Using Phenotypic Data from the Electronic Health Record (EHR) to Predict Discharge Destination: A Predictive Model based on A Single-Center Retrospective Cohort

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Abstract

Background: Timely discharge to post-acute care (PAC) settings, such as skilled nursing facilities, requires early identification of eligible patients. We sought to develop and internally validate a model which predicts a patient's likelihood of requiring PAC based on information obtained in the first 24 hours of hospitalization.

Methods: This was a retrospective observational cohort study. We collected clinical data and commonly used nursing assessments from the electronic health record (EHR) for all adult inpatient admissions at our academic tertiary care center from September 1, 2017 to August 1, 2018 We performed a multivariable logistic regression to derive the model from the derivation cohort of the available records. A secondary analysis was then conducted to evaluate the capability of the model to predict discharge destination on an internal validation cohort.

Results: Age (adjusted odds ratio (AOR), 1.04 [per year]; 95% Confidence Interval (CI), 1.03 to 1.04), admission to the intensive care unit (AOR, 1.51; 95% CI, 1.27 to 1.79), admission from the emergency department (AOR, 1.53; 95% CI, 1.31 to 1.78), taking more home medications (AOR, 1.06 [per medication count increase]; 95% CI 1.05 to 1.07), and higher Morse fall risk scores at admission (AOR, 1.03 [per unit increase]; 95% CI 1.02 to 1.03) were independently associated with higher likelihood of being discharged to PAC facility. The c-statistic of the model derived from the primary analysis was 0.875, and the model predicted the correct discharge destination in 81.2% of the validation cases.

Conclusions: A model that utilizes clinical factors and risk assessments has excellent model performance in predicting discharge to a PAC facility.

Background

Effective discharge planning (DP) is critical to successful transitions of care from the hospital to the post-acute care (PAC) setting. PAC settings include Skilled Nursing Facilities, Long Term Acute Care facilities, and Inpatient Rehabilitation. Previous studies suggest that early and effective DP decreases hospital length of stay and readmissions.(1) Decision-making regarding discharge destination, however, may occur late during hospitalization, leaving little time to improve the transition to PAC.(2, 3)

Availability of a tool to predict discharge destination early in the hospitalization may improve transitions of care to PAC facilities by enabling social services to contact facilities, coordinate insurance authorizations, engage physical therapy to conduct a timely assessments, and aid the primary team in tailoring the patient's discharge planning for PAC(4, 5) Currently, there are a small number of predictive models, with only one of these using data from the first day on admission.(6–8) Other models draw from a wide range of clinical contexts including cardiac surgery(9), orthopedics(10, 11), and trauma.(12) However, there are few models which could be applied across an entire hospital population.

An ideal prediction tool for broad clinical application would automatically, immediately generate a score following admission, using objective data from the electronic health record (EHR). Improvements in bioinformatics now allow for automated analysis of data routinely collected and collated in the EHR. Such EHR-derived scores have been developed for prediction of readmission(13) and physiologic deterioration.(14) The primary aim of this study was to develop and validate an EHR-derived model that produces a score predictive of discharge to PAC, using data readily available within 24 hours of admission.

Methods

Study Design

After obtaining approval from the Institutional Review Board at our institution, we conducted a retrospective cohort model development and validation study. The Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) guidelines were used in the planning and execution of the study.(15)

Study Setting and Participants

We included all adult (≥ 18 years old) inpatient admissions at our center from September 1, 2017, to August 1, 2018. An individual patient could account for multiple admissions during this time period. We excluded patients admitted to "observation status", patients transferred to another acute care hospital, patients discharged on the day of admission, and patients who left the hospital against medical advice. Patients who were transferred by a court or law enforcement or could not have their admission source or discharge destination identified were excluded (Additional File 1).

Data Source

We extracted study data from the Perioperative Data Warehouse (PDW), a de-identified database of adult hospital patient information, using structured query language (SQL). PDW information mirrors clinical data from the EHR system, Epic©, (Epic Systems Corporation, Verona, WI), and includes data from all patients, not just those who are admitted to surgical services.

Model Candidate Predictors

Predictor variables were generated and screened based on a literature review of risk factors predictive of discharge destination which are also collected routinely by the EHR early in the course of hospitalization (< 24 hours from admission time). Based on a literature review we identified candidate variables including age(7, 8, 10, 16), gender, (9) insurance status, pre-hospital location(7), admission source, admission service, and markers of frailty.(6–8, 10) (Table 1).

Table 1
Candidate variables assessed for inclusion in our post-acute care prediction model.

