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Machine learning prediction of hospital patient need for post-acute care using an admission mobility measure is robust across patient diagnoses

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ABSTRACT

Objective: One-fifth of patient discharges from the acute hospital are delayed due to non-medical reasons. Prior research on small specific samples shows that patient mobility is important for predicting post-acute care (PAC) need. Our purpose was to create a disposition prediction model for PAC need in a large, clinically diverse.

Methods: A random forest (RF) was constructed to analyze patient admissions at 2 hospitals. The primary outcome was discharge disposition (home or PAC). Predictors included the lowest AM-PAC '6-clicks' mobility score within 48-hours of admission (primary predictor) and demographic and clinical characteristics. A global summary tree was constructed to summarize the RF.

Results: Among 34,432 patient admissions, the most important variables for predicting PAC placement were AM-PAC, BMI, and age. The AUC was 0.80 (95% confidence interval: 0.79, 0.81). Using a predicted probability for PAC of 0.25 or higher, the sensitivity, specificity and overall accuracy was 76%, 70% and 72%, respectively. Patients 66 years or older with AM-PAC of <31 had the highest probability (0.76) for discharge to PAC. Patients with AM-PAC of >43 had the highest probability for discharge to home.

Conclusions: Systematic assessment of inpatients admission mobility should be implemented and used for discharge planning. Electronic medical record systems should be designed to collect and facilitate availability of mobility data on all patients to providers who play key roles in discharge planning.

Public Interest Summary: Patient's mobility status during hospitalization has been used to predict their next level of care at discharge, but this work has been done with more limited methods and focused on select patient groups. Using a machine learning technique on thousands of patients with very different medical problems, this study shows that mobility status very early in hospitalization predicts post-acute care (PAC) needs. Based on this study we recommend that early assessment of patient mobility in the hospital should occur for all patients as it can facilitate more effective discharge planning.

Introduction

The hospital discharge signifies more than just the endpoint of an acute hospital stay. Rather, it represents a time-dependent and vulnerable chapter in the patient pathway. Approximately one-fifth of hospital discharges suffer delays due to non-medical reasons, including failure to plan early for post-acute care [1,2]. One of the main factors that contributes to these delays is providers inadequate assessment and recognition of barriers to discharge when patients are first admitted [3]. Providers typically focus on the acute medical condition that led to hospitalization and have poor knowledge of a patient's social and other clinical factors that influence discharge location (i.e., living situation at home, a patient's prior and current level of physical function, etc.). Clinicians also frequently overlook hospital-acquired functional limitations until after resolution of acute medical/surgical issues [4]. This leads to delays in hospital discharge [5], exacerbation of

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hospital-associated functional losses and disability, both of which could be ameliorated with earlier discharge planning [6,7].

Prior research on predicting disposition has focused only on neurological and surgical patients [8–10]. More recent work demonstrates a relationship between a measure of patient's mobility status during hospitalization and their next level of care at discharge [11–13]. A commonly used tool to assess a patient's basic mobility is the Activity Measure for Post-Acute Care Inpatient Mobility '6-clicks' Short Form (AM-PAC). A strong correlation between AM-PAC scores at hospital admission and discharge location has been observed [11], and a classification-tree approach demonstrated the predictive ability of a patient's admission AM-PAC mobility score in identifying post-acute care need among neurological/neurosurgical patients [12]. However, these findings were based on relatively small samples and may not generalize to non-neurological/neurosurgical patients. Further, potential predictors of patient disposition that were previously evaluated excluded clinical markers of medical complexity, patient prior level of function, living situation, and social support. Medical complexity, prior level of function, living situation, and social support are all hypothesized, or known to influence disposition so need to be included in future prediction work [14–16].

This paper expands upon the prior investigations in a robust way by considering additional factors that may be predictive of disposition across a much larger and more diverse patient population at two hospital sites using a more advanced machine-learning ensemble approach [17]. We hypothesize that a patient's mobility status is the most important variable in predicting a patient's discharge location across all inpatient specialties. Our specific aim was to see if a standardized assessment of a patient's mobility status completed very early during a hospitalization (within the first 48 h) was predictive of patient discharge to post-acute care facilities within this larger and more diverse patient population.

Methods

Population

This study used a retrospective cohort of 34,432 patient admissions to two hospitals within Johns Hopkins Medicine (JHM), Johns Hopkins Hospital and Johns Hopkins Bayview Hospital, between November 2016 and December 2019. Patient admissions were excluded if their duration was <72 h, the admission was to psychiatry, pediatrics, or labor and delivery service, or resulted in patient death. Admission data was extracted from the JHM electronic medical record (EMR) system. The outcome and predictors described below represent discrete data fields within the EMR facilitating accurate acquisition.

