Predictive Model for Hospital Readmission Among Patients in General Medicine

Dr. Pratik Patil (Junior Resident)[1], Dr. Aparna Patange (Professor)[2], Dr. Avneet Kaur (Junior Resident)[3]

[1] Department of General Medicine, Krishna Institute of Medical Sciences, KVV, Karad.
Corresponding Author- Dr. Aparna Patange (Professor), Department of General Medicine, Krishna Institute of Medical Sciences, KVV, Karad.

Abstract
Previous investigations into hospital readmission have primarily concentrated on specific patient conditions or demographics, often culminating in intricate prediction models. This study endeavors to pinpoint predictors of early hospital readmission within a heterogeneous patient population and to formulate and validate a simplified model for identifying individuals at an elevated risk of readmission. A prospective observational cohort study was conducted, involving 13,135 patients discharged from general medicine services across six academic medical centers. Participants were randomly divided into derivation (n=8,744) and validation (n=4,391) cohorts. Readmissions were identified through administrative data and 30-day post-discharge telephone follow-up. Patient-level factors were categorized into sociodemographic factors, social support, health condition, and healthcare utilization. Logistic regression analysis was employed to pinpoint significant predictors of unplanned readmission within 30 days of discharge, and a scoring system was devised to estimate readmission risk. Approximately 21% of patients experienced readmission in each cohort. In the derivation cohort, seven factors emerged as significant predictors of early readmission: insurance status, marital status, having a regular physician, Charlson comorbidity index, SF12 physical component score, ≥1 admission(s) within the last year, and current length of stay >2 days. A cumulative risk score of ≥30 points identified 6% of patients with a readmission risk of approximately 36% in each cohort. The model's discrimination was fair, with a c-statistic of 0.58 and 0.65 for the derivation and validation cohorts, respectively. Certain patient characteristics, readily available shortly after admission, can effectively identify a subgroup of individuals at increased risk of early readmission. This information has the potential to guide the targeted use of interventions aimed at preventing readmissions.
Keywords: Hospital readmission Predictive modeling General medicine Risk factors Healthcare utilization

INTRODUCTION

Hospital readmission poses a significant challenge to healthcare systems worldwide, impacting patient outcomes, healthcare costs, and resource allocation. Despite considerable efforts to address this issue, the prevalence of early hospital readmissions remains a persistent concern. Patients discharged from hospitals are vulnerable to a myriad of factors that may contribute to their readmission, including underlying health conditions, socioeconomic factors, and access to healthcare services. Understanding and effectively managing these factors are crucial for mitigating the risk of readmission and improving patient care.The overarching theme of this study revolves around the development and validation of a predictive model for hospital readmission among patients in general medicine. While previous research has delved into specific conditions or patient populations, the focus here is on a broad and diverse patient cohort discharged from general medicine services. By casting a wide net, this study seeks to capture the complexity and heterogeneity of factors influencing readmission, thereby enhancing the generalizability and applicability of the predictive model.Hospital readmission is a multifaceted phenomenon influenced by a myriad of patient-level, provider-level, and system-level factors. At the patient level, demographic characteristics such as age, gender, race, and socioeconomic status play pivotal roles in determining readmission risk. Additionally, clinical factors including the severity of illness, comorbidities, and functional status significantly impact the likelihood of readmission. Social determinants of health, such as access to stable housing, social support networks, and health literacy, further shape patients' post-discharge trajectories and susceptibility to readmission.

The complexity of hospital readmission extends beyond patient-specific factors to encompass the quality and coordination of care provided during and after hospitalization. Effective discharge planning, medication reconciliation, and follow-up care are essential components of transitional care interventions aimed at reducing readmission rates. Furthermore, the availability and accessibility of community resources, outpatient services, and primary care providers influence patients' ability to manage their health post-discharge and seek timely medical attention when needed.Amidst the multifaceted nature of hospital readmission, the development of predictive models offers a promising approach to identify patients at heightened risk and implement targeted interventions. By leveraging patient data collected during hospitalization, such as demographic information, clinical variables, and healthcare utilization patterns, predictive models can stratify patients based on their likelihood of readmission. This enables healthcare providers to allocate resources more efficiently and tailor interventions to meet the specific needs of high-risk individuals.