Demographics	**Age**
	Gender
	Race
	Health Insurance,
	Pre-Hospital Location
	Hospital Length of Stay
Markers of Comorbidities	Body mass index
	Cognitive decline index (MMSE/RASS)
	Number of hospitalizations in previous 2 years
	Number of MedicationsAdmission Unit (Surgical vs. Medical vs. ICU)
Nursing Data	Braden Score
	Fall Risk Assessment Score
Markers of Illness Severity	Vital Signs
	Arterial/Venous Blood Gas
	Electrolytes
	Liver Function Tests
	Complete Blood Count
	Coagulation Studies
	Glasgow Coma Scale Score
	Number of medications on the Pre-Hospital List
Covariant Data	Health Insurance Information
	Pre-hospital Location
	Hospital Length of Stay
	Health Insurance

The primary type of health insurance plan(7, 10, 16) for each patient was categorized as, 1) Medicare (which included patients whose primary insurance type was Medicare or Medicare Advantage); 2) Medicaid (which included patients whose primary insurance type was Medicaid and TennCare); 3) Private; and 4) Self-pay/Other (which included patients who paid the bill on their own or their insurance information was unknown). For patients covered by multiple insurance plans, we used the first presented insurance during the admissions. The patient's pre-hospital location(6) was divided into three categories: Home, Outside Facility (which included SNFs, Long Term Acute Care facilities, and Inpatient Rehabilitation), or Physician/Clinic Office. The admission source was grouped into two categories: Admitted through the Emergency Department versus other (e.g., direct admission, transfer). Admission services were categorized into intensive care unit (ICU), obstetrics/gynecology, and medical/surgical. Six services qualified as ICU: Trauma, Burn, Cardiac, Neurological, Medical, and Surgical Intensive Care Units. Labor and Delivery, Post-partum, Maternal Care, and Women's Surgery were all considered obstetrics/gynecology admissions. The remaining admissions were considered general medical/surgical.

Factors that reflected the presence of geriatric syndromes included the Braden Score(17), Morse Fall Risk Score(18), and polypharmacy(12, 19). The Braden Score, ranging from less than or equal to 9 to as high as 23, is a nursing assessment performed after admission to determine a patient's risk of developing pressure ulcers.(20) Braden score has been shown to be associated with discharge location.(21, 22) We retrieved measurements from the first evaluation after admission, and the maximum and minimum values within 24 hours when multiple measurements were available. Similar to Braden Score, Morse Fall Risk Score is another nurse-reported patient assessment, with a range of 0 to 125. The first, minimum and maximum fall risk measurements within 24 hours after admission were obtained. Both Braden Score and Morse Fall Risk Score were treated as continuous variables, and simple imputations of median values were imputed for missing data. Pre-hospital medications was defined as a count of all medications the patient was taking before hospital admission, as entered by the primary treatment team or pharmacist as part of the admission medication reconciliation. These included medications taken as needed, on a short-term basis, and topically.

Primary Outcome

Discharge destination was classified into two categories: PAC (rehabilitation facility, skilled nursing facility, long term acute care) versus all other discharges that may include home, hospice, and deceased. The primary event of interest of this study was discharge to PAC versus non-PAC discharge.

Statistical Analysis

Demographic and clinical variables were used to characterize the study sample with means and standard deviations (SDs) for parametric variables, with medians and interquartile ranges (IQRs) for nonparametric variables and with percentages for categorical variables, as appropriate.

The entire cohort was randomly split into a derivation and a holdout group. The derivation cohort was used to examine the association of each potential factor with discharge destination, and the holdout cohort was used to validate the model's performance. Given the imbalanced ratio of discharges to PAC relative to discharges to home, a random undersampling approach was applied to the derivation cohort for developing the best fit model without introducing bias into the covariates' parameter estimates.[25,26] The parameter estimates, odds ratios, and their confidence intervals of covariates are unaffected by the stratified sampling methods, while the intercept parameter estimate is the only part in the model that is affected by the resampling.

Based on plausibility, pragmatism, and availability within 24 hours of admission, we first conducted univariate screening for candidate predictors (Table 1) using an uncorrected chi-square test for categorical variables or a Mann-Whitney test for ordinal and continuous variables. A restricted cubic splines approach was applied for modeling non-linear associations. The primary analysis was performed using multivariable logistic regression. A stepwise selection approach was then applied to identify statistically significant covariates for inclusion in regression model. In order to minimize the risk of overfitting, we limited the number of predictors included in the final model following the rule of no less than 20 subjects per variable.(23) The associations were summarized using the odds ratios (ORs) with 95% confidence intervals (CIs) and tested using the Wald multiple degree of freedom Chi-squared test. The variance inflation factors (VIFs) were computed to detect potential collinearity, by assessing the variance change of an estimated regression coefficient.[27] A calibration plot was generated to assess goodness of fit.

A secondary analysis was then conducted to evaluate the predictive ability of the model. The validation was performed by applying the model to the randomly selected holdout dataset. We derived a predictive score for each patient using the regression coefficients generated from primary analysis, and a matrix was developed to compare the observed with predicted discharge disposition. Sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were calculated to characterize the performance of the predictive model we generated in primary analysis. The area under the curve (AUC) of the Receiver Operating Characteristic (ROC) curve was created to assess the discrimination ability of the model A two-sided hypothesis testing with a p-value of less than 0.05 deemed to indicate statistical significance. All statistical programming was implemented in SAS 9.4 (SAS Institute Inc., Cary, NC, USA).

Results

Characteristics of Study Population

Between September 2017 and August 2018, 78,659 visits were retrieved electronically from the PDW database. After applying exclusion criteria, 23,566 cases met the inclusion criteria (Additional File 1). Of all eligible cases, 19,363 (82.2%) were discharged home, 3041 (12.9%) were discharged to PAC, 762 (3.2%) died and 400 (1.7%) were discharged to hospice.

