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Lace Index: Predict the High-Risk of 30-Days Readmission of Patients With Acute Myocardial Infarction: National Health Insurance Claims Data 2011–2020

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ABSTRACT

Background: Readmission following acute myocardial infarction (AMI) poses significant challenges to health systems and patient outcomes. The LACE index, a composite of Length of stay, Acuity of admission, Comorbidities, and Emergency department visits, is widely used for readmission prediction. However, its performance in large-scale, real-world Korean cohorts remains understudied.

Objective: This study aimed to validate the predictive performance of the LACE index for 30-day readmissions in AMI patients using a nationally representative Korean cohort.

Methods: This retrospective cohort study analyzed data from the Korean National Health Insurance Service Sample (NHISS) database from 2011 to 2020. A total of 609,640 adult patients hospitalized for AMI were included. The LACE index was calculated for each patient, and 30-day readmissions were identified. Logistic regression was used to estimate odds ratios (ORs) for readmission. Model discrimination was assessed using ROC curve analysis and C-statistics. Subgroup and survival analyses were performed by age, LACE score, and comorbidity burden.

Results: Among 609,640 AMI patients, 205 (0.034%) experienced 30-day readmission. Patients with a LACE score of ≥ 10 had significantly higher odds of readmission (OR = 2.65; 95% CI: 1.68–4.19, $p < 0.001$) compared to those with scores 0–4. Middle-aged adults (35–64 years) also showed elevated readmission risk (OR = 3.42; 95% CI: 1.74–6.73, $p < 0.001$), while older adults (≥ 65 years) did not have significantly different risk. The LACE index showed moderate discriminatory performance (C-statistics = 0.71). Kaplan–Meier survival curves demonstrated significantly lower 30-day survival among patients with LACE ≥ 10.

Conclusions: Study findings suggest the LACE index is a useful tool for predicting 30-day readmissions among AMI patients in Korea. Its simplicity and moderate accuracy support its application in clinical and policy-level risk stratification strategies. Future prospective studies should refine prediction models by incorporating additional clinical variables.

Abbreviations: AMI, acute myocardial infarction; AUC, area under the curve; BUN, blood urea Nitrogen; CCI, Charlson Comorbidity Index; CI, confidence interval; DBP, diastolic blood pressure; ER, emergency room; GFR, Glomerular filtration rate; HDL, high-density lipoprotein; ICD-10, International Classification of Diseases, 10th Revision; LDL, low-density lipoprotein; NHI, National Health Insurance; NHISS, National Health Insurance Service Sample; OR, odds Ratio; Ref, reference category; ROC, receiver operating characteristic; SBP, systolic blood pressure; SD, standard deviation; WBC, white blood cell count.

1 | Introduction

Hospital readmissions within 30 days of discharge are widely recognized as a key indicator of healthcare quality and health system efficiency [1]. These unplanned readmissions impose substantial financial burdens and often indicate failures in transitional care, chronic disease management, or discharge planning [2]. Reducing preventable readmissions is thus a critical objective for clinicians, health systems, and policymakers worldwide.

Acute myocardial infarction (AMI) is *a major* contributor to hospital readmissions, particularly among aging populations with multiple comorbidities [3, 4]. Globally, AMI accounts for over seven million deaths annually and remains a significant public health concern [5]. In South Korea, this burden is exacerbated by demographic aging and rising cardiovascular risk profiles [6, 7]. National data indicate a growing incidence of AMI and related hospitalizations, leading to increased resource use, longer lengths of stay, and high 30-day readmission rates [8–10].

To improve care planning and allocate post-discharge resources efficiently, predictive tools have been developed to identify patients at high risk of readmission [11, 12]. Among these, the LACE Index based on Length of stay (L), Acuity of admission (A), Charlson comorbidity index (C), and Emergency department visits within 6 months before admission (E) is widely used due to its simplicity, accessibility through administrative data, and applicability across clinical contexts [13]. The LACE Index assigns a score from 0 to 19, with scores ≥ 10 indicating elevated readmission risk. Its ease of use has supported its integration into hospital workflows for risk stratification and discharge planning.

Previous studies, including systematic reviews and meta-analyses, have validated the LACE Index across general medical, surgical, and cardiac cohorts, demonstrating moderate predictive performance [14–21]. To assess its relevance in the Korean context, we first conducted a systematic review to examine the LACE Index's prediction ability of hospital readmission [22]. Following this, we applied the index to electronic medical records from a university-affiliated tertiary hospital to conduct preliminary validation among AMI patients [23]. These initial findings provided foundational evidence for broader population-level investigation.

