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Original Report

All-Cause Readmission or Potentially Avoidable Readmission: Which Is More Predictable Using Frailty, Comorbidities, and ADL?

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Abstract

Background and Objectives: Readmission-related health care reforms have shifted their focus from all-cause readmissions (ACR) to potentially avoidable readmissions (PAR). However, little is known about the utility of analytic tools from administrative data in predicting PAR. This study determined whether 30-day ACR or 30-day PAR is more predictable using tools that assess frailty, comorbidities, and activities of daily living (ADL) from administrative data.

Research Design and Methods: This retrospective cohort study was conducted at a large general acute care hospital in Tokyo, Japan. We analyzed patients aged ≥70 years who had been admitted to and discharged from the subject hospital between July 2016 and February 2021. Using administrative data, we assessed each patient's Hospital Frailty Risk Score, Charlson Comorbidity Index, and Barthel Index on admission. To determine the influence of each tool on readmission predictions, we constructed logistic regression models with different combinations of independent variables for predicting unplanned ACR and PAR within 30 days of discharge.

Results: Among 16 313 study patients, 4.1% experienced 30-day ACR and 1.8% experienced 30-day PAR. The full model (including sex, age, annual household income, frailty, comorbidities, and ADL as independent variables) for 30-day PAR showed better discrimination (C-statistic: 0.79, 95% confidence interval: 0.77–0.82) than the full model for 30-day ACR (0.73, 0.71–0.75). The other prediction models for 30-day PAR also had consistently better discrimination than their corresponding models for 30-day ACR.

Discussion and Implications: PAR is more predictable than ACR when using tools that assess frailty, comorbidities, and ADL from administrative data. Our PAR prediction model may contribute to the accurate identification of at-risk patients in clinical settings who would benefit from transitional care interventions.

Keywords: Care coordination, Care transitions, Epidemiology, Health service, Quality of care

Translational Significance: Readmission-related health care reforms have shifted their focus from all-cause readmissions (ACR) to potentially avoidable readmissions (PAR). However, little is known about the utility of analytic tools from administrative data in predicting PAR. Here, we showed that PAR is more predictable than ACR when using tools that assess frailty, comorbidities, and activities of daily living from administrative data. Moreover, our PAR prediction model may contribute to the accurate identification of at-risk patients in clinical settings who would benefit from transitional care interventions, because the discrimination of our full 30-day PAR model was higher than that of previously developed models.

The occurrence of unplanned hospital readmissions soon after discharge can impose a heavy burden on patients, health care providers, and payers. In the United States, almost one-fifth of Medicare beneficiaries were readmitted within 30 days after hospital discharge, and unplanned readmissions are estimated to cost US$17 billion annually (1). Transitional care interventions have been shown to reduce early unplanned readmissions among older patients (2). To efficiently provide targeted

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interventions and prevent readmissions, there is a need to accurately identify at-risk patients who require transitional care.

In Japan, many acute care hospitals use the Diagnosis Procedure Combination (DPC) case-mix patient classification system. The DPC system was launched in 2003, and was designed to encourage shorter length of stay (LOS) durations through financial incentives. Although DPC hospitals have generally shown reductions in mean LOS after adopting this system, their readmission rates have increased (3). A recent government survey found that approximately 11% of patients discharged from DPC hospitals were readmitted within 4 weeks (4). Japan's public insurance-covered transitional care services are currently more focused on reducing the LOS rather than preventing early readmissions, as shown by a lack of association between these services and readmission rates (5). The prompt and accurate identification of patients with a higher risk of early readmission may help to improve these services in Japan and prevent readmissions. Recent studies have focused on the development of prediction models for all-cause readmissions (ACR) using analytic tools that assess frailty and comorbidities based on administrative data and electronic health records, but these models have generally shown only moderate predictive performance (6,7).