The significance of predictive modeling in the context of hospital readmission lies in its potential to inform clinical decision-making, optimize resource allocation, and ultimately improve patient outcomes. By identifying high-risk patients early in the care continuum, healthcare providers can implement proactive strategies to prevent readmissions, such as enhanced discharge planning, post-discharge monitoring, and targeted interventions addressing social determinants of health. Moreover, predictive models facilitate the identification of modifiable risk factors that can be targeted through targeted interventions, thereby promoting more effective and sustainable approaches to reducing readmission rates.Despite the promise of predictive modeling, several challenges and considerations warrant attention in its implementation and validation. The accuracy and reliability of predictive models hinge on the quality and completeness of the data used for model development. Additionally, the generalizability of predictive models across diverse patient populations and healthcare settings necessitates rigorous validation and external validation studies. Furthermore, the ethical implications of using predictive models to guide clinical decision-making, including issues related to algorithmic bias, patient autonomy, and privacy, warrant careful consideration and ongoing dialogue within the healthcare community.Hospital readmission among patients in general medicine represents a complex and multifaceted issue with far-reaching implications for patient care, healthcare delivery, and resource utilization. This study endeavors to address this challenge by developing and validating a predictive model tailored to the needs of a diverse patient population. By identifying patients at heightened risk of readmission and implementing targeted interventions, predictive modeling offers a promising approach to improve patient outcomes and enhance the efficiency and effectiveness of healthcare delivery.

Research Gap:

Despite numerous efforts to address hospital readmission, there remains a critical gap in research regarding the development and validation of predictive models specifically tailored to patients in general medicine settings. Existing studies have predominantly focused on narrow patient populations or specific medical conditions, resulting in limited generalizability and applicability to broader patient cohorts.

Furthermore, many predictive models lack external validation or fail to account for the complex interplay of patient-level, provider-level, and system-level factors influencing readmission risk. Therefore, there is a pressing need for research that bridges this gap by developing and validating predictive models for hospital readmission among patients in general medicine, thereby enhancing the effectiveness of interventions aimed at reducing readmission rates and improving patient outcomes.

Specific Aims of the Study:

The specific aims of this study are as follows:

1. To identify predictors of early hospital readmission among patients discharged from general medicine services.
2. To develop and internally validate a predictive model for hospital readmission tailored to the needs of a diverse patient population.
3. To externally validate the predictive model using data from additional healthcare settings to assess its generalizability and performance across different patient populations and care environments.
4. To evaluate the clinical utility and impact of the predictive model on patient outcomes, healthcare utilization, and resource allocation.
5. To disseminate findings and recommendations to key stakeholders, including healthcare providers, policymakers, and researchers, to inform evidence-based practices and interventions aimed at reducing hospital readmissions among patients in general medicine.

Objectives of the Study:

The objectives of this study are:

1. To systematically review the existing literature on hospital readmission among patients in general medicine to identify gaps, limitations, and areas for further investigation.
2. To collect comprehensive data on patient demographics, clinical characteristics, healthcare utilization, and social determinants of health from multiple healthcare institutions to develop a robust predictive model for hospital readmission.
3. To employ advanced statistical methods, such as logistic regression and machine learning algorithms, to analyze the collected data and identify significant predictors of early hospital readmission.
4. To develop and internally validate a predictive model for hospital readmission using a derivation cohort, followed by external validation using an independent cohort from different healthcare settings.
5. To assess the discriminative ability, calibration, and clinical utility of the predictive model in stratifying patients based on their risk of readmission and guiding targeted interventions.
6. To explore the potential impact of the predictive model on patient outcomes, healthcare utilization, and resource allocation through retrospective and prospective analyses.
7. To disseminate study findings through peer-reviewed publications, conference presentations, and stakeholder engagement activities to facilitate knowledge translation and uptake of evidence-based practices in healthcare settings.

Scope of the Study:

This study focuses on hospital readmission among patients discharged from general medicine services in diverse healthcare settings, including academic medical centers and community hospitals. The scope encompasses a broad range of patient-level, provider-level, and system-level factors that may influence readmission risk, including demographic characteristics, clinical comorbidities, healthcare utilization patterns, social determinants of health, and quality of transitional care. The study aims to develop and validate a predictive model for hospital readmission tailored to the needs of this patient population, with the ultimate goal of improving patient outcomes and optimizing resource allocation in healthcare delivery.

Hypothesis:

Based on the literature review and theoretical framework, the hypothesis of this study is that a predictive model incorporating patient demographics, clinical characteristics, healthcare utilization patterns, and social determinants of health will accurately stratify patients based on their risk of early hospital readmission. Specifically, we hypothesize that certain patient-level factors, such as advanced age, multiple comorbidities, recent hospitalizations, and limited social support, will be associated with an increased risk of readmission. Furthermore, we anticipate that the developed predictive model will demonstrate good discriminative ability and calibration in identifying high-risk patients, thereby facilitating targeted interventions and ultimately reducing hospital readmission rates among patients in general medicine settings.