Outcome

Discharge location, the primary outcome, was defined as post-acute care (PAC; i.e., skilled nursing or acute inpatient rehabilitation) or home (with or without services). Approximately 300 manual chart audits were completed to verify the validity of this outcome. These audits confirmed that the discharge location recorded within the EMR was the same as the actual disposition in all cases.

Predictors

The primary predictor is a measure of patient mobility, the AM-PAC Mobility '6-clicks' Short Form, which is documented at admission, and at least three times a week for all patients by nursing staff throughout the hospitals. The AM-PAC measures a patient's functional capacity. Using a 4-point Likert scale, nurses indicate how much help from another person a patient requires for six activities: turning over in bed, sitting and standing from a chair, moving from lying to sitting in bed, moving from bed to chair, walking in the room, and climbing 3–5 steps [18]. The item scores can be generated based on observed activity or the provider's expectation of the patient's need for help from another person to complete the activity. For example, if the patient requires a lot (score of 2) of assistance to move from bed to chair, the provider could expect the patient would require total (score of 1) assistance to climb stairs. Lower scores indicate greater functional limitations. The AM-PAC has high interrater reliability among nurses (Intraclass Correlation Coefficient, ICC: 0.97), and when comparing nurses to physical therapists (ICC: 0.96) [18]. Scores for each of the 6 items are entered into the EMR which automatically calculates a total raw score. For analysis, raw scores were converted to t-scale scores. T-scale scores are provided in conversion tables by the tool's developers and reflect the underlying weight of each AM-PAC item [19,20]. The measure of patient mobility included in our analysis is the lowest recorded AM-PAC T-scale score within the first 48-hours of hospital admission.

Other predictors included a priori selected demographic and clinical characteristics that are routinely available in most EMRs and may be prognostic of discharge location. Demographic characteristics included BMI, age, race, gender, prior functional status (independent, modified independent, needs assistance), living situation prior to admission (lives alone, lives with someone), and insurance type (private/commercial/HMO, Medicare/Medicaid, other). Clinical characteristics included primary medical service (medicine, neurology, general surgery, neurosurgery, other surgery, orthopedics), and whether the patient was admitted to the ICU or required mechanical ventilation within the first 48-hours of admission.

Lastly, several variables collected by JHM but which were not assumed to be collected by other health care systems were considered, including the Agency for Healthcare Research and Quality (AHRQ) Elixhauser comorbidity count, the Early Screen for Discharge Planning (ESPD) items (Self-rated walking limitation, Age, Prior living status, and Modified Rankin Disability Score), and the Area Deprivation Index (ADI). ADI is an indicator of neighborhood characteristics and is felt to be a good proxy for socioeconomic status [21].

Statistical analysis

The unit of analysis is a patient admission given the main objective to predict discharge location for each hospitalization. Descriptive statistics were used to summarize and compare the characteristics of the patient admissions across discharge location. The proportion of missing values was computed for each variable and missing values were replaced with the mean or mode for continuous and categorical variables, respectively.

A random forest (RF), an ensemble learning approach, was used to predict discharge location for each admission using the AM-PAC score and demographic and clinical characteristics [22]. While more computationally intensive and difficult to interpret, the predictions from a RF compared to a single decision tree are more accurate and have less risk of overfitting [22]. The random forest was constructed using all of the patient admissions and consisted of 1000 classification trees where a random sample of 2 predictors were considered for the next possible branch of each classification tree and the minimum number of patient admissions in each branch was 5. Each classification tree is constructed from a bootstrap sample (with replacement) of the data; the patient admissions included in the construction of the classification tree are referred to as the in-bag sample and those excluded the out-of-bag sample (mimicking the training and testing sample construction procedure used when generating a single classification tree). For each patient admission, the out-of-bag predicted probability of discharge to PAC (the proportion of out-of-bag classification trees that assign discharge to PAC) and the out-of-bag predicted discharge location (assigned PAC if the out-of-bag predicted probability was greater than 0.5) were computed. The number of predictors to consider for the next possible branch was set by constructing RFs varying this number from 1 to the total number of predictors and selecting the value that minimized the out-of-bag error, the proportion of patient admissions incorrectly classified using the out-of-bag predicted discharge location. The stability of the out-of-bag error as a function of the number of trees in the RF was visually inspected to ensure 1000 trees were sufficient. The discriminatory power of the RF was quantified with the area under (AUC) the receiver operating characteristic curve (ROC) using the out-of-bag predicted discharge location for each patient admission. Additionally, key predictors were identified using variable importance statistics. A second random forest was constructed to determine if the JHM-specific predictors improved the ability to predict discharge location.