In primary analysis, a holdout cohort of 2,000 discharges was randomly selected. The random undersampling approach was then applied to the derivation group and a total of 6,000 cases were selected with the ratio of discharge to Home vs. PAC was 1.22. Table 2 shows the demographics and characteristics of all three cohorts. In brief, the average age of the entire cohort was 53.6 years (SD = 18.8), study cohort 58.0 (18.9), and the holdout cohort 53.0 (18.9). White patients comprised 77.3% of the entire cohort, 78.2% of study cohort, and 77.2% of holdout group. Approximately 52.8% of the eligible patient encounters were admissions from the Emergency Department. Most patients resided at home immediately prior to admission (67.9%), and most were admitted by Medical/Surgical services (69.9%). In the overall group, 12.9% of patients were discharged to PAC, while in the oversampled derivation sample 45% of patients were discharged to PAC.

Table 2
Patient Demographics and Clinical Characteristics of the Study Sample.

Variables	**Entire Cohort**	**Study Cohort**	**Holdout Cohort**
	(n = 23,566)	**(n = 6,000)**	**(n = 2,000)**
Age in years, mean (SD)	53.6 (18.8)	58.0 (18.9)	53.0 (18.9)
Gender (%)			
Female	12,309 (52.2%)	2,946 (49.1%)	1,040 (52.0%)
Race (%)			
White	18,225 (77.3%)	4,690 (78.2%)	1,543 (77.2%)
African American	3,689 (15.7%)	967 (16.1%)	316 (15.8%)
Others/Unknown	1,652 (7.0%)	343 (5.7%)	141 (7.0%)
Emergency Admission (%)			
Yes	12,436 (52.8%)	3,594 (59.9%)	1,036 (51.8%)
Surgical Case (%)			
Yes	11,598 (49.2%)	2,963 (49.4%)	1,010 (50.5%)
Pre-hospital Medication Count, median (IQR)	13 (7–20)	16 (10–22)	13 (7–19)
Hospital Length of Stay in days, median (IQR)	3.7 (2.2–6.5)	5 (2.9–8.9)	3.7 (2.3–6.2)
First Braden Score, median (IQR)	20 (18–22)	20 (16–21)	20 (19–22)
Maximum Braden Score, median (IQR)	21 (19–22)	20 (17–22)	21 (19–23)
Minimum Braden Score, median (IQR)	19 (17–20)	18 (15–20)	19 (17–21)
First Morse Fall Risk Score, median (IQR)	35 (20–50)	45 (30–60)	35 (20–50)
Maximum Morse Fall Risk Score, median (IQR)	45 (35–60)	45 (35–70)	45 (30–60)
Minimum Morse Fall Risk Score, median (IQR)	35 (20–45)	35 (20–50)	35 (20–45)
Admission Source (%)			
Intensive Care Unit	4,233 (18.0%)	1,412 (23.5%)	332 (16.6%)
Obstetrics and Gynecology	2,841 (12.1%)	490 (8.2%)	250 (12.5%)
Medical/Surgical	16,492 (69.9%)	4,098 (68.3%)	1,418 (70.9%)
Pre-hospital Location (%)			
Home	15,993 (67.9%)	3,961 (66.0%)	1,359 (68.0%)
Outside Hospital or Facility	5,149 (21.9%)	1,559 (26.0%)	436 (21.8%)

Variables	Entire Cohort	Study Cohort	Holdout Cohort
	(n = 23,566)	(n = 6,000)	(n = 2,000)
Physician or Clinic Office	2,424 (10.3%)	480 (8.0%)	205 (10.2%)
Type of Insurance (%)			
Medicare	9,552 (40.5%)	3,001 (50.0%)	796 (39.8%)
Medicaid/TennCare	2,800 (11.9%)	606 (10.1%)	223 (11.2%)
Private	7,250 (30.8%)	1,475 (24.6%)	619 (31.0%)
Self-pay/Others	3,964 (16.8%)	918 (15.3%)	362 (18.1%)
Discharge Destination (%)			
Home	19,363 (82.2%)	3,300 (55.0%)	1,735 (86.8%)
Post-acute Care	3,041 (12.9%)	2,700 (45.0%)	265 (13.2%)
Hospice	400 (1.7%)	-	-
Deceased	762 (3.2%)	-	-
SD: Standard Deviation; IQR: Interquartile Range;			

PAC-Predict Model Development and Internal Validation (Fig. 1)

Table 3
Performance Matrix of Implementing the Predictive Model on Validation Cohort.

Predicted Discharge Disposition	Observed Discharge Disposition		
Frequency (N)	Post-acute Care	Home	
Post-acute Care	218	342	Positive Predictive Value = 38.9%
Home	47	1393	Negative Predictive Value = 96.7%
Total	Sensitivity = 82.3%	Specificity = 80.3%	

We conducted a post-hoc sensitivity analysis to assess the predictive performance of our model on medical versus surgical patients (Additional File 3), and obstetric/gynecology patients versus those who were not (Additional File 4). Performance between medical and surgical patients was similar. Discharge to PAC for obstetric/gynecology patients is a rare event, hence the model could not assess positive predictive value in the validation cohort.