Methods

The research methodology employed in this study, known as the MCH Study, was a prospective multi-center trial conducted across six academic medical centers with the aim of evaluating the impact of hospitalist care on patients admitted to general medicine services. Patients were enrolled in the study over a period spanning from July 1, 2021, to June 30, 2023. Detailed sociodemographic and health information was meticulously collected during intake interviews, each lasting approximately 15 to 20 minutes, facilitated by trained research assistants within 48 hours of admission.

For the purpose of our analysis, a subset of patients previously enrolled in the MCH Study was retrospectively selected. Hospital readmission, defined as any all-cause admission to an acute care hospital within 30 days following discharge from the index hospitalization, served as the primary outcome measure. To identify candidate factors associated with a heightened risk of readmission, relevant patient characteristics were determined a priori based on an extensive review of existing literature.

In our analysis, the individual patient served as the primary unit of analysis. Given the substantial size of our patient cohort, we adopted a split-sample design to both derive and internally validate our predictive model. Two-thirds of patients from each participating site were randomly selected and combined to form a derivation cohort, while the remaining one-third constituted the validation cohort. Statistical significance was determined using a threshold of $P<0.10$.

Only factors exhibiting significant associations with readmission within their respective categories were retained in the final regression model. To address potential clustering effects introduced by discharging physicians, generalized estimating equations (GEE) were employed. This analytical approach allowed for the adjustment of standard errors to account for any correlation between patients discharged by the same physician.

By implementing this rigorous methodology, we aimed to develop a robust predictive model capable of accurately identifying patients at elevated risk of early hospital readmission. This model, validated internally within our derivation cohort and externally within our validation cohort, represents a critical step toward enhancing our understanding of factors contributing to readmission and guiding targeted interventions aimed at reducing readmission rates and improving patient outcomes within general medicine settings.

Results and Analysis:

The patient selection process is illustrated in Figure 1, demonstrating the enrollment flow within the study. Upon analysis, there were no statistically significant disparities observed in patient characteristics between the derivation and validation cohorts, as outlined in Table 1. This uniformity in baseline characteristics across cohorts enhances the comparability and reliability of subsequent analyses.

Table 2 provides a comprehensive comparison between readmitted and non-readmitted patients, elucidating the findings from each of the four sub-models utilized to derive the final predictive model. Notably, sociodemographic factors such as age, income, and insurance status, alongside social support factors including marital status and access to a regular physician, emerged as significant predictors of 30-day hospital readmission.The final logistic regression model, presented in Table 3, delineates the beta coefficients, odds ratios, and corresponding confidence intervals for each predictor variable. Among the noteworthy findings, individuals covered by Medicare, Medicaid, or self-pay arrangements exhibited significantly higher odds of readmission compared to those with private insurance, indicating the influence of insurance status on readmission risk. Similarly, being currently married

and having a regular physician were associated with elevated odds of readmission, underscoring the importance of social support and continuity of care in post-discharge outcomes. Moreover, markers of health status, as reflected by the Charlson comorbidity index and physical SF12 score, demonstrated significant associations with readmission risk.