The out-of-bag predicted probabilities of discharge to PAC may subsequently be used in a decision tool to aid clinical practice or direct hospital resources. In such a tool, patients would be flagged as having a high probability of discharge to PAC if their predicted probability from the RF exceeded a threshold, e.g., 0.3. To quantify the operating characteristics of such a decision tool, we computed the sensitivity (probability of correctly flagging a patient as high probability of discharge to PAC), specificity (probability of correctly flagging a patient as high probability of discharge home), overall accuracy and the proportion of patients flagged as high probability of discharge to PAC for the range of thresholds from 0.01 to 0.99. Further, we explored whether the operating characteristics of the decision tool vary across the medical services by computing the same statistics separately within patient admissions from each medical service.

One criticism of the use of RFs or other ensemble learners is the inability to interpret and translate the prediction model within the context of the clinical application [23]. One simple approach to address this criticism is to construct a *global summary tree*, a regression tree constructed using the out-of-bag predicted probabilities from the RF as the outcome and same set of predictors as used to construct the RF [24]. The resulting global summary tree can be used to illustrate the key features of the RF. To quantify how representative the global summary tree is to the RF, a model R^2 statistic was computed [24].

This study was approved by the XX IRB with a waiver of patient consent. All authors contributed to the conceptual design of the study and writing of the paper. LAF and EC conducted the statistical analysis and provided results from those analysis with consultation about interpretation for the remaining study team. The analyses were conducted with SAS® version 9.4 (2016; SAS Institute Inc., Cary, North Carolina), and the R statistical package procedure *randomForest,* which was used to implement Breiman's random forest algorithm for classification and regression trees.

Results

Characteristics of the patient admissions

The study population included 34,432 patient admissions representing 25,341 unique patients, with 79%, 13% and 8% of the patients contributing 1, 2 and 3 or more admissions, respectively. Our objective is to predict discharge location for each patient admission, as such, the unit of analysis is the patient admission. Table 1 displays the characteristics of the patients across the 34,432 patient admissions included in the analysis. Approximately 32% of patient admissions resulted in discharge to PAC (n = 11,035). The average patient age at admission was 65 years (25th and 75th percentiles: 53.0, 75.0). Patients were older (average age 69 vs. 62) had lower AM-PAC scores indicating greater mobility impairment (median AM-PAC score 32 vs. 41) and were more likely to be in the ICU or receiving mechanical ventilation at the time of their first AM-PAC score (18% vs. 13%) if their admission resulted in discharge to PAC compared to those resulting in discharge home. There was minimal missing data for the predictor variables, ranging from 0.01% (race and payor) to 4.8% (lives alone) (Table 1).

Summary of random forest prediction model

The RF generated a prediction model with high discriminatory power to differentiate between patient admissions with discharge to

Table 1
Characteristics of patient admissions resulting in discharge to home versus post-acute care. statistics provided are N (%) unless otherwise noted.

Demographic and clinical characteristics	Total (N = 34,432)	D/C Home (N = 23,397)	D/C PAC (N = 11,035)
Age, median (IQR)	65.0 (53.0,75.0)	62.0 (51.0,72.0)	69.0 (59.0,79.0)
Female	18,477 (53.7)	12,577 (53.8)	5900 (53.5)
Race[1]			
Black	11,962 (34.7)	8090 (34.6)	3872 (35.1)
White	19,966 (58.0)	13,406 (57.3)	6560 (59.5)
Other	2363 (6.9)	1812 (7.7)	551 (5.0)
Unknown/declined	136 (0.4)	86 (0.4)	50 (0.5)
BMI, median (IQR)	27.1 (22.8,32.6)	27.3 (23.0,32.8)	26.7 (22.5,32.3)
Payor[1]			
Commercial or HMO	7720 (22.4)	6190 (26.5)	1530 (13.9)
Government	26,092 (75.8)	16,707 (71.4)	9385 (85.0)
Other	617 (1.8)	497 (2.1)	120 (1.1)
Residence prior to hospitalization			
Home	24,162 (93.9)	14,897 (94.1)	9265 (93.4)
Facility	824 (3.2)	473 (3.0)	351 (3.5)
Other	757 (2.9)	454 (2.9)	303 (3.1)
Lives alone[1]	7759 (23.7)	4441 (20.0)	3318 (31.5)
Medical specialty			
Medicine	20,022 (58.1)	13,721 (58.6)	6301 (57.1)
Neurology	2296 (6.7)	1291 (5.5)	1005 (9.1)
General surgery	1875 (5.4)	1279 (5.5)	596 (5.4)
Neurosurgery	4861 (14.1)	3581 (15.3)	1280 (11.6)
Other surgery	1417 (4.1)	1046 (4.5)	371 (3.4)
Orthopedics	3961 (11.5)	2479 (10.6)	1482 (13.4)
In ICU or on mechanical ventilation at time of first AM-PAC mobility score	5056 (14.7)	3119 (13.3)	1937 (17.6)
AM-PAC mobility t-scale score, median (IQR)	39.7 (32.2,44.0)	41.1 (35.6,45.6)	32.2 (25.8,38.3)
Prior function			
Independent	4944 (14.4)	3146 (13.4)	1798 (16.3)
Modified independent	25,834 (75.0)	17,842 (76.3)	7992 (72.4)
Needed assistance	3654 (10.6)	2409 (10.3)	1245 (11.3)
AHRQ comorbidity count[1], median (IQR)	4.0 (3.0,6.0)	4.0 (2.0,6.0)	5.0 (3.0,6.0)
Area Deprivation Index, median (IQR)	7.0 (4.0,9.0)	7.0 (4.0,9.0)	7.0 (5.0,9.0)
ESDP total score[1]	10.0 (6.0,14.0)	9.0 (6.0,12.0)	13.0 (10.0,18.0)
ESDP walking limitations[1]			
No	14,341 (42.4)	11,731 (50.9)	2610 (24.1)
Yes	19,510 (57.6)	11,305 (49.1)	8205 (75.9)
ESDP age group[1]			
18–44	4868 (14.4)	3971 (17.2)	897 (8.3)
45–64	12,152 (35.9)	9070 (39.4)	3082 (28.5)
65–79	11,471 (33.9)	7251 (31.5)	4220 (39.0)
≥80	5359 (15.8)	2736 (11.9)	2623 (24.2)
ESDP prior living status[1]			
With others or in a facility	26,547 (78.4)	18,681 (81.1)	7866 (72.7)
Lived alone	7293 (21.6)	4341 (18.9)	2952 (27.3)
ESDP Rankin disability score[1]			
No significant disability	11,279 (33.3)	9444 (41.0)	1835 (17.0)
Slight disability	14,950 (44.2)	10,208 (44.3)	4742 (43.8)
Moderate or greater disability	7611 (22.5)	3368 (14.6)	4243 (39.2)