Discussion

We sought to develop a general adult hospital prediction model that would identify, within the first 24 hours of hospitalization, patients at the highest risk of requiring PAC services following discharge. We developed and internally validated a parsimonious prediction model that was well calibrated, and had high accuracy, and had an AUC of 0.875. Importantly, the prediction model exclusively utilized structured and readily available risk factors from the EHR, allowing for calculation of risk in the first 24 hours. Such a model may allow hospital services to initiate earlier DP and better target case management, social work, and therapy services to those at highest risk of requiring PAC.

The current research builds upon previously published work that predicts PAC placement. Previous studies have focused on specific inpatient populations, including patients with coronary artery bypass graft surgery(9), lower limb fractures(10), acute myocardial infarction(16), older age(7, 8), or internal medicine patients(6, 7, 24). Our study is unique in that it is a generalizable model that applies to all adult hospitalized patients and performs with equal or better predictive ability as compared to previously published models. For example, a model developed on older medical inpatients, utilizing an in person questionnaire that assessed activities of daily living (ADL) had an AUC of 0.81(6). Another recent model developed upon medical inpatients that utilized nurse intake ADL information has an AUC of 0.82(7). Our study confirms the importance of functional data to predict PAC discharge, and demonstrates the ability to apply it broadly across medical and surgical populations. We improve upon previous models by avoiding reliance on an additional functional assessment which would need to be conducted at admission.

By including the entire adult hospital population, this model could allow for a hospital to more holistically measure and guide resources which are often shared across services lines (e.g., case management, social work, physical therapy). In addition, it allows for the implementation of a single model into the informatics infrastructure, rather than unique models for each care area. The value of the model will be greatest in clinical areas with highest risk factor burden including increasing medication counts, fall risk, and advancing age. The one service area, as demonstrated in sensitivity analyses, for which this model would not provide additional guidance to DP is obstetrics and gynecology. These patients are, not surprisingly, at substantially reduced risk for PAC, as a large proportion of such admissions are for uncomplicated deliveries. This does not, however, diminish the validity with which it can be applied to the remaining medical and surgical populations.

Some may feel that prediction of PAC discharge is intuitive and does not require an automated score. However, the utility of an automated tool is to point busy health team members towards patients who would benefit most from early DP when the clinician may not have activated appropriate resources to arrange for timely transfer. Previously published models predict PAC discharge with the inclusion of data that can only be identified after many days in the hospital, or even after discharge. This may include risk factors such as length of stay, administrative variables (e.g., ICD-9, ICD-10 codes) that are often coded after hospital discharge(8, 10, 16). Using data available within 24 hours of admission allows for real-time calculation, and therefore, can be clinically applied in real-time. Without an automatic trigger, the timing of case management, social work, or physical therapy initiation of care may be delayed on account of referral behaviors, of admission timing, the location of the patient, or even the order of a patient in a standard database (e.g., alphabetically).(7)

The predictor selection is another area that our model advances prior research, particularly in using routine nursing functional assessments This is not surprising when considering many prior models have demonstrated the relative importance of functional impairment in predicting PAC discharge[10,12,28]. Many functional predictors, however, require in-person research measurements or manually abstracted patient responses. Our current model extends the application of clinical measures that are markers for mobility, fall risk, and polypharmacy. The Braden Risk Score, Morse Fall Risk Score, and pre-admission medication are routinely measured for the clinical care purposes unrelated to predicting PAC risk, however, each are independently predictive of PAC discharge. We specifically chose these variables as they are commonly measured early during the hospital stay and have the potential to be generalizable to other hospitals that routinely measure these. An illness severity index was not necessary for creating a high-performing model, and may have added unnecessary complexity if these are not routinely calculated for all admissions.

Among the limitations of this analysis are the fact that it is a retrospective study that examines a diverse population but only at a single center which contains its own local discharge practices. Misclassification bias could alter the results of the study, as potentially some discharge destinations could be misidentified in the EHR. It is possible that the absence of such patients may have biased the model, however, the direction of the bias is not known and is again thought to be small. While the random undersampling approach addressed the problem of class imbalance, the deletion of cases from the majority class may result in losing information. Furthermore, our model does not account for a growing emphasis on PAC which can be delivered in a home-based setting.(25, 26) Finally, our model is parsimonious and does not include alternative variables that could predict discharge destination (e.g., social determinants of health).

CONCLUSIONS AND IMPLICATIONS

We have developed a PAC discharge prediction model for an adult hospital population. The model is parsimonious, includes EHR-derived data, and is calculated from data within 24 hours of admission. Despite the limited number of variables and calculation early in the hospital stay, it is remarkably accurate with excellent calibration. Further research could externally validate as well as understand the impact of model calculations on changing and improving DP. As the model is deployed in the hospital EHR system, it may assist in targeting DP to the highest need patients and may improve the patient and provider experience of the overall discharge process.