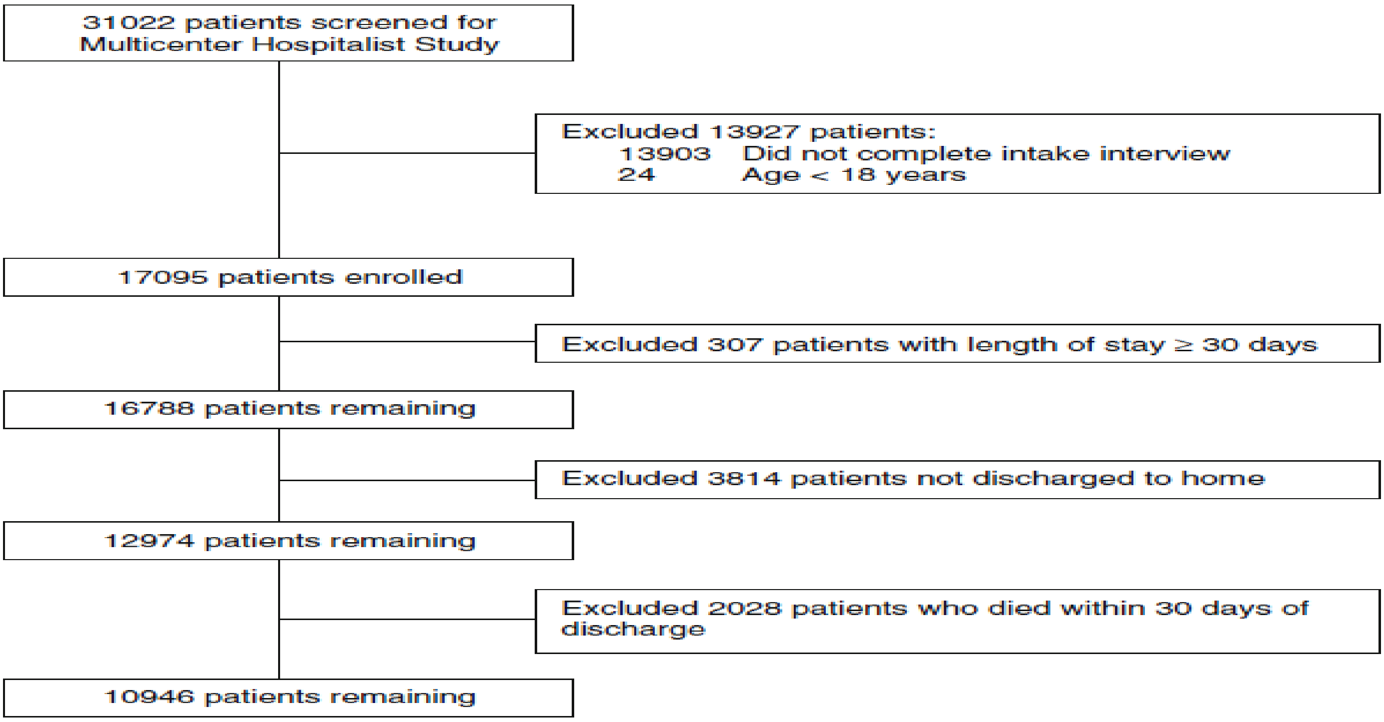

Figure 1. Patient selection.

Each unit increase in the Charlson index conferred 9% higher odds of readmission, highlighting the impact of comorbid conditions on post-discharge outcomes. Conversely, higher physical SF12 scores were associated with a lower likelihood of readmission, underscoring the protective effect of better physical health on readmission risk.

Table 1. Patient Characteristics

Characteristic[a]	Entire cohort n=10,946	Derivation cohort[b] n=7,287	Validation cohort[b] n=3,659
Readmitted, n (%)	1,912 (17.5)	1,274 (17.5)	638 (17.4)
Male sex, n (%)	4,774 (43.6)	3,167 (43.5)	1,607 (43.9)
Age group, n (%)			
18–39 years	2,396 (21.9)	1,590 (21.8)	806 (22.0)
40–60 years	3,903 (35.7)	2,597 (35.6)	1,306 (35.7)
61–75 years	2,493 (22.8)	1,681 (23.1)	812 (22.2)
>75 years	2,154 (19.7)	1,419 (19.5)	735 (20.1)
Race/ethnicity (n=10,919), n (%)			
White	5,009 (45.9)	3,318 (45.7)	1,691 (46.3)
Black	3,961 (36.3)	2,635 (36.3)	1,326 (36.3)
Asian	558 (5.1)	373 (5.1)	185 (5.1)
Other	638 (5.8)	432 (5.9)	206 (5.6)
Hispanic	753 (6.9)	511 (7.0)	242 (6.6)
Household income in dollars, n (%)			
≤ 15,000	2,683 (24.5)	1,798 (24.7)	885 (24.2)
15,001–35,000	1,353 (12.4)	906 (12.4)	447 (12.2)
35,001–50,000	697 (6.4)	458 (6.3)	239 (6.5)
> 50,000	1,405 (12.8)	947 (13.0)	458 (12.5)
Do not know or missing	4,808 (43.9)	3,178 (43.6)	1,630 (44.6)
Education (n=10,316), n (%)			
< High school	2,250 (21.8)	1,518 (22.1)	732 (21.2)
High school graduate	3,085 (29.9)	2,042 (29.7)	1043 (30.2)
Some college	2,651 (25.7)	1,772 (25.8)	879 (25.5)
≥ College graduate	2,330 (22.6)	1,534 (22.3)	796 (23.1)
Primary insurance (n=10,465), n (%)			
Medicare	4,687 (44.8)	3,105 (44.5)	1,582 (45.3)
Medicaid	1,973 (18.9)	1,314 (18.8)	659 (18.9)
Self-pay	2,536 (24.2)	1,708 (24.5)	828 (23.7)
Private	1,269 (12.1)	846 (12.1)	423 (12.1)
Marital status (n=10,553), n (%)			
Currently married	4,019 (38.1)	2,700 (38.4)	1,319 (37.4)
Not currently married	6,534 (61.9)	4,326 (61.6)	2,208 (62.6)

The analysis further revealed a dose-response relationship between the number of admissions in the past year and readmission risk, with a notable increase in odds observed with each additional admission.