Early unplanned readmissions may be indicative of incomplete care or discharge coordination issues between hospitals and community care providers, and the focus of readmission-related health care reforms has shifted from ACR to potentially avoidable readmissions (PAR) (5,8–12). PAR is considered to be a better indicator of the quality of transitional care than ACR because a substantial portion of hospital readmissions are potentially avoidable, and PAR is more likely to be prevented through effective transitional care programs than ACR (8,9). Although a few studies have developed PAR prediction tools using comorbidities from administrative data, their predictive performance was relatively modest (C-statistic: HOSPITAL score, 0.71; PAR-Risk score, 0.699) (9,10,13). Moreover, a recent review of ACR risk prediction models using medical records reported that frailty and functional decline in activities of daily living (ADLs) are important predictors of early readmission (6). To the best of our knowledge, no studies have developed PAR prediction models that include frailty and ADLs from administrative data. We posit that the predictive performance of such models could be improved with the inclusion of these factors.

Frailty, comorbidities, and ADL disability are known risk factors for poor clinical outcomes, including unplanned readmissions (5,6,11,14,15). Analytic tools have been developed to assess these factors. For example, the Hospital Frailty Risk Score (HFRS) identifies older patients with frailty at higher risk of adverse outcomes (16), and the Charlson Comorbidity Index (CCI) utilizes a weighted aggregate score of various comorbidities to predict mortality (17,18). In Japan, each DPC hospital generates and submits administrative data (referred to as DPC data) in a standardized format to the Ministry of Health, Labour, and Welfare for insurance claims (19). DPC data include information on diagnoses, treatments, prescribed drugs, and ADL assessment scores (19). Although the performance of HFRS and CCI in ACR prediction has been examined (7), studies have yet to evaluate the feasibility of using tools that assess frailty, comorbidities, and ADL in PAR prediction. Furthermore, studies have not been conducted to determine whether ACR or PAR is more predictable using these tools. We hypothesized that 30-day PAR would be more predictable than 30-day ACR using such tools from administrative data because PAR involves specific conditions, such as pneumonia and heart failure, that are more likely to occur in older adults with frailty or ADL disability (20). If so, this would provide important evidence to support the further development and refining of PAR prediction models (rather than ACR prediction models) using administrative data, which could contribute to the efficient and accurate identification of at-risk patients for transitional care programs in the clinical setting. Therefore, this study was conducted to determine whether 30-day ACR or 30-day PAR is more predictable using tools that assess frailty, comorbidities, and ADL from administrative data.

Research Design and Methods

Study Design and Patients

In this retrospective cohort study, we used an anonymized DPC database obtained from a large general acute care hospital in Tokyo, Japan. The DPC data comprised patient-level demographic characteristics, diagnoses (International Classification of Diseases, 10th Revision [ICD-10] codes), treatments, and prescribed drugs during all insurance-covered clinical encounters. Data from July 2016 to March 2021 were obtained for analysis.

Our study focused on patients who had been admitted to and discharged from the subject hospital between July 2016 and February 2021; this hospitalization episode was designated the index admission. Data from March 2021 were used as a follow-up period to identify 30-day readmission in patients who were discharged in February 2021. For patients who were admitted twice or more during the study period, the first hospitalization episode was designated the index admission. We excluded the following cases: patients discharged to other hospitals, patients discharged within one day, patients aged <70 years, and patients with missing data in the study variables. Patients aged <70 years were excluded due to their lack of information on annual household income.

The study protocol was approved by the Ethics Committee of the Tokyo Metropolitan Geriatric Hospital and Institute of Gerontology. This study used an opt-out approach because all data were anonymized before being received by the authors. The study was performed in accordance with the Ethical Guidelines for Medical and Health Research Involving Human Subjects issued by the Japanese government.

Study Variables

From the DPC data of the subject hospital, we collected information on patient sex, age (70–74, 75–84, and ≥85 years), and annual household income at the index admission. Each patient's annual household income was determined based on his/her recorded insurance copayment rate. Copayment rates refer to the designated rates that patients must pay at the point of care under Japan's health insurance system. The copayment rates are 10% and 20% for patients aged ≥75 years and 70–74 years, respectively, with an annual household income below ¥3.7 million (approximately US$34 007; US$1 = ¥108.8 in 2016). In contrast, the copayment rate is 30% for patients aged ≥70 years with an annual household income of ¥3.7 million or higher (21). As we were unable to determine the annual household income of patients who received public medical assistance, these cases were categorized as

"unknown." Therefore, annual household income was analyzed into 3 categories: <¥3.7 million, ≥¥3.7 million, and unknown.