Abbreviations

DP	Discharge Planning

PAC Post-Acute Care

EHR Electronic Health Record

SNF Skilled Nursing Facility

TRIPOD The Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis

VUMC Vanderbilt University Medical Center

PDW Perioperative Data Warehouse

ICU Intensive Care Unit

ED Emergency Department

SD Standard Deviation

IQR Interquartile Range

OR Odds Ratio

CI Confidence Interval

PPV Positive Predictive Value

NPV Negative Predictive Value

AUC Area Under the Curve

ROC Receiver Operating Characteristic

Declarations

Ethics Approval: We obtained approval to conduct this study from the Vanderbilt University Medical Center's Institutional Review Board (IRB 151741). All methods in this protocol were carried out in accordance with institutional guidelines and regulations, and Institutional Review Board of Vanderbilt University Medical Center has granted waiver of informed consent as this was a retrospective review/study of patient records.

Consent for publication: Not applicable

Availability of data and materials: Data used in the generation of this model is stored in the Perioperative Data Warehouse at VUMC. The deidentified datasets analyzed during the current study are available from the corresponding author on reasonable request and with a data use agreement.

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

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Authors' contributions: EV conceptualized the project and coordinated IRB approval of the study. JPW led data collection. JME assisted with study design and data collection. GL performed the statistical analyses and generated all tables and figures. MCB obtained grant funding and drafted the manuscript.

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References

1. Fox MT, Persaud M, Maimets I, Brooks D, O’Brien K, Tregunno D. Effectiveness of early discharge planning in acutely ill or injured hospitalized older adults: a systematic review and meta-analysis. BMC Geriatr. 2013 Jul;6:13:70.
2. Harrison JD, Greysen RS, Jacolbia R, Nguyen A, Auerbach AD. Not ready, not set… discharge: Patient-reported barriers to discharge readiness at an academic medical center. J Hosp Med. 2016 Sep;11(9):610–4.
3. Gadbois EA, Tyler DA, Shield R, McHugh J, Winblad U, Teno JM, et al. Lost in transition: A qualitative study of patients discharged from hospital to skilled nursing facility. J Gen Intern Med. 2019 Jan;34(1):102–9.
4. Kripalani S, Theobald CN, Anctil B, Vasilevskis EE. Reducing hospital readmission rates: Current strategies and future directions. Annu Rev Med. 2014 Jan;14(1):471–85. 65(.
5. Oldmeadow LB, McBurney H, Robertson VJ, Kimmel L, Elliott B. Targeted postoperative care improves discharge outcome after hip or knee arthroplasty1,212. Arch Phys Med Rehabil. 2004 Sep;85(9)(1):1424–7.
6. Louis Simonet M, Kossovsky MP, Chopard P, Sigaud P, Perneger TV, Gaspoz JM. A predictive score to identify hospitalized patients’ risk of discharge to a post-acute care facility. BMC Health Serv Res. 2008 Jul 22;8:154.
7. Oseran AS, Lage DE, Jernigan MC, Metlay JP, Shah SJ. A “Hospital-Day-1” model to predict the risk of discharge to a skilled nursing facility. J Am Med Dir Assoc. 2019 Jun;20(6)(1):689–95.e5.
8. Liu SK, Montgomery J, Yan Y, Mecchella JN, Bartels SJ, Masutani R, et al. Association Between Hospital Admission Risk Profile Score and Skilled Nursing or Acute Rehabilitation Facility Discharges in Hospitalized Older Adults. J Am Geriatr Soc. 2016 Oct;64(10):2095–100.

9. Chang DC, Joyce DL, Shoher A, Yuh DD. Simple index to predict likelihood of skilled nursing facility admission after coronary artery bypass grafting among older patients. Ann Thorac Surg. 2007 Sep;84(3):829–34. discussion 834–835.
10. Kimmel LA, Holland AE, Edwards ER, Cameron PA, Steiger RD, Page RS, et al. Discharge destination following lower limb fracture: Development of a prediction model to assist with decision making. Injury. 2012 Jun 1;43(6):829–34.
11. Hansen VJ, Gromov K, Lebrun LM, Rubash HE, Malchau H, Freiberg AA. Does the Risk Assessment and Prediction Tool Predict Discharge Disposition After Joint Replacement? Clin Orthop. 2015 Feb;473(2):597–601.
12. Evans DC, Cook CH, Christy JM, Murphy CV, Gerlach AT, Eiferman D, et al. Comorbidity-Polypharmacy Scoring Facilitates Outcome Prediction in Older Trauma Patients. J Am Geriatr Soc. 2012 Aug 1;60(8):1465–70.
13. Amarasingham R, Velasco F, Xie B, Clark C, Ma Y, Zhang S, et al. Electronic medical record-based multicondition models to predict the risk of 30 day readmission or death among adult medicine patients: validation and comparison to existing models. BMC Med Inform Decis Mak. 2015 May 20;15(1):39.
14. Evans RS, Kuttler KG, Simpson KJ, Howe S, Crossno PF, Johnson KV, et al. Automated detection of physiologic deterioration in hospitalized patients. J Am Med Inform Assoc. 2014 Aug 27;amiajnl-2014-002816.
15. Collins GS, Reitsma JB, Altman DG, Moons KG. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD Statement. BMC Med. 2015 Jan;6(1):1. 13(.
16. Wasfy Jason H, Kennedy Kevin F, Masoudi Frederick A, Ferris Timothy G, Arnold Suzanne V, Vinay K, et al. Predicting Length of Stay and the Need for Postacute Care After Acute Myocardial Infarction to Improve Healthcare Efficiency. Circ Cardiovasc Qual Outcomes. 2018 Sep 1;11(9):e004635.
17. Bergstrom N, Braden B, Kemp M, Champagne M, Ruby E. Predicting pressure ulcer risk: a multisite study of the predictive validity of the Braden Scale. Nurs Res. 1998 Oct;47(5):261–9.
18. Morse JM, Morse RM, Tylko SJ. Development of a Scale to Identify the Fall-Prone Patient. Can J Aging Rev Can Vieil. 1989 ed;8(4):366–77.
19. Shmuel S, Lund JL, Alvarez C, Hsu CD, Palta P, Kucharska-Newton A, et al. Polypharmacy and Incident Frailty in a Longitudinal Community-Based Cohort Study. J Am Geriatr Soc. 2019;67(12):2482–9.
20. Jentzer JC, Anavekar NS, Brenes-Salazar JA, Wiley B, Murphree DH, Bennett C, et al. Admission Braden Skin Score Independently Predicts Mortality in Cardiac Intensive Care Patients. Mayo Clin Proc. 2019;94(10):1994–2003.
21. Bandle B, Ward K, Min SJ, Drake C, McIlvennan CK, Kao D, et al. Can Braden Score Predict Outcomes for Hospitalized Heart Failure Patients? J Am Geriatr Soc. 2017 Feb 1;n/a-n/a.