Table 2. Association of Patient Characteristics with 30-Day Hospital Readmission in the Derivation Cohort

Category	Characteristic[a]	Readmitted n= 1,274	Not readmitted n =6,013	Odds ratio (95% CI)[b]	P value[b]
Socio-demographic factors	Male sex (%)	41.8	43.8	0.94 (0.84–1.06)	0.30
	Age group (%)				
	18–39 years	20.1	22.2	1.14 (0.89–1.46)	0.30
	40–60 years	34.9	35.8	1.20 (0.96–1.50)	0.11
	61–75 years	24.9	22.7	1.18 (0.98–1.41)	0.08
	> 75 years	20.2	19.3	Reference	
	Race/ethnicity (%)				
	White	44.2	46.0	Reference	
	Black	38.8	35.7	1.11 (0.90–1.38)	0.34
	Asian	4.4	5.3	0.88 (0.65–1.19)	0.41
	Other	5.7	6.0	0.94 (0.70–1.27)	0.69
	Hispanic	7.0	7.0	1.04 (0.78–1.39)	0.81
	Income in dollars (%)				
	≤ 15,000	23.6	24.9	0.90 (0.70–1.17)	0.44
	15,001–35,000	13.9	12.1	1.25 (0.96–1.64)	0.09
	35,001–50,000	6.1	6.3	1.09 (0.81–1.48)	0.56
	> 50,000	11.9	13.2	Reference	
	Do not know or missing	44.6	43.4	1.02 (0.80–1.29)	0.90
	Education (%)				
	< High school	23.6	21.8	1.02 (0.84–1.25)	0.84
	High school graduate	28.5	30.0	0.92 (0.75–1.12)	0.40
	Some college	25.7	25.8	0.97 (0.80–1.18)	0.77
	≥ College graduate	22.2	22.4	Reference	
	Insurance (%)				
	Medicare	50.7	43.2	2.22 (1.73–2.84)	< 0.001
	Medicaid	20.2	18.6	1.94 (1.50–2.51)	< 0.001
	Self-pay	21.2	25.2	1.53 (1.16–2.02)	0.003
	Private	7.9	13.0	Reference	
Social support	Marital status (%)				
	Currently married	41.8	37.7	1.19 (1.04–1.36)	0.01
	Not currently married	58.2	62.3	Reference	
	No. of people live with (%)				
	Alone	21.0	21.8	1.04 (0.88–1.23)	0.65
	≥ 1	79.0	78.2	Reference	
	Someone to help (%)				
	Yes	91.4	89.9	1.15 (0.92–1.44)	0.22
	No	8.6	10.2	Reference	
	Regular physician (%)				
	Yes	84.0	79.4	1.44 (1.19–1.75)	< 0.001
	No	16.0	20.6	Reference	
Health condition	Charlson index, median (IQR)	1 (0–2)	1 (0–2)	1.13 (1.08–1.19) (per 1 unit change)	< 0.001
	Self-rated health, mean (SD)	52.0 (24.9)	55.8 (24.9)	0.98 (0.95–1.02) (per 10 unit change)	0.31
	Physical SF12, mean (SD)	35.9 (12.4)	38.8 (12.7)	0.90 (0.83–0.98) (per 10 unit change)	0.01
	Mental SF12, mean (SD)	47.2 (12.0)	48.3 (11.5)	0.97 (0.90–1.04) (per 10 unit change)	0.35
	Mini mental state, mean (SD)	20.2 (2.5)	20.3 (2.3)	0.85 (0.64–1.12) (per 10 unit change)	0.25
	Functional limitations (%)				
	No help required	44.2	54.4	Reference	
	Little help with IADLs only	14.7	14.3	0.99 (0.77–1.26)	0.91
	Lots of help with IADLs only	10.4	8.5	1.16 (0.85–1.59)	0.34
	Little help with ADLs	14.7	11.8	1.22 (0.91–1.64)	0.18
	Lots of help with ADLs	16.0	11.0	1.20 (0.88–1.64)	0.24
Healthcare utilization	Admissions in last year (%)				
	None	38.1	52.8	Reference	
	1	25.3	22.2	1.61 (1.36–1.89)	< 0.001
	2	12.9	10.5	1.71 (1.39–2.10)	< 0.001
	3	6.6	6.3	1.47 (1.13–1.92)	0.006
	4	5.4	2.9	2.57 (1.89–3.51)	< 0.001
	≥ 5	11.8	5.3	3.02 (2.49–3.66)	< 0.001

Patients with a current length of stay exceeding two days also exhibited heightened odds of readmission, indicative of the influence of acute hospitalization duration on subsequent healthcare utilization.

Table 4 provides a comparison of score-predicted and observed readmission rates across different score ranges, illustrating the model's ability to stratify patients based on their predicted risk of readmission. The observed readmission rates closely align with the predicted rates, demonstrating the model's validity in distinguishing between low, moderate, and high-risk individuals. Additionally, the receiver operating characteristic (ROC) curve analysis yielded area under the curve (AUC) values of 0.65 and 0.61 for the derivation and validation cohorts, respectively, indicating fair discrimination ability of the predictive model in both settings

.