Abbreviations: ESDP – Early Screen for Discharge Planning, D/C – discharge, PAC – post-acute care, BMI – body mass index.

[1] Variables contained missing values, summarized as N (%). Race: 5 (0.01), Payor: 3 (0.01), Lives alone: 1662 (4.8), AHRQ comorbidity count: 3 (0.01), ESDP total score: 627 (1.8), ESDP walking limitations: 581 (1.7), ESDP age group: 582 (1.7), ESDP prior living status: 592 (1.7), ESDP Rankin disability score: 592 (1.7). Missing values were replaced with the mean or mode for continuous and categorical variables, respectively.

PAC vs. home (AUC: 0.80, 95% Confidence Interval, CI: 0.79 - 0.81). Among the possible predictors, the AM-PAC score ranked as the most important variable followed by BMI and age (Fig. 1). The service to which a patient was admitted is the fourth most important variable in the RF. The remaining demographic and clinical characteristics, race, functional status prior to admission ("prior function"), payor type ("payor"), gender, whether a patient lived alone prior to admission ("lives alone"), admitted for surgery, admitted to the ICU or on mechanical ventilation (ICU/MV), and where a patient lived prior to admission ("prior residence") were ranked below medical service and had similar variable importance statistics.

Evaluation of JHM-specific predictors

When the JHM-specific predictors were included in the construction of the RF, the discriminating power increased modestly (AUC: 0.82, 95% CI: 0.81–0.82) and the top three most important predictors remained AM-PAC, BMI, and age (Appendix Fig. 1). However, the AHRQ comorbidity count, ESDP total score, and ADI all ranked as more important than the medical service to which a patient was admitted. Additional changes in the ranked importance of the predictors included race followed by ESDP Rankin disability score, which was then followed by prior function, ESDP walking limitation, gender, ESDP age, admitted to surgery, payor, lives alone, ICU/MV, prior residence, and ESDP prior living status.

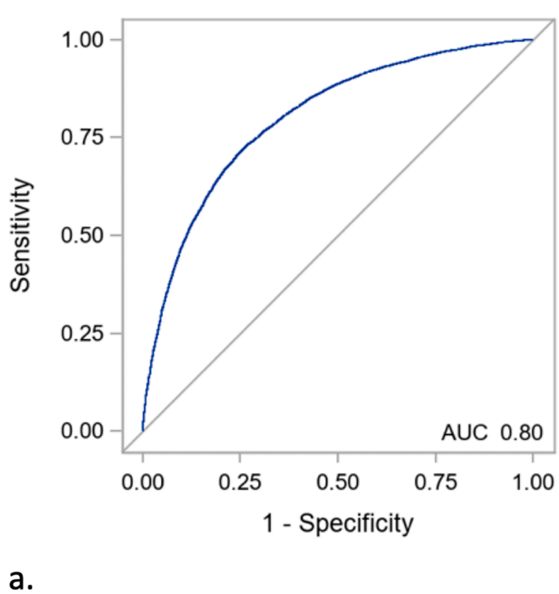
Using the random forest as a decision tool