22. Cohen RR, Lagoo-Deenadayalan SA, Heflin MT, Sloane R, Eisen I, Thacker JM, et al. Exploring predictors of complication in older surgical patients: a deficit accumulation index and the Braden Scale. J Am Geriatr Soc. 2012 Sep;60(9):1609–15.
23. Austin PC, Steyerberg EW. The number of subjects per variable required in linear regression analyses. J Clin Epidemiol [Internet]. 2015 Jan [cited 2015 Feb 4]; Available from: http://linkinghub.elsevier.com/retrieve/pii/S0895435615000141.
24. Koch D, Schuetz P, Haubitz S, Kutz A, Mueller B, Weber H, et al. Improving the post-acute care discharge score (PACD) by adding patients' self-care abilities: A prospective cohort study. PLoS ONE. 2019 Mar;28(3):e0214194. 14(.
25. Burke RE, Xu Y, Ritter AZ, Werner RM. Postacute care outcomes in home health or skilled nursing facilities in patients with a diagnosis of dementia. Health Serv Res [Internet]. 2021 Aug 12 [cited 2021 Aug 23]; Available from: http://onlinelibrary.wiley.com/doi/10.1111/1475-6773.13855.
26. DeCherrie LV, Wajnberg A, Soones T, Escobar C, Catalan E, Lubetsky S, et al. Hospital at Home-Plus: A Platform of Facility-Based Care. J Am Geriatr Soc. 2019;67(3):596–602.