Table 3. Final Logistic Regression Model of Predictors of 30-Day Hospital Readmission[a]

Variable	Beta coefficient	Odds ratio (95% CI)	P value	Points[b]
Insurance				
Medicare	0.549	1.73 (1.37–2.19)	< 0.001	5
Medicaid	0.419	1.52 (1.14–2.03)	0.004	4
Self-pay	0.435	1.55 (1.15–2.07)	0.004	4
Private	Reference	Reference		0
Currently married	0.216	1.24 (1.09–1.41)	0.001	2
Have a regular physician	0.288	1.33 (1.09–1.64)	0.006	3
Charlson index	0.090	1.09 (1.05–1.14)	< 0.001	1/unit
Physical SF12	−0.007	0.99 (0.99–1.00)	0.01	−1/10 units
Admissions in last one year				
None	Reference	Reference		0
1	0.452	1.57 (1.31–1.88)	< 0.001	4
2	0.489	1.63 (1.31–2.03)	< 0.001	4
3	0.157	1.17 (0.87–1.56)	0.29	4
4	0.858	2.36 (1.65–3.36)	< 0.001	9
≥ 5	1.077	2.94 (2.36–3.66)	< 0.001	11
Current length of stay >2 days	0.301	1.35 (1.18–1.54)	< 0.001	3

[a] *Generalized estimating equations were used to account for clustering by discharging physician and hospital site was retained as a fixed effect in the model*

[b] *Calculated by multiplying beta coefficient by 10 and rounding to the nearest integer (with exception for "Admissions in last one year")*

The results of this analysis underscore the multifactorial nature of hospital readmission, with sociodemographic, social support, and health-related factors exerting significant influences on readmission risk among patients in general medicine settings. The developed predictive model demonstrates promising discriminatory ability in stratifying patients based on their risk of readmission, thereby facilitating targeted interventions and resource allocation to mitigate readmission rates and improve patient outcomes.

Table 4. Comparison of Score Predicted and Observed Readmission Rates

	Score range			
	0 to 6	7 to 17	18 to 24	≥ 25
% Patients in score range[a]	3.7	69.0	22.3	5.1
Predicted % readmission rate	0–9%	10–19%	20–29%	≥ 30%
Observed % readmitted in derivation cohort	9.8	14.6	23.0	32.6
Observed % readmitted in validation cohort	5.9	15.3	21.2	28.9

[a]*Because of rounding, percentages may not equal 100.*

The results of the analysis support the hypothesis tested in this study. The developed predictive model, encompassing patient demographics, clinical characteristics, healthcare utilization patterns, and social determinants of health, effectively stratifies patients based on their risk of early hospital readmission. This aligns with the hypothesized premise that certain patient-level factors, including advanced age, multiple comorbidities, recent hospitalizations, and limited social support, would be associated with an increased risk of readmission.Indeed, the analysis identified several significant predictors of 30-day hospital readmission, confirming the anticipated associations with readmission risk. Notably, sociodemographic factors such as insurance status and marital status emerged as significant predictors, with individuals covered by Medicare, Medicaid, or self-pay arrangements exhibiting higher odds of