Fig. 2 displays the sensitivity, specificity, overall accuracy, and the proportion of patient admissions that would be flagged as having high probability of discharge to PAC under the range of possible thresholds. Fig. 2 demonstrates the tradeoffs that different probability thresholds for a decision tool would create. To illustrate we selected two probability thresholds 0.25 and 0.40. When the probability of 0.25 or greater is used to define patients with high probability of discharge to PAC, the sensitivity (78%) and overall accuracy (70%) of the decision tool are both at most 70%, yet the tool has lower specificity (66%) and would flag 48% of the patient admissions as high probability of being discharged to PAC, whereas only 32% were (Fig. 2, Table 2). The decision tool based on a threshold of 0.40 would flag 35% of the patient admissions as high probability of discharge to PAC (like the observed proportion discharged to PAC), has improved specificity (79%) and accuracy (75%) but a reduction in sensitivity to 65%.

Table 2 displays the operating characteristics of the two decision tools (i.e., threshold of 0.25 vs. 0.40) based on the RF when applied separately to each medical service. The operating characteristics follow the same pattern as described above for all medical services except neurology. The greatest improvement in overall accuracy when comparing the two decision tools (threshold 0.25 vs. 0.40) is observed for neurosurgery (70% vs. 79%), other surgery (66% vs. 75%) and orthopedics (66% vs. 75%). The decision tools for medicine patients are impacted the least by changing the threshold (70% vs. 73% overall accuracy for 0.25 vs. 0.40 thresholds, respectively). Both decision tools for neurology accurately predict discharge location for 79% of neurology patients.

Global summary tree

Fig. 3 displays the global summary tree, a single regression tree representing the 1000 classification trees in the RF. The R^2 quantifying the proportion of the variation in the RF predictions that is captured by the global summary tree is 82%. Patients with an AM-PAC score of less than 38 have probability of discharge to PAC of at least 0.26. Patients with the highest probability of discharge to PAC include those with AM-PAC scores less than 31 who are 66 years old or older (0.76), those with AM-PAC scores less than 31 who are under 55 years of age and admitted into neurology (0.67), and those with AM-PAC scores ranging from 31 to 37 who live alone (0.66). Patients with AM-PAC scores of 38 or greater have probabilities of discharge to PAC ranging from 0.05 to 0.41, where the AM-PAC scores, age, whether a patient lives alone, and medical service differentiate patients in this group. For example, patients with AM-PAC scores of 43 or higher who do not live alone have a probability



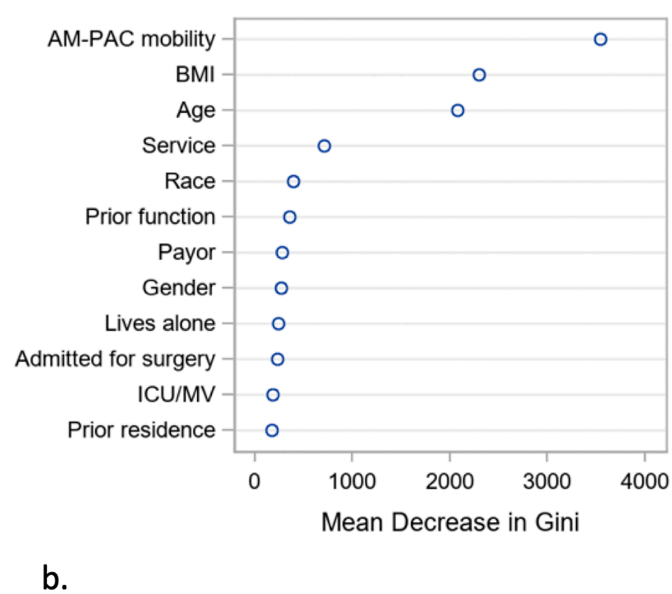


Fig. 1. Model and variable statistics from random forest analysis of entire sample a: Area under (AUC) the receiver operating characteristic curve (ROC) b:Variable importance statistics – Items with greater decrease in Gini have greater variable importance. This graph shows that AM-PAC mobility has the highest variable importance of all the variables considered. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