By comparing DPC data with medical chart data, a previous study showed that the validity of diagnoses for CCI and several procedure records in the DPC database was generally high (22). Based on previously designated ICD-10 codes (16–18,23–25), we calculated the (a) HFRS from all diagnosis categories and (b) CCI from all recorded comorbidities in each patient's index admission. The HFRS, which was developed in the United Kingdom to identify older adults with characteristics of frailty who are at higher risk of adverse outcomes, allocates patients into 3 categories: low levels of frailty risk (HFRS <5), intermediate levels of frailty risk (HFRS 5–15), and high levels of frailty risk (HFRS >15) (7,16,23–25). As a preliminary analysis showed that there were only a few patients with high levels of frailty risk in our sample, HFRS was analyzed as 2 categories for this study (0–4.9 and ≥5). The CCI score was divided into 3 categories (0, 1–2, and ≥3) as described in previous studies (5,7).

ADL at admission was assessed using the Barthel Index (BI), which is recorded in the DPC data. The BI scale measures performance in 10 basic ADL (bowels, bladder, grooming, toilet use, feeding, transfers, mobility, dressing, stairs, and bathing). Each item is given a score of 0, 5, 10, or 15 which reflects the patient's independence in that activity (26). The overall score ranges from 0 to 100, with higher scores representing higher independence. For this study, BI was analyzed as a continuous variable.

Outcome Measures

We identified unplanned emergency readmissions and unplanned nonemergency readmissions from the DPC data, which include labels to designate such cases for each hospitalization episode. The study outcome measures were (a) the occurrence of unplanned ACR within 30 days of discharge from the subject hospital (30-day ACR) and (b) the occurrence of unplanned PAR within 30 days of discharge from the subject hospital (30-day PAR). The causes of all readmissions were identified using admission-precipitating diagnoses recorded with ICD-10 codes (5). We defined 30-day ACR as the first unplanned readmission within 30 days of discharge for any admission-precipitating diagnosis. Next, we defined 30-day PAR as the first unplanned readmission within 30 days of discharge due to any one of 17 admission-precipitating diagnoses identified in previous studies (5,12,27,28). These conditions were selected based on diagnoses for potentially avoidable hospitalizations identified by the US Centers for Medicare & Medicaid Services, and were recoded from ICD-9 to ICD-10 in a previous Japanese study (27).

Statistical Analysis

We first compared the differences in characteristics between patients with and without 30-day ACR or PAR using the chi-square test and Mann–Whitney *U* test. To determine the relative influence of each independent variable, we constructed 6 multivariable logistic regression models for 30-day ACR and 30-day PAR: (Model 1) Basic (independent variables: sex, age, and annual household income), (Model 2) Basic + HFRS, (Model 3) Basic + CCI, (Model 4) Basic + HFRS + CCI, (Model 5) Basic + BI, and (Model 6) Basic + HFRS + CCI + BI.

For each model, we calculated the C-statistic and its 95% confidence interval (CI) to evaluate its discrimination in predicting 30-day ACR and 30-day PAR. The use of the C-statistic allows for comparisons with other studies because it provides a general measure of a model's discriminative ability. A C-statistic of 0.5 indicates no predictive ability beyond random chance, whereas a C-statistic of 1.0 indicates perfect predictive power. The Brier score was also used to assess the accuracy of each model. Brier scores range from 0 to 1, with lower scores indicating more accurate predictions (29). Model 6 was also assessed using calibration curves that show the relationship between the predicted probability and the observed probability of the event (30).