Figures

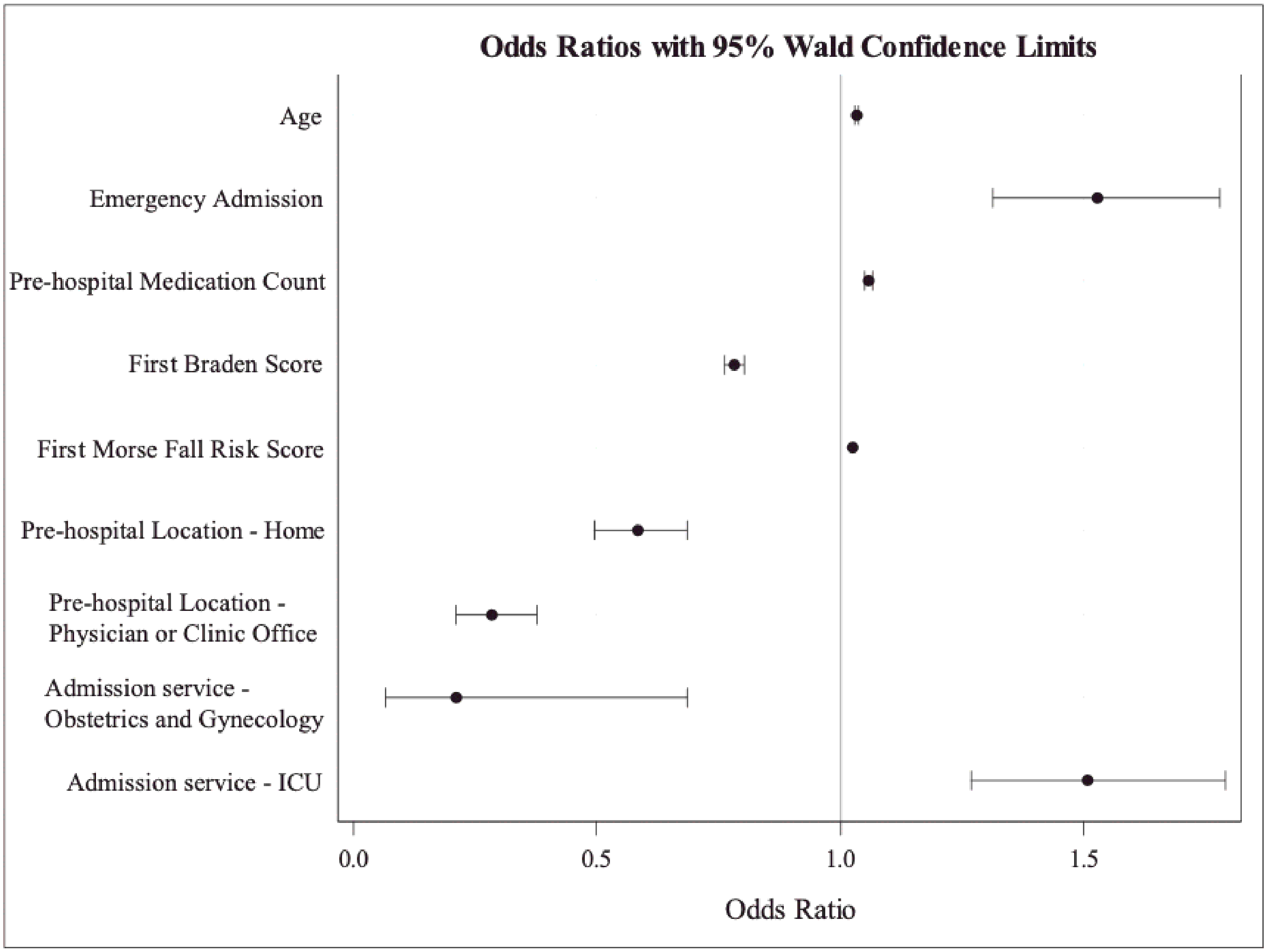

Figure 1

Visualization of the primary analysis results that derived from multivariable logistic regression model. The odds ratio estimates and their corresponding 95% Wald confidence intervals demonstrate the odds of post-acute care discharge associated with the change in the corresponding covariates.