This study aims to evaluate the predictive performance of the LACE Index in identifying patients at risk for 30-day hospital readmissions following an index hospitalization for AMI, using the National Health Insurance Service Sample (NHISS) claims data from 2011 to 2020. By validating LACE Index in a real-world, nationally representative data set, this study contributes evidence to support clinical decision-making, improve risk-based care planning, and inform health policy efforts to reduce preventable readmissions in South Korea.

2 | Methods and Materials

2.1 | Study Design, Setting and Participants

A retrospective cohort study used data from the National Health Insurance Service scheme (NHISS) claims cohort database in Korea between 2011 and 2020. The NHISS is a nationally representative sample of Korean inpatients and contains information required for reimbursement, including demographic characteristics (age, sex, disability status, and monthly insurance premiums, which serve as a proxy for household income) and diagnostic codes. Patient-specific information included the primary admission diagnosis, length of hospital stay, type of admission, presence of comorbidities, and frequency of emergency department visits. We analyzed 609,640 patients aged ≥ 19 years who were hospitalized with acute myocardial infarction (AMI) during the study period. AMI cases were identified using the NHISS database, defined as hospitalizations with AMI recorded as the principal diagnosis and confirmed with International Classification of Diseases, 10th Revision (ICD-10) codes I20–I25. Patients who were transferred to other hospitals or who were not admitted directly through the emergency department were excluded.

This study was approved by the Institutional Review Board of Yonsei University (IRB No. 2021-3670-002). The requirement for informed consent was waived, as all data were deidentified in accordance with national guidelines to protect patient confidentiality.

2.2 | Outcome Variables

The primary outcome of this study was hospital readmission within 30 days of discharge among patients hospitalized with AMI as the index diagnosis. The LACE index score was calculated for each patient and included four components: length of stay (L), acuity of admission (A), comorbidities (C), and emergency department visits within the past 6 months (E), following methods reported in previous studies (van Walraven et al., 2010; Desai et al., 2019). The length of stay was defined as the number of days between hospital admission and discharge. Acuity was determined by whether the patient was admitted via the emergency department. Comorbidity was measured using the Charlson Comorbidity Index (CCI), based on ICD-10 codes. Emergency visits were counted over the 6 months before admission, with multiple visits occurring within a 24-h period considered as one.

2.3 | Covariates

Covariates included demographic and clinical characteristics such as patient age, sex, region of residence, type of health insurance (e.g., National Health Insurance, Medicare, or others), and type of hospital admission (emergency, outpatient, or transfer from another hospital). Discharge information included status (Regular, against medical advice, or deceased) and destination (home, transfer, or death). Additional clinical variables retrieved from the hospital electronic medical records (EMR) included length of stay, comorbidities by ICD-10 codes, treatment specialty, and primary diagnosis. Readmission within 30 days was tracked by linking patient discharge and subsequent admission records and confirmed through manual chart review to ensure data validity.

2.4 | Data Analysis

Data analysis was conducted in three stages. First, normality testing showed that continuous variables were not normally distributed. Therefore, these variables were summarized as medians with interquartile ranges (IQRs), and group comparisons were performed using the non-parametric Mann–Whitney U test. Categorical variables were summarized as frequencies and percentages, and comparisons between the readmission and non-readmission groups were conducted using chi-square (χ^2) tests. Second, binary logistic regression was used to identify factors associated with 30-day readmissions, with results presented as odds ratios (ORs) and 95% confidence intervals (CIs). Additionally, linear regression analyses were conducted on all clinical variables to examine their associations with 30-day readmission. Third, to evaluate the predictive ability of the LACE index, we generated receiver operating characteristic (ROC) curves and calculated the area under the curve (AUC or C-statistic), where a value of 0.5 indicates no discrimination and 1.0 indicates perfect discrimination. Sensitivity and specificity analyses were conducted to determine the optimal cutoff for the LACE score. Subgroup analyses were also performed to compare prediction accuracy and Calibration plot was generated to assess agreement between predicted and observed probabilities of readmission across 30-day readmission. All analyses were conducted using SAS version 9.4 (SAS Institute Inc., Cary, NC, USA), and a two-sided p-value of less than 0.05 was considered statistically significant.

3 | Results

This study validates the predictive power of the LACE index to identify the AMI patients at high risk for 30-days readmission using nationwide cohort data. The annual 30-day readmission rate for AMI patients fluctuated above 10% between 2011 and 2014, followed by a gradual decline from 12.4% in 2015% to 8.1% in 2019. A dramatic reduction to 5.5% in 2020 is predicted due to the COVID-19 pandemic's influence on healthcare utilization and readmission patterns. (Supplementary Figure 1).