In addition, we conducted sensitivity analyses to assess the discrimination of the prediction models under various conditions. First, we calculated HFRS and CCI for a 2-year lookback period (ie, 2 years prior to and including the index admission) instead of the index admission only using the subject hospital's data, and applied these to the 30-day ACR and 30-day PAR prediction models. The use of lookback periods allows analysts to examine longer-term frailty and comorbidities, which may increase the predictive power of each model (7,31). Recent studies from Japan have calculated HFRS based on admission data (24,25), but there was a general lack of consistency in the hospitalization durations (32). We selected the 2-year lookback period due to its use in previous studies on HFRS (7,16,23). Second, we calculated HFRS and CCI as continuous variables because the cutoff points used in the main analysis have not yet been validated using DPC data. Third, we evaluated the discrimination of the 30-day ACR and 30-day PAR prediction models among patients who were admitted after the start of the coronavirus 2019 (COVID-19) pandemic in Japan. We set the start of the COVID-19 pandemic as April 2020 because Japan's first state of emergency began in Tokyo on April 7, 2020. In addition, the first COVID-19 case admitted to our subject hospital was in April 2020. Therefore, this sensitivity analysis was conducted using data from April 2020 to March 2021 (end of the study period).

We calculated the odds ratios (ORs) and 95% CIs of the independent variables in each model. p Values (2-tailed) below 0.05 were considered statistically significant. SPSS version 27.0 (IBM Corp., Armonk, NY, USA) was used to conduct the statistical analyses, and Stata version 17.0 (Stata Corp LLC, Texas, USA) was used to calculate the Brier scores and plot the calibration curves.

Results

Figure 1 shows the patient selection process. We first identified 25 754 candidate patients who were admitted to the subject hospital and discharged to home or a care facility during the study period. After applying the exclusion criteria, our final study sample consisted of 16 313 patients. The patients' basic characteristics are presented in Table 1. Their mean age was 81.3 years (standard deviation: 6.7 years), and women accounted for 59.0% of all patients. When HFRS and CCI were calculated using the index admission only, 8.0% of patients had an HFRS ≥5 and 6.5% of patients had a CCI score ≥3.

Among the 16 313 patients, 661 (4.1%) experienced 30-day ACR and 290 (1.8%) experienced 30-day PAR. Table 1 shows the 30-day ACR and 30-day PAR rates according to

patient characteristics. Patients with 30-day ACR had significantly higher proportions of HFRS ≥5 and CCI scores ≥3 than patients without 30-day ACR (HFRS ≥5: 18.6% vs 7.6%, $p < .001$, CCI ≥3: 12.6% vs 6.2%, $p < .001$). Similarly, patients with 30-day PAR had significantly higher proportions of HFRS ≥5 and CCI scores ≥3 than patients without 30-day PAR (HFRS ≥5: 21.4% vs 7.8%, $p < .001$, CCI ≥3: 10.3% vs 6.4%, $p < .001$). BI scores were significantly lower among patients with 30-day ACR and 30-day PAR than patients without 30-day ACR or 30-day PAR, respectively.

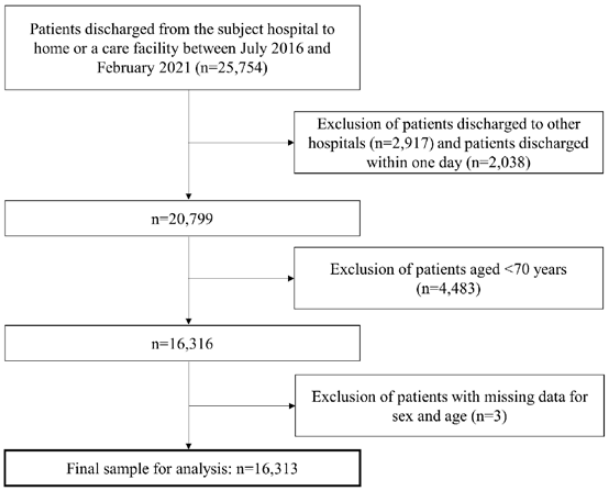

Figure 1. Flow chart of patient selection.

The full model (Model 6) was the strongest prediction model for both outcomes (Table 2). Furthermore, Model 6 for 30-day PAR showed better discrimination (C-statistic: 0.79, 95% CI: 0.77–0.82; Brier score: 0.017) than Model 6 for 30-day ACR (C-statistic: 0.73, 95% CI: 0.71–0.75; Brier score: 0.038). The other prediction models for 30-day PAR also had consistently better discrimination than their corresponding models for 30-day ACR. The inclusion of BI improved model discrimination for both 30-day ACR and 30-day PAR.