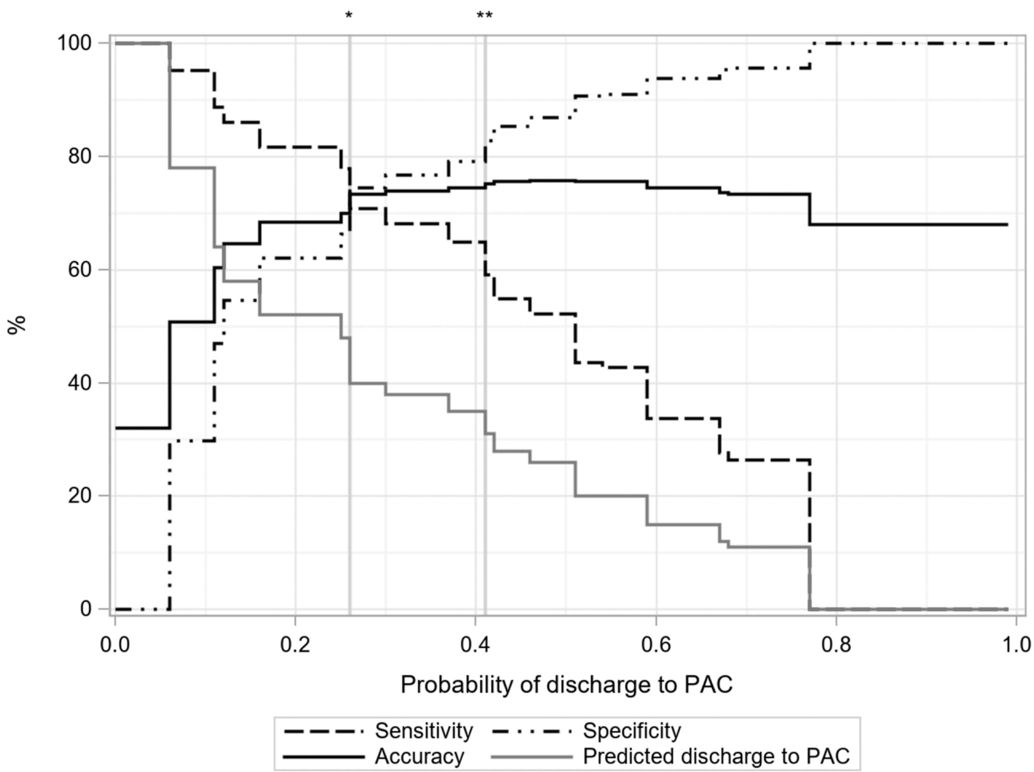


Fig. 2. Random forest results for sensitivity, specificity, accuracy in predicting post-acute care (PAC), and the proportion of all patients that would be flagged as needing PAC across the range of predicted probabilities for PAC (horizontal axis).
* The point maximizing sensitivity, specificity, and accuracy, ** The point at which the% flagged is approximately the same as the percent discharged to PAC

Table 2
Examples of 2 probability level thresholds for predicted probability of post-acute care.

Service	Probability 0.25 Sensitivity	Specificity	Accuracy	% flagged*	Probability 0.40 Sensitivity	Specificity	Accuracy	% flagged*
All Services	78 (77,79)	66 (66,67)	70 (70,70)	48	65 (64,66)	79 (79,80)	75 (74,75)	35
Medicine	75 (74,77)	68 (67,69)	70 (70,71)	46	64 (63,65)	77 (77,78)	73 (72,74)	36
Neurology	84 (82,86)	75 (73,78)	79 (78,81)	51	80 (78,83)	78 (76,81)	79 (78,81)	47
General surgery	75 (72,79)	59 (57,62)	65 (62,67)	52	58 (54,62)	78 (76,80)	71 (69,73)	33
Neurosurgery	78 (76,80)	68 (66,69)	70 (69,72)	44	58 (55,60)	87 (86,88)	79 (78,80)	25
Other surgery	74 (70,79)	63 (60,65)	66 (63,68)	47	61 (56,66)	80 (77,82)	75 (72,77)	31
Orthopedics	86 (84,88)	55 (53,57)	66 (65,68)	60	69 (66,71)	78 (77,80)	75 (73,76)	39
Acuity								
ICU/Mechanical ventilation	90 (89,92)	46 (44,47)	63 (61,64)	68	81 (79,83)	63 (61,65)	70 (69,71)	54
General Ward	75 (74,76)	69 (69,70)	71 (71,72)	44	61 (60,62)	82 (81,82)	75 (75,76)	32

* Proportion of patients that would be flagged as needing post-acute care.

of discharge to PAC of 0.05, whereas patients with AM-PAC scores from 38 to 42 and live alone have probability 0.24.

Discussion

In this study we sought to evaluate the ability of a machine-learning ensemble approach to use patient's mobility status at hospital admission to predict their subsequent discharge to PAC across a wide variety of patient populations in more than one hospital. We were able to obtain a sample of more than 34,000 patient admissions (25,000 patients) at 2 hospital sites from 6 different medical services. Most importantly we have demonstrated that, consistent with earlier more restricted samples, the relationship between early hospital mobility, as measured by AM-PAC, and disposition is robust across patient diagnoses. We further found that patient age continues to be an important consideration [12, 25], but new in this work, body mass index was observed to be an important variable in predicting disposition.

