume that these disposition decisions were not much different from the current environment, where COVID-19 tests in different locations may result in hours to days.

As this was a retrospective chart review, the decision to admit to a non-ICU vs an ICU floor was up to provider discretion. It is possible that some providers would have admitted some of these patients to the ICU initially. Conversely, some patients admitted to the ICU, and subsequently excluded from our patient population, might have been admitted to a non-ICU setting by a different provider. At most facilities, the decision about what level of care a patient is admitted to is made jointly by the emergency physician and an admitting provider. It was not possible to ascertain if there were disagreements about level of care initially, or how this might have impacted our results. Furthermore, though rare in our facilities, the lack of ICU bed availabilities could have contributed to a non-ICU floor admission. We did not have a way to control for variation in admitting practices or for daily bed availabilities, but our 10% decompensation rate is high enough to suggest that there are systematic challenges related to determining which of these patients are likely to deteriorate quickly, rather than a series of “triage errors” by a subset of inpatient or emergency providers. Similarly, for any number of reasons, such as bed availability or patient choice, some patients may have been discharged and then re-presented within 24 hours requiring admission to the ICU.

There were several patients with missing variables. The decision to order labs and imaging was completely dependent on the provider. Most patients had basic laboratory testing ordered, but more specialized labs and imaging studies such as LDH, d-dimer, lactates, and CT scans were inconsistently ordered. If patients deemed higher risk by their clinicians underwent more labs testing, there could be a bias towards more abnormal findings, potentially confounding our results. Similarly, the providers were not blind to any of the clinical data which could have confounded our results if providers were more likely to upgrade a patient to ICU status if they had abnormal labs. It seems likely that most of the patients who met the primary outcome had a legitimate need for ICU care, as the majority were intubated within 24 hours of arrival. Lastly, this data was also collected from a single healthcare system in one state, which may limit generalizability.

CONCLUSIONS:

Our model of history of HF, initial oxygen saturation at a cutoff of 93%, and either WBC at a cutoff of 6.4 or GFR at a cutoff of 46 can assist in predicting which COVID-19 patients initially thought to not require ICU level care are either particularly high or low risk for decompensating and requiring ICU admission within the first 24 hours. However, its application does require further validation and it did not perform well enough to stand alone as a decision guide.

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Table 1. Characteristics of admitted patients who required ICU care within 24 hours of admission compared those who did not

	ICU (N= 46)	**Non-ICU (N= 410)**
Age (years), Average (Range)	62.2 (35-94)	62.9 (21-98)
Gender (%)		
Female	14 (30.4%)	215 (52.4%)
Male	32 (69.6%)	195 (47.5%)
Race		
White	22 (47.8%)	217 (52.9%)
Black	17 (37.0%)	159 (38.8%)
Hispanic	7 (15.2%)	25 (6.1%)
Asian	0 (0.0%)	8 (2.0%)
Native Hawaiian	0 (0.0%)	1 (0.2%)
Co-morbidities		
Obesity	22 (47.8%)	150 (36.6%)
Smoking	2 (4.3%)	34 (8.3%)
Diabetes mellitus	16 (34.8%)	150 (36.6%)
Hyperlipidemia	28 (60.9%)	160 (39.0%)
Hypertension	30 (65.2%)	271 (66.1%)
Heart failure	10 (21.7%)	46 (11.2%)
Ischemic Heart Disease	7 (15.2%)	55 (13.4%)
Cancer	2 (4.3%)	11 (2.7%)
COPD	5 (10.9%)	48 (11.7%)
Asthma	7 (15.2%)	42 (10.2%)
HIV/AIDS	1 (2.2%)	3 (0.7%)

Table 2. Factors associated with decompensation within 24 hours with p-value ≤ 0.2

Factor	**Odds ratio**	**95% CI**
Receiving non-rebreather mask or greater supplemental oxygen upon ED presentation	6.18	2.09-18.28
PCU admission	5.52	2.93-10.45
Initial ED oxygen saturation <93%	4.387	2.41-9.87
Higher WBC	3.09	1.58-6.04
Lower GFR	3.03	1.16-7.69
Hispanic race	2.76	1.07-7.11
Multi-focal findings on chest radiography	2.74	1.19-6.27
Male sex	2.50	1.30-4.76
History of heart failure	2.20	1.02-4.72
Lower lymphocyte count	1.69	0.87-3.33
Last ED respiratory rate	1.10	1.04-1.16
Initial respiratory rate	1.10	1.03-1.14

Table 3. Three models and their test characteristics

	Model	OR (CI)	AUC	Sens	Spec	PPV/NPV
1	•Disposition location (Ward v PCU) •history of HF •WBC count •initial O2 saturation •GFR ≤ 46	• 4.17 (2.12-8.33) •2.54 (1.01-6.39) •1.14 (1.03-1.26) •1.14 (1.08-1.22) •6.63 (2.03-21.6)	0.84	*	*	*
2a	• History of heart failure **AND** •initial oxygen saturation <93% **AND** •(WBC > 6.4 **OR** GFR <46)	5.43 (1.74-16.99)	0.54	0.11	0.98	PPV: 0.36
2b	• No history of heart failure **AND** •initial oxygen saturation ≥93% **AND** •(WBC ≤ 6.4 **OR** GFR ≥46)	0.20 (0.09-0.46)	0.66	0.85	0.48	NPV:0.96
3a	*Adjusted for age and disposition location (ward versus PCU)* •History of heart failure **AND** •initial oxygen saturation <93% **AND** •(WBC> 6.4 **OR** GFR <46)	5.26 (1.45-19.10)	0.76	*	*	*
3b	*Adjusted for age and disposition location (ward versus PCU)* • No history of heart failure **AND** •initial oxygen saturation ≥93% **AND** •(WBC ≤ 6.4 **OR** GFR ≥46)	0.21 (0.09-0.49)	0.81	*	*	*

*No sensitivity/specificity/NPV presented because model 1 and 3 included non-binary variables or included adjusted variables respectively.