Although the C-statistics were higher in several models when HFRS and CCI were calculated using the 2-year look-back period (n = 10 676), these differences were very small (Supplementary Table 1). The results were similar when HFRS and CCI were analyzed as continuous variables instead of categorical variables (Supplementary Table 2). Furthermore, the analysis of the COVID-19 period showed that Model 6 for 30-day ACR and 30-day PAR had better discrimination than the main analysis (Supplementary Table 3).

Figure 2 shows the calibration curves of Model 6 for both outcomes. In both outcomes, the plotted points of Model 6 were relatively close to the diagonal until approximately 10% predicted probability, after which they fell slightly below the diagonal; this indicated possible overprediction. Supplementary Table 4 presents the sensitivity, specificity, and positive predictive value (PPV) for different cutoff points of predicted probability in the full 30-day PAR prediction model. At the 70th centile, the sensitivity, specificity, and PPV were 75.9%, 70.7%, and 4.5%, respectively.

Table 3 shows the associations of HFRS, CCI, and ADL with 30-day PAR. HFRS ≥5 was significantly and positively associated with 30-day PAR in Model 2 (reference: HFRS

Table 1. Differences in Basic Characteristics Between Patients With and Without Readmission

Characteristics	Total, n = 16 313	With 30-day ACR, n = 661, 4.1%	Without 30-day ACR, n = 15 652, 95.9%	p-Value*	With 30-day PAR, n = 290, 1.8%	Without 30-day PAR, n = 16 023, 98.2%	p-Value*
Sex, %							
Men	41.0	46.7	40.8	.002	40.7	41.0	.911
Women	59.0	53.3	59.2		59.3	59.0	
Age, %							
70–74 years	18.4	9.7	18.7	<.001	6.2	18.6	<.001
75–84 years	50.0	45.1	50.2		38.6	50.2	
≥85 years	31.6	45.2	31.1		55.2	31.2	
Annual household income, %							
<¥3.7 million	82.8	83.1	82.8	.045	86.2	82.7	.021
≥¥3.7 million	11.8	9.8	11.9		6.9	11.9	
Unknown	5.4	7.1	5.3		6.9	5.3	
HFRS							
0–4.9	92.0	81.4	92.4	<.001	78.6	92.2	<.001
≥5	8.0	18.6	7.6		21.4	7.8	
CCI							
0	59.3	39	60.2	<.001	33.4	59.8	<.001
1–2	34.2	48.4	33.6		56.2	33.8	
≥3	6.5	12.6	6.2		10.3	6.4	
BI at admission, median (interquartile interval)	85 (50–100)	45 (5–80)	85 (50–100)	<.001	25 (0–60)	85 (50–100)	<.001

Notes: ACR = all-cause readmissions; BI = Barthel Index; CCI = Charlson Comorbidity Index; HFRS = Hospital Frailty Risk Score; PAR = potentially avoidable readmissions.
*Chi-square test or Mann–Whitney U test.

Table 2. Comparison of Model Discrimination in Predicting 30-Day ACR and 30-Day PAR

Models	30-Day ACR			30-Day PAR		
	C-Statistic (95% CI)		Brier Score	C-Statistic (95% CI)		Brier Score
(Model 1) Basic (sex, age, and annual household income)	0.62	(0.59–0.64)	0.039	0.66	(0.63-0.69)	0.017
(Model 2) Basic + HFRS	0.64	(0.62–0.66)	0.039	0.69	(0.66–0.72)	0.017
(Model 3) Basic + CCI	0.66	(0.64–0.68)	0.038	0.71	(0.68–0.73)	0.017
(Model 4) Basic + HFRS + CCI	0.67	(0.65–0.69)	0.038	0.72	(0.69–0.74)	0.017
(Model 5) Basic + BI	0.72	(0.70–0.74)	0.038	0.78	(0.76–0.81)	0.017
(Model 6) Basic + HFRS + CCI + BI	0.73	(0.71–0.75)	0.038	0.79	(0.77–0.82)	0.017

Notes: ACR = all-cause readmissions; BI = Barthel Index; CCI = Charlson Comorbidity Index; CI = confidence interval; HFRS = Hospital Frailty Risk Score; PAR = potentially avoidable readmissions.