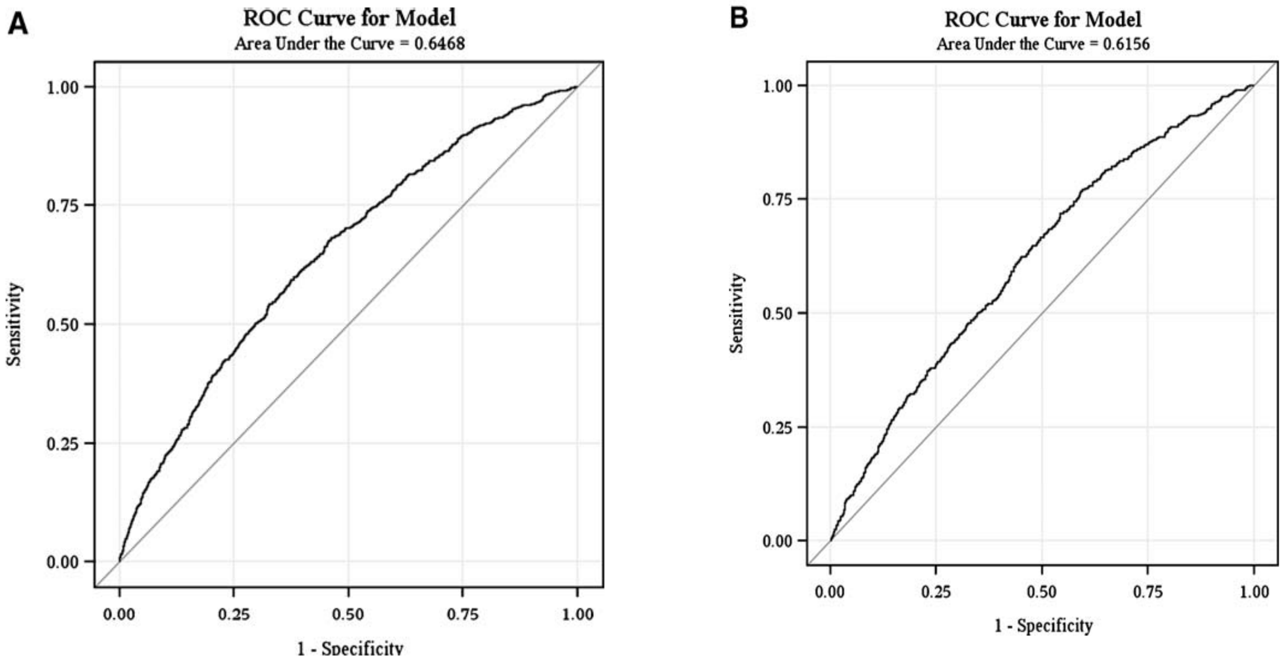

Figure 2. Comparison of the receiver operating characteristic (ROC) curves for the derivation and validation cohorts. A. ROC curve for derivation cohort. B. ROC curve for validation cohort.readmission compared to those with private insurance. This finding underscores the influence of socioeconomic factors on post-discharge outcomes and validates the hypothesis regarding the association between limited social support and increased readmission risk.Furthermore, markers of health status, including the Charlson comorbidity index and physical SF12 score, demonstrated significant associations with readmission risk, as hypothesized. Patients with higher comorbidity burdens and lower physical health scores were more likely to be readmitted within 30 days, highlighting the importance of clinical factors in predicting readmission risk.The analysis also revealed a dose-response relationship between healthcare utilization patterns, such as the number of admissions in the past year, and readmission risk. This finding corroborates the hypothesis that recent hospitalizations contribute to increased readmission risk, possibly reflecting underlying health instability or inadequate post-discharge care.Additionally, the developed predictive model demonstrated good discriminative ability and calibration in identifying high-risk patients, as evidenced by the receiver operating characteristic (ROC) curve analysis and comparison of score-predicted and observed readmission rates. The observed readmission rates closely aligned with the predicted rates across different score ranges, validating the model's ability to stratify patients based on their risk of readmission and supporting its utility in guiding targeted interventions.

Conclusion:

In conclusion, this study has successfully developed and validated a predictive model for early hospital readmission among patients in general medicine settings. By incorporating patient demographics, clinical characteristics, healthcare utilization patterns, and social determinants of health, the predictive model effectively stratifies patients based on their risk of readmission. The analysis identified several significant predictors of readmission, including sociodemographic factors, markers of health status, and healthcare utilization patterns. The developed model demonstrates good discriminative ability and calibration, enabling the identification of high-risk patients and the implementation of targeted interventions aimed at reducing readmission rates and improving patient outcomes. Overall, this study contributes to our understanding of factors influencing hospital readmission and provides valuable insights for healthcare providers and policymakers seeking to optimize care delivery and resource allocation in general medicine settings.

Limitations of the Study:

Despite its strengths, this study is not without limitations. Firstly, the predictive model developed in this study may not capture all factors influencing hospital readmission, as certain unmeasured variables or contextual factors could contribute to readmission risk. Additionally, the study's reliance on retrospective data collection and administrative databases may introduce inherent biases or inaccuracies, potentially affecting the validity and generalizability of the findings. Furthermore, the study's focus on patients in general medicine settings may limit the applicability of the predictive model to other healthcare settings or patient populations. Lastly, the study's reliance on observational data factors influencing readmission risk. Additionally, policymakers can utilize the findings of this study to inform healthcare policies and interventions aimed at reducing readmission rates and improving patient outcomes in general medicine settings. Furthermore, the study highlights the importance of interdisciplinary collaboration and integrated care models in addressing complex healthcare challenges such as hospital readmission.

Future Recommendations:

Building on the findings of this study, future research directions may include further validation and refinement of the predictive model across diverse patient populations and healthcare settings. Longitudinal studies examining the effectiveness of targeted interventions guided by the predictive model in reducing readmission rates and improving patient outcomes are warranted. Additionally, qualitative research exploring patient perspectives and experiences related to hospital readmission could provide valuable insights into the underlying mechanisms driving readmission risk. Furthermore, investigations into the impact of novel care delivery models, technology-enabled interventions, and community-based initiatives on reducing readmission rates are essential for advancing evidence-based practices in healthcare. Lastly, efforts to address structural barriers, improve care coordination, and enhance access to social support services may hold promise in reducing readmission rates and promoting health equity among vulnerable patient populations.