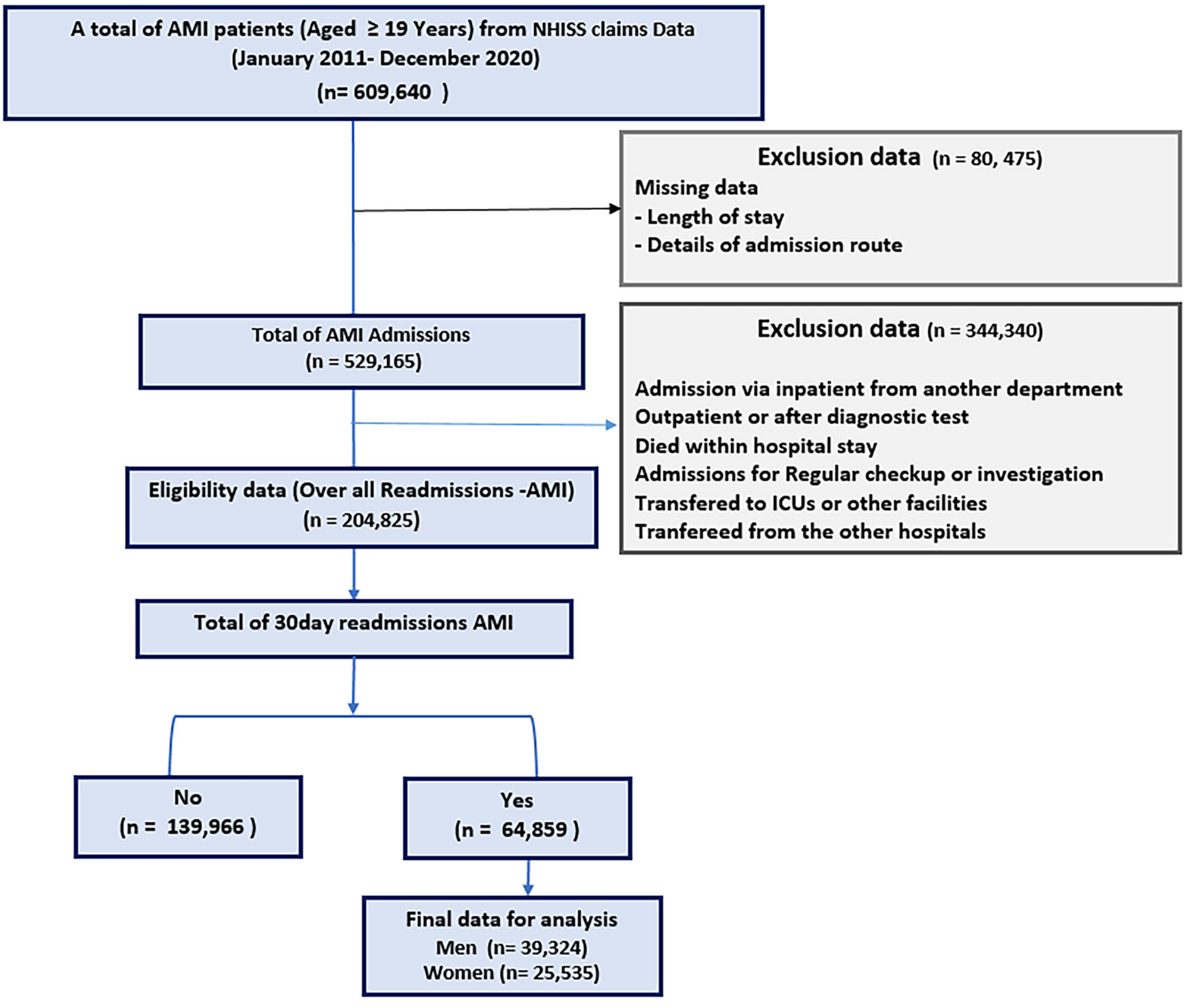

FIGURE 1 | Flowchart for selection of the study population.

TABLE 1 | Comparation of general characteristics for all the AMI patients with or without 30-days readmission.