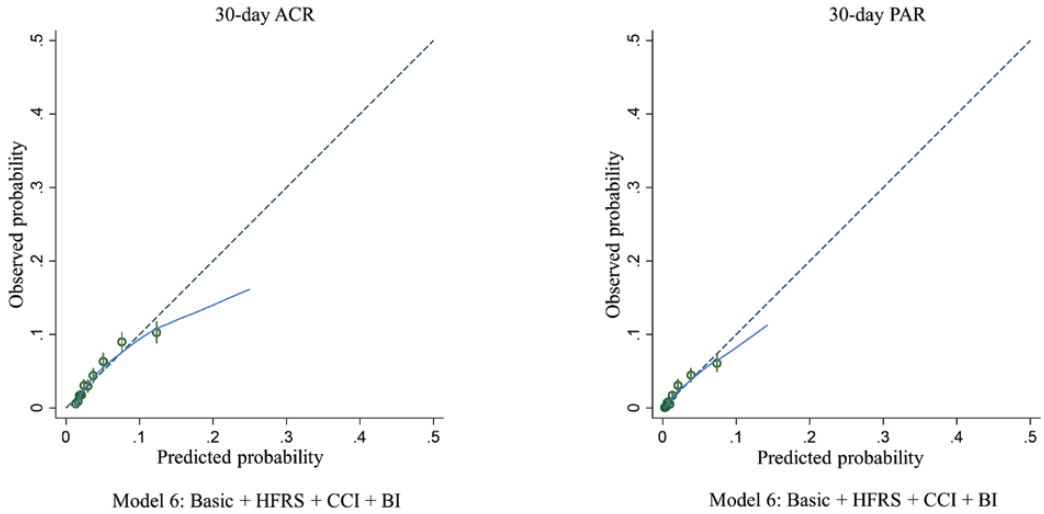

Figure 2. Calibration plots of Model 6 for 30-day ACR and 30-day PAR. Basic includes sex, age, and annual income. The solid curves are loess calibration curves. ACR = all-cause readmissions; BI = Barthel Index; CCI = Charlson Comorbidity Index; HFRS = Hospital Frailty Risk Score; PAR = potentially avoidable readmissions.

= 0–4.9; OR: 2.54, 95% CI: 1.90–3.40) and Model 4 (OR: 1.94, 95% CI: 1.44–2.62). This association was weaker and not significant in Model 6 (OR: 1.14, 95% CI: 0.84–1.55). BI was significantly and negatively associated with 30-day PAR in Model 5 (OR: 0.98, 95% CI: 0.97–0.98) and Model 6 (OR: 0.98, 95% CI: 0.97–0.98).

Discussion and Implications

This retrospective cohort study is the first to demonstrate that 30-day PAR is more predictable than 30-day ACR when using tools that assess frailty, comorbidities, and ADL from hospital administrative data. Our analysis showed that each model that included HFRS, CCI, and/or BI for 30-day PAR had better discrimination than the corresponding model for 30-day ACR. The clinical implementation of PAR prediction models constructed using routinely collected administrative data may contribute to the identification of patients who would benefit from targeted transitional care interventions. For example, these prediction models could be incorporated into clinical assessment tools that present readmission risks to medical staff and transitional care management staff before discharge. Future studies are needed to develop and validate these clinical assessment tools to identify patients with an elevated risk of PAR from hospital administrative data.