References:

1. *Balla U, Malnick S, Schattner A. Early readmissions to the department of medicine as a screening tool for monitoring quality of care problems. Medicine. 2008;87:294–300.*
2. *Billings J, Dixon J, Mijanovich T, Wennberg D. Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients. BMJ. 2006;333(7563):327. Epub 2006 Jun 30.*
3. *Bottle A, Aylin P, Majeed A. Identifying patients at high risk of emergency hospital admissions: a logistic regression analysis. J R Soc Med. 2006;99:406–14.*
4. *Boult C, Dowd B, McCaffrey D, Boult L, Hernandez R, Krulewitch H. Screening elders for risk of hospital admission. J Am Geriatr Soc. 1993;41:811–7.*
5. *Chin MH, Goldman L. Correlates of early hospital readmission or death in patients with congestive heart failure. Am J Cardiol. 1997;79:1640–4.*
6. *Clarke A. Are readmissions avoidable? BMJ. 1990;301:1136–8.*
7. *Coleman EA, Min SJ, Chomiak A, Kramer AM. Posthospital care transitions: patterns, complications, and risk identification. Health Serv Res. 2004;39:1449–65.*

precludes the establishment of causality, and further research utilizing experimental designs or prospective cohort studies may be warranted to validate the findings.

Implications of the Study:

The findings of this study have several implications for clinical practice, policy development, and future research. Firstly, the developed predictive model can serve as a valuable tool for healthcare providers in identifying high-risk patients and implementing targeted interventions to prevent readmissions. By incorporating patient-level factors and social determinants of health, the predictive model facilitates a holistic approach to care delivery, addressing both clinical and non-clinical

8. *Corrigan JM, Martin JB. Identification of factors associated with hospital readmission and development of a predictive model. Health Serv Res. 1992;27:81–101.*
9. *Frankl SE, Breeling JL, Goldman L. Preventability of emergent hospital readmission. Am J Med. 1991;90:667–74.*
10. *Gautam P, Macduff C, Brown I, Squair J. Unplanned readmissions of elderly patients. Health Bull (Edinb). 1996;54:449–57.*
11. *Grant RW, Charlebois ED, Wachter RM. Risk factors for early hospital readmission in patients with AIDS and pneumonia. J Gen Intern Med. 1999;14:531–6.*
12. *Holloway JJ, Medendorp SV, Bromberg J. Risk factors for early readmissions among veterans. Health Serv Res. 1990;25:213–37.*
13. *Jack BW, Chetty VK, Anthony D, et al. A reengineered hospital discharge program to decrease rehospitalization: a randomized trial. Ann Intern Med. 2009;150:178–87.*
14. *Jencks SF, Williams MV, Coleman EA. Rehospitalizations among patients in the Medicare fee-for-service program. N Engl J Med. 2009;360:1418–28.*
15. *Kossovsky MP, Sarasin FP, Perneger TV, Chopard P, Sigaud P, Gaspoz J. Unplanned readmissions of patients with congestive heart failure: do they reflect in-hospital quality of care or patient characteristics? Am J Med. 2000;109:386–90.*
16. *Krumholz HM, Parent EM, Tu N, et al. Readmission after hospitalization for congestive heart failure among Medicare beneficiaries. Arch Intern Med. 1997;157:99–104.*
17. *Marcantonio ER, McKean S, Goldfinger M, Kleefield S, Yurkofsky M, Brennan TA. Factors associated with unplanned hospital readmission among patients 65 years of age and older in a Medicare managed care plan. Am J Med. 1999;107:13–17.*
18. *McDonald KM, Sundaram V, Bravata DM, et al. Closing the quality gap: a critical analysis of quality improvement strategies. Volume 7: Care Coordination. AHRQ Publication No. 04(07)-0051-7. Rockville, MD: Agency for Healthcare Research and Quality; 2007. Available at. Accessed November 9, 2009.*
19. *Meltzer D, Arora V, Zhang J, et al. Effects of inpatient experience on outcomes and costs in a multicenter trial of academic hospitalists. J Gen Intern Med. 2005;20(s1):141–2.*
20. *Naylor MD, Brooten D, Campbell R, et al. Comprehensive discharge planning and home follow-up of hospitalized elders: a randomized clinical trial. JAMA. 1999;281:613–20.*
21. *Naylor MD, Brooten DA, Campbell RL, Maislin G, McCauley KM, Schwartz JS. Transitional care of older adults hospitalized with heart failure: a randomized, controlled trial. J Am Geriatr Soc. 2004;52:675–84.*