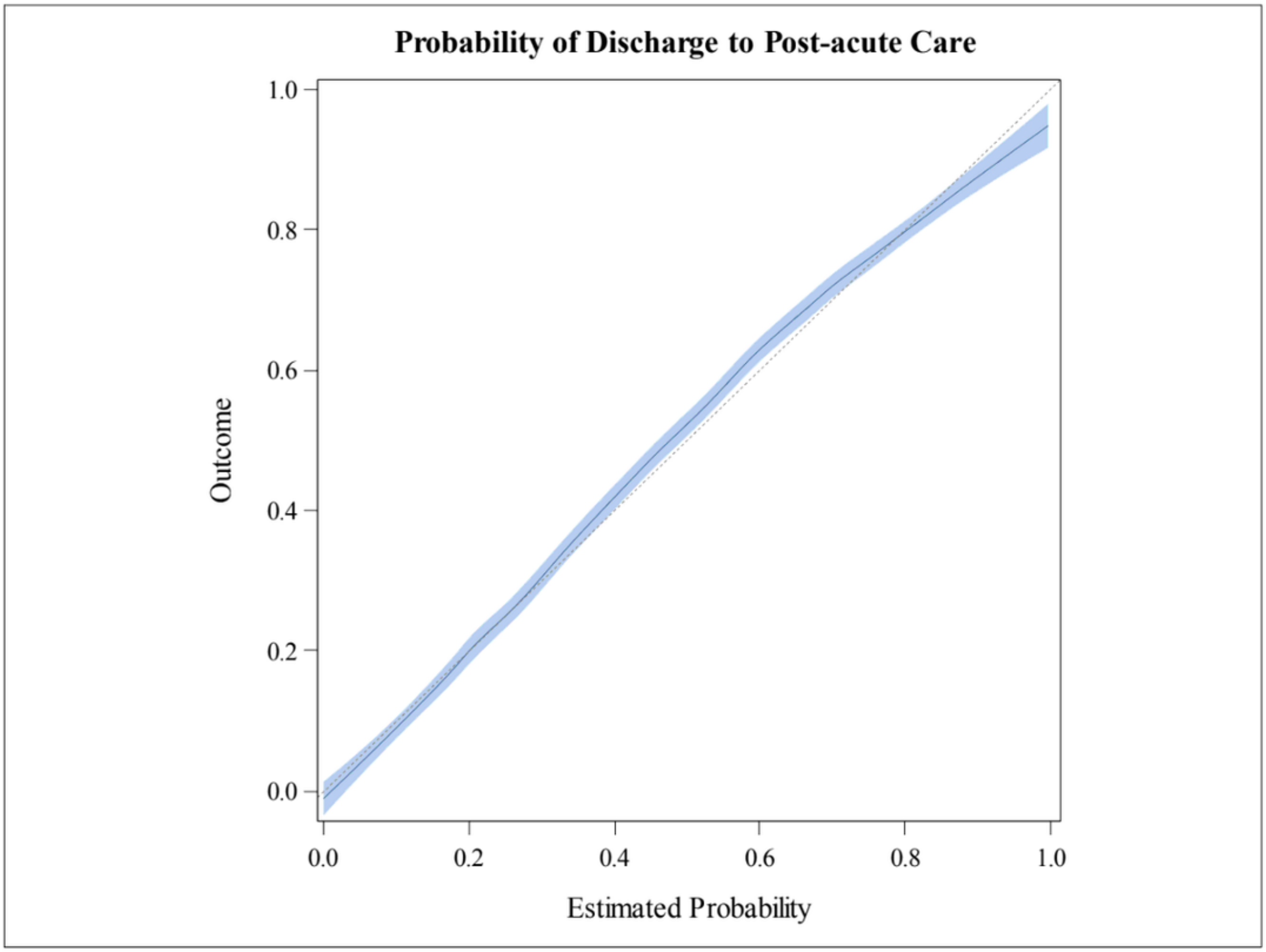

Figure 2

Calibration plot of the model’s predicted probability of PAC discharge. The estimate and 95% upper and lower confidence bounds are represented by the blue line and boundaries, respectively.

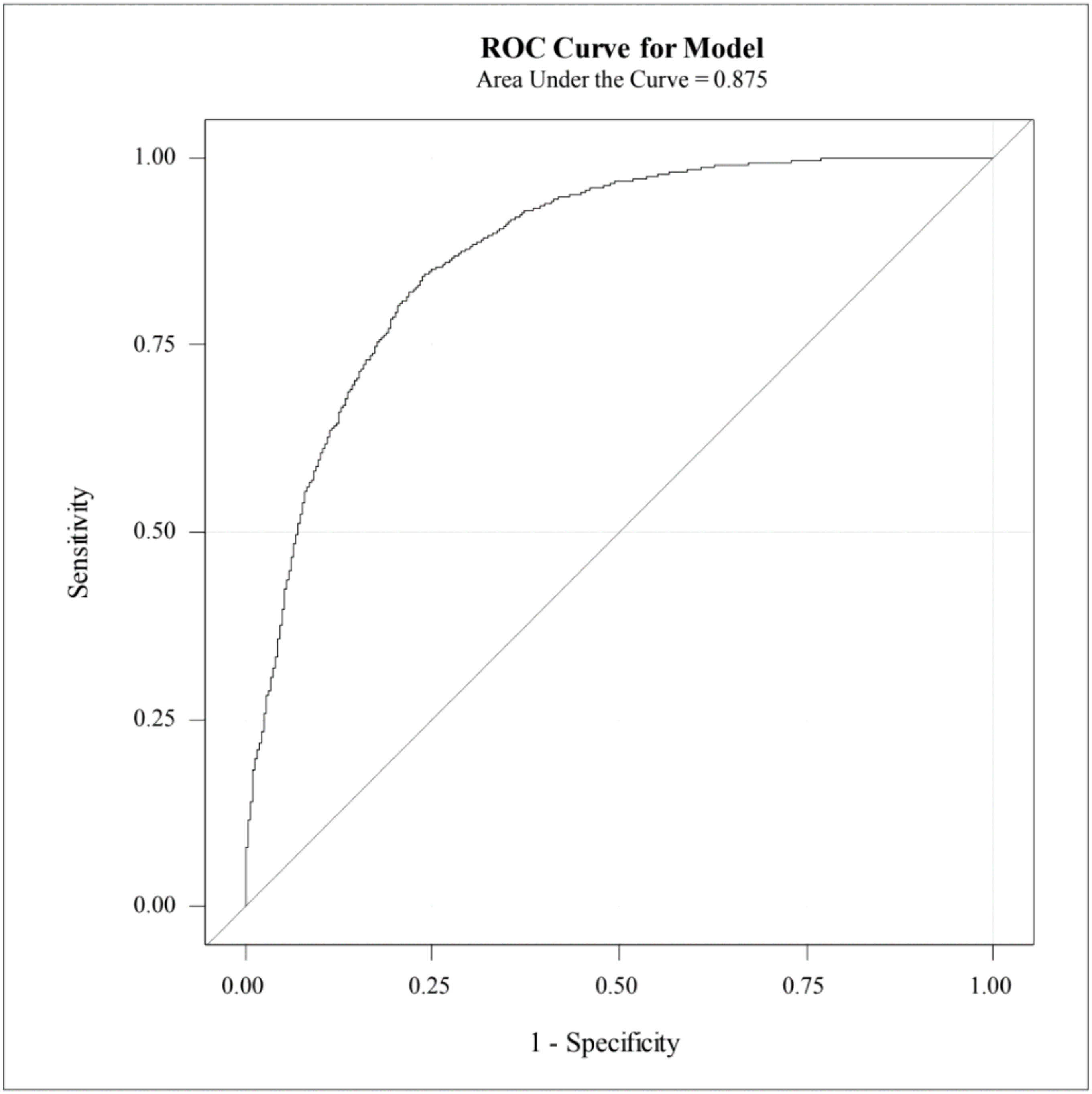

Figure 3

The receiver operator characteristic (ROC) plot for the prediction of discharge to the post-acute care setting.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AdditionalFile1.pdf

- AdditionalFile2.docx
- AdditionalFile3.docx
- AdditionalFile4.docx