When comparing the models that included HFRS and CCI (Model 3), the model for 30-day PAR showed better discrimination than the model for 30-day ACR. This suggests that the medical conditions that lead to PAR are associated with frailty and comorbidities at the index admission. For example, frailty and comorbidities are reportedly associated with an elevated risk of pneumonia and early rehospitalization due to pneumonia and heart failure (20,33), which were included as admission-precipitating diagnoses for PAR. An additional analysis of our data showed that over half of 30-day PAR cases were caused by respiratory infections (including pneumonia) and congestive heart failure (Supplementary Table 5), which was consistent with prior studies (5,12,27). Prediction models that incorporate tools to assess comorbidities and frailty from administrative data could be more accurate at identifying patients at high risk of PAR than ACR. Readmission prevention strategies have shifted their focus from ACR to PAR, which has increased the importance of accurate PAR prediction models. As transitional care may help to reduce PAR more than ACR, future studies are needed to improve the accuracy of PAR prediction models to identify at-risk

Table 3. Associations of Frailty, Comorbidities, and ADL With 30-Day PAR

Independent variables	Model 1*	Model 2†	Model 3‡	Model 4§	Model 5‖	Model 6¶
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Sex (reference: men)						
Women	0.87 (0.68–1.10)	0.85 (0.67–1.08)	0.94 (0.74–1.2)	0.91 (0.72–1.17)	0.83 (0.65–1.06)	0.86 (0.67–1.1)
Age (reference: 70–74 years)						
75–84 years	2.35 (1.43–3.88)	2.24 (1.36–3.70)	2.26 (1.37–3.73)	2.18 (1.32–3.59)	1.95 (1.18–3.23)	1.89 (1.14–3.13)
≥85 years	5.57 (3.40–9.11)	4.85 (2.95–7.98)	4.79 (2.92–7.85)	4.38 (2.66–7.20)	2.79 (1.68–4.63)	2.65 (1.59–4.39)
Annual household income (reference: <¥3.7 million)						
≥¥3.7 million	0.55 (0.35–0.88)	0.56 (0.35–0.89)	0.55 (0.35–0.87)	0.55 (0.35–0.88)	0.55 (0.35–0.87)	0.55 (0.35–0.88)
Unknown	1.55 (0.97–2.47)	1.56 (0.98–2.49)	1.48 (0.93–2.37)	1.50 (0.94–2.40)	1.42 (0.89–2.28)	1.41 (0.88–2.27)
HFRS (reference: 0–4.9)						
≥5	NA	2.54 (1.90–3.40)	NA	1.94 (1.44–2.62)	NA	1.14 (0.84–1.55)
CCI (reference: 0)						
1–2	NA	NA	2.64 (2.04–3.41)	2.39 (1.84–3.10)	NA	1.64 (1.25–2.15)
≥3	NA	NA	2.54 (1.67–3.86)	2.21 (1.44–3.38)	NA	1.53 (1.00–2.36)
BI at admission	NA	NA	NA	NA	0.98 (0.97–0.98)	0.98 (0.97–0.98)

Notes: ADL = activities of daily living; OR = odds ratio; BI = Barthel Index; CCI = Charlson Comorbidity Index; CI = confidence interval; HFRS = Hospital Frailty Risk Score; PAR = potentially avoidable readmissions.
* Model 1, Basic (sex, age, and annual household income).
† Model 2, Basic + HFRS.
‡ Model 3, Basic + CCI.
§ Model 4, Basic + HFRS + CCI.
‖ Model 5, Basic + BI.
¶ Model 5, Basic + HFRS + CCI + BI.

patients. These studies could include the use of machine learning similar to that examined in previous research on ACR prediction (34–36).

In our study, the inclusion of BI into Model 5 (basic variables) and Model 6 (basic variables, HFRS, and CCI) for 30-day PAR and ACR improved their discrimination. Also, the associations of HFRS and CCI with 30-day PAR were weaker in models with BI than models without BI. The finding that BI was a stronger predictor of 30-day PAR than HFRS and CCI suggests that objective assessment tools for functional status are important clinical indicators of this outcome. These results were consistent with previous studies that reported functional disability at admission to be an important risk factor for readmission (6,11,12,14,15). The discrimination of our full 30-day PAR model (Model 6) was higher than that of previously developed models (9,10). Although this model produced slight overestimations near 10% predicted probability, its overall calibration was acceptable. Therefore, the full 30-day PAR prediction model developed in this study has the potential to identify at-risk patients in clinical settings who would benefit from transitional care interventions.