One of the most surprising findings in our analysis was the low importance of variables we originally hypothesized would help discriminate in predicting home versus post-acute care. Factors such as prior level of function, living alone, and needing ICU care all had quite low variable importance. Patient mobility early in hospital admission is likely a composite indicator of several factors that can influence discharge needs. It directly reflects the need for functional support and rehabilitation services in PAC and appears to reflect other health status measures, such as a patient's vulnerability to medical complications [26]. As such, these results support the need for standardized assessments of patient mobility, such as the AM-PAC '6-clicks', to be collected as part of routine care in the acute hospital [27,28].

When we compared our prediction accuracy across patients under different medical services (e.g. medicine, neurology, surgery, etc.), we observed very modest differences. This is to be expected given the low variable importance we observed in the RF. When others have evaluated the association between patient mobility as measured by the AM-PAC and discharge disposition, they have also observed results like ours. This relationship has been reported in studies of entire hospitals [29,30],

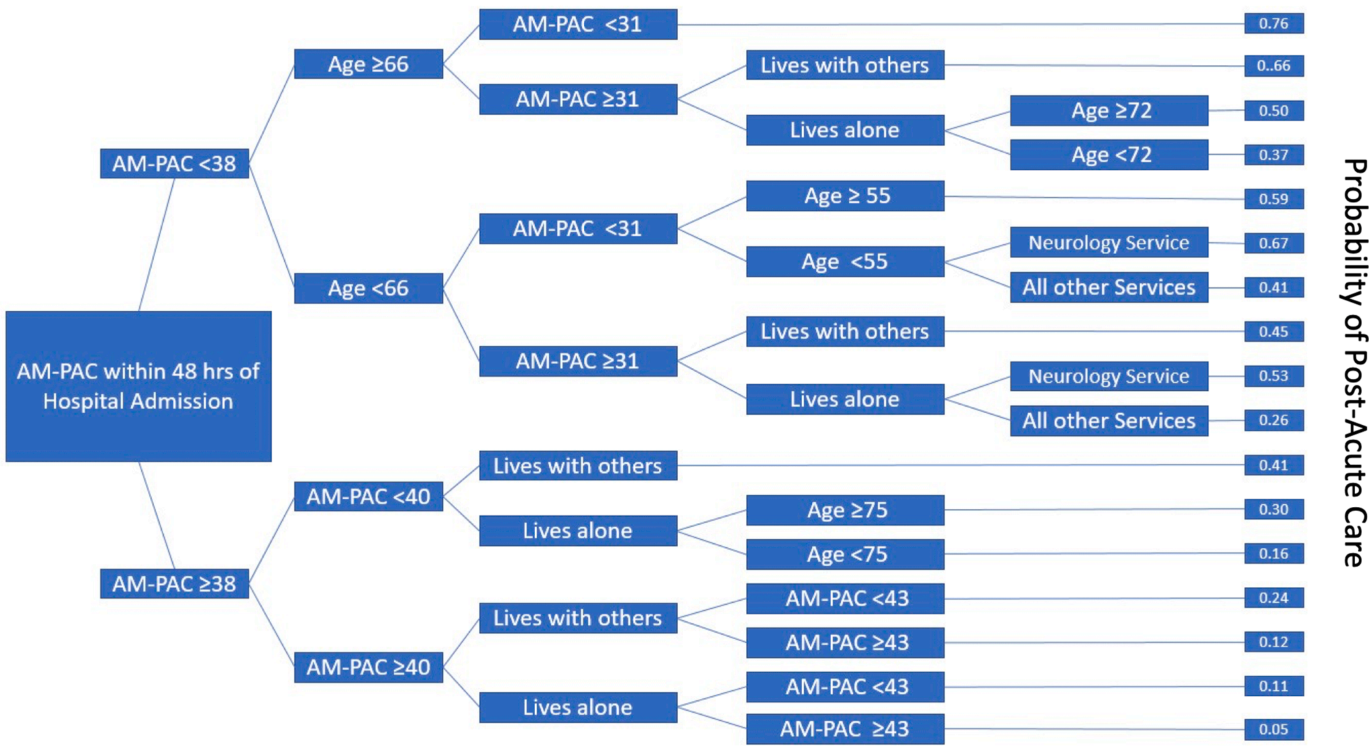


Fig. 3. Global summary tree.
Constructed from a regression of the entire random forest, For example, a 62-year-old patient admitted to the neurology service for stroke with an AM-PAC of 35 (raw score 14) who previously lived alone would have a predicted probability for post-acute care of 53% *AM-PAC = Activity Measure for Post-Acute Care Basic Mobility '6-clicks' Short Form, **Service included: Medicine, Neurology, General surgery, Neurosurgery, Other surgery, Orthopedics

and among patients with specific diagnosis such as traumatic brain injury [31], cardiac intensive care [32], cardiovascular disease [33], COVID-19 [34], and total joint replacement [35]. This may suggest that a single approach could be applied to predict disposition for different patient populations, but this should be tested further.