Our finding that the inclusion of functional status can contribute to the identification of patients at risk for PAR may have potential implications outside of the Japanese context. For example, 2 U.S. studies have used the Inpatient Rehabilitation Facility-Patient Assessment Instrument, which incorporates patient functional status from Medicare fee-for-service claims data, to examine the association of functional status with early readmission in the inpatient rehabilitation setting (11,37). Because Japanese acute care hospitals generally also provide postacute care, rehabilitation services are regularly provided during the same hospitalization episode as acute care services. Therefore, although the average LOS in acute care hospitals is longer in Japan (16.4 days) than in the United States (5.4 days) (38), the Japanese acute care setting would have a large degree of overlap with the U.S. inpatient rehabilitation setting. For this reason, our prediction models may also have good performance in U.S. inpatient rehabilitation facilities. The PPV of our full PAR prediction model was low, but the PPV of prediction models can be increased when applied to populations with a higher prevalence of the targeted outcome (39). The prevalence of 30-day PAR among older persons in U.S. inpatient rehabilitation facilities is more than twice that of our subject hospital (11). Accordingly, the PPV of a similar prediction model would be higher in that context than in our study, but it would still not be particularly high. Sequential tests may improve the specificity and PPV of prediction models (39). The full 30-day PAR prediction model using secondary data introduced in this study may be an appropriate starting point for a sequential test because it can be applied at low cost and low clinical burden for hospitalized patients. Moreover, a relatively higher proportion of false positive screening test outcomes due to a low PPV might be acceptable under several circumstances (eg, when an intervention to protect against a target condition is unlikely to cause harm to patients even if that condition is absent) (40). Transitional care programs are not harmful but can benefit patients at low risk of PAR through successful care transitions, such as ensuring medication continuity from the discharging hospital (41). Therefore, the relatively low PPV of the 30-day PAR prediction model could be acceptable in the clinical setting.

Although the model discriminations for 30-day ACR and 30-day PAR using HFRS and CCI from a 2-year lookback period were better than that from the index admission only, these differences were marginal. Our 30-day PAR prediction model using HFRS and CCI from the index admission demonstrated fair discriminative ability, indicating that it has potential clinical applications. However, the applicability of HFRS has yet to be validated in the Japanese health care

system (12,32). There is therefore a need to further examine the association of HFRS with outcomes (eg, mortality or early readmission) using Japanese administrative data.

This study has several limitations. First, our database did not include patients who were readmitted to other hospitals and those who had died after discharge, which may have led to an underestimation of readmissions. As such misclassifications of outcomes would occur independently of the models' variables, this would be a form of nondifferential misclassification. Nondifferential misclassifications tend to bias the ORs toward a value of one (42), indicating that the strength of associations between the predictors and outcomes in our study may be underestimated. Second, our study was conducted in a single acute care hospital in Japan, and its findings may not be generalizable to other hospitals. Our estimated rates of 30-day ACR and 30-day PAR were slightly lower than those of other acute care hospitals in Japan (5,43), which may be due to institutional variations in patient case-mix or discharge services. Moreover, our findings may not be directly generalizable to other countries due to inherent differences in health care systems. For example, the inclusion of postacute care services in Japanese acute care hospitals may contribute to the lower readmission rates when compared with U.S. hospitals. Stringent validation analyses are needed to test the performance of ACR and PAR prediction models in local patient populations before applying them to other hospitals or countries. Third, although recent Japanese studies have reported that HFRS is associated with mortality and complications at admission (24,25), its methodology and applicability have yet to be validated in the Japanese health care system. Further analyses are required to identify the optimal cutoff points of HFRS using multi-institutional Japanese data. Finally, the study period included the COVID-19 pandemic. Our sensitivity analysis showed that the full models using patients who were admitted after April 2020 had better discrimination than the main analysis. It has been reported that patient ADL on admission and at discharge generally decreased after the start of the COVID-19 pandemic (44). Therefore, ADL may have become a stronger predictor for early readmission during the COVID-19 period.

Supplementary Material

Supplementary data are available at *Innovation in Aging* online.

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Conflict of Interest

None declared.

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