It is important to note that in all these other studies, AM-PAC scores were obtained by physical therapists who are not involved in the care of every hospital patient. When they do see hospitalized patients, physical therapists typically begin treatment after patients are medically stable. The effects of this delayed mobility assessment on discharge planning and utility of AM-PAC scores needs further investigation. Because all patients receive nursing care while in the hospital, and nurses perform assessments of patient mobility, we advocate for a standardized approach to mobility assessments on all patients by nursing with a tool such as AM-PAC [18,36].

When interpreting the results of the RF, we created the global summary tree and illustrated how to construct a decision tool using different probability thresholds. This combined with consideration of sensitivity and specificity can help providers when thinking clinically about discharge planning. As with most diagnostic tools, we observed tradeoffs between sensitivity and specificity. This tradeoff consideration should include the consequences of false positives, incorrectly thinking a patient will need PAC, and false negatives, incorrectly thinking a patient will not need PAC. The value of disposition prediction lies in early planning so that patients, payers, and facilities are ready to transition when hospitalization is no longer required. If the resources required to make those plans (e.g., social work, case management, therapy, physiatry), are more expensive than the cost of delayed discharge, then specificity (fewer false positives) should be prioritized. If, however, the cost of delayed discharge is greater than that of early planning, sensitivity (fewer false negatives) should be prioritized. As a screening tool we recommend a cutoff with higher sensitivity that also considers overall prediction accuracy.

Not all hospitals have the same information available as discrete data fields in their EMR [37–39]. In order to maximize generalizability of our work, we analyzed our data with and without some variables that may not be common at other hospitals such as the Early Screen for Discharge Planning (ESDP). Encouragingly, we observed that including these variables provided only modest improvements in our prediction. The variables that were most important are ones that hospitals already collect or could easily.

We observed that not all variables with high variable importance from the RF analysis appeared in the global summary tree. For example, in our analysis BMI had a greater variable importance value than age but did not appear in the global summary tree while age did. Because the global summary tree is a single tree constructed from a regression of the 1000 trees in the RF, not all variables will appear [24]. Even a variable with high variable importance in the RF may not be as important as the variable selected at any single node in the global summary tree. So while people with higher BMI often experience greater challenges in mobility and self-care activities [40–42], much of the information from BMI and its relationship to disposition may already be captured by AM-PAC since difficulty with mobility is likely a primary reason BMI is related to disposition.

Our study has several limitations. First, we do not attempt to distinguish between levels of PAC or support at home. There are at least three distinct PAC settings, long-term acute care, acute inpatient rehabilitation, and skilled nursing [43]. The determination of which would be best for the patient is multifactorial and depends on payer, patient preference, and regional differences in practice across these settings [4,6,43]. This also applies to home discharge where support at home might include home-health or outpatient rehabilitation services [44,45]. Models that effectively incorporate these factors and distinguish among patients that need different levels of PAC are needed. Second, there are challenges in translating the random forest or even the global summary tree into a clinical heuristic for easy decision making. We believe that mobile smartphone applications or intelligent EMR system software could help with clinical application of our results, but we leave to future work the development and testing of such methods and procedures. Finally, we do not know if the PAC provided to patients is always ideal. Our prediction assumes that the PAC received was appropriate in the past and can be used to guide future care; however, this needs to be empirically evaluated. Despite these limitations the very large and diverse sample we included does provide robust generalizable findings.

Conclusion

In conclusion we observed that mobility assessed very early in hospitalization predicts PAC needs across diverse patients with a wide variety of medical issues. Other patient factors, easily obtained in clinical care or from the EMR also influence prediction of PAC needs. While small differences do exist across patient populations, there is striking similarity in the factors and accuracy of PAC prediction. Early assessment of patient mobility in the hospital can facilitate more effective discharge planning and so hospitals should look for ways to measure mobility even before rehabilitation formally begins.

Author contribution

DLY, RE, EC, LAF, and EHH contrubuted equally to investigation, methodology, and writing of the original draft and reviewing & editing subsequent drafts. DLY, EHH, EC and LAF contrubuted equally to conceptualization, data curation, formal analysis, funding acquisition, resources, software, validtion, and visualization. DLY, EHH, EC contrubuted equally to project administration, supervision.

Ethical approval

This study was approved by the Johns Hopkins IRB with a waiver of patient consent.

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Declaration of Competing Interest

None declared.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.hlpt.2023.100754.

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