Variables	Characteristics	30-days Readmission (2011–2020)						
		Total		Yes		No		
		N	%	*N*	%	*N*	%	*p*[a]
		204,825		54,859	26.8	149,966	73.2	
LACE index Score	0–4	39,631	19.3	9621	22.3	30,010	77.7	< 0.001
	5–9	64,580	31.5	15,958	24.7	48,622	75.3	
	≥ 10	100,614	49.1	29,280	29.1	71,334	70.9	
Age (years)	19–44	38,904	19.0	9621	24.7	29,283	75.3	0.021
	45–64	69,538	33.9	15,958	22.9	53,580	77.1	
	≥ 65	96,383	47.1	29,280	30.4	67,103	69.6	
Sex	Female	98,313	48.0	26,689	27.8	71,624	63.2	0.008
	Male	106,512	52.0	49,059	36.6	67,453	71.4	
Health insurance	NHI	125,276	61.2	35,159	28.1	90,117	71.9	< 0.001
	Medicare	66,673	32.6	17,412	26.1	49,261	73.9	
	Others	12876	6.3	2288	17.8	10,588	82.2	
Residence (areas)	Seoul and capital cities	138,596	67.7	41,598	30.0	96,998	67.6	< 0.001
	Other Cities	53,676	26.2	9497	26.7	44,179	73.3	
	Rural	12,553	6.1	3764	22.0	8789	78.0	
Length of stay	≥ 2	56,289	27.5	10,656	45.4	45,633	54.6	0.043
	3	61,461	30.0	13,526	55.0	47,935	45.0	
	4	29,489	14.4	11,510	39.0	17,979	61.0	
	5	33,879	16.5	7853	23.2	26,026	76.8	
	6	14,813	7.2	6423	43.4	8390	56.6	
	≥ 7	8,894	4.3	4891	22.0	4003	78.0	
Admission route	ER	109,612	53.5	38,589	35.2	71,023	64.8	0.017
	OP	88,424	43.2	16,624	18.8	71,800	81.2	
	Transfer from other hospital	6789	3.3	2146	31.6	4643	68.4	
Comorbidities (CCI)[a]	1	56,336	27.5	12,589	22.3	43,747	77.7	< 0.001
	2	64,234	31.4	13,325	20.7	50,909	79.3	
	≥ 3	84,255	41.1	28,945	34.4	55,310	65.6	
Emergency visits (past 6 months)	Yes	150,896	73.7	38,521	36.8	112,375	63.2	< 0.001
	No	53,929	26.3	16,338	25.5	37,591	74.5	
Discharge destination	Normal	150,961	73.7	37,865	25.1	113,096	74.9	0.029
	Others[b]	53,864	26.3	16,994	31.5	36,870	68.5	
Laboratory findings (M ± SD)	SBP (mmHg)			159.0 ± 26.1		125.1(15.6)		0.091
	DBP (mmHg)			87.1 ± 16.3		87.6 ± 15.4		
	Haemoglobin			10.4 ± 1.9		14.1 ± 1.7		< 0.001
	White blood cell, ×103/UL			5.8 (3.0)		3.6 (1.1)		0.441
	Platelet, $\times 10^3$/μL			231.5 ± 68.6		238.3 ± 66.1		0.418
	Total cholesterol, mg/dl			188.6 ± 48.4		191.8 ± 46.5		0.604
	Triglyceride, mg/dl			166.4 ± 131.4		141.2 ± 127.2		0.305
	HDL mg/dl			48.1 ± 11.6		49.3 ± 12.2		0.189
	LDL mg/dl			113.0 ± 42.6		109.4 ± 40.6		0.389
	Creatinine, mg/dL			0.8 ± 0.4		0.9 ± 0.3		0.541

(Continues)

TABLE 1 | (Continued)

		30-days Readmission (2011–2020)						
		Total		Yes		No		
Variables	Characteristics	*N*	%	*N*	%	*N*	%	p[a]
	Potassium, mmol/L			4.04 (3.2)		3.9 (0.5)		0.842
	Sodium, mmol/L			139.5 (4.1)		137.2 (4.5)		0.391
	Blood urea nitrogen, mg/dl			17.7 ± 7.6		16.4 ± 5.4		0.177
	Estimated GFR (mL/min/m2)			41 (28)		39 (25.8)		0.411

Abbreviations: GFR, Glomerular filtration rate; HDL, high-density lipoprotein; CCI, Charlson Comorbidity Index; LDL, low-density lipoprotein.
[a]Chi-square; M, Mean; SD, Standard deviation; NHI, National health insurance;
[b]Home with support services, Transfer to long-term care/other institution, Left against medical advice.

Figure 1 illustrates the selection flow of AMI patients aged ≥ 19 years from NHISS claims data between January 2011 and December 2020. Out of 609,640 initial cases, exclusions were made for missing data ($n = 80{,}475$) and clinical criteria ($n = 344{,}340$), resulting in 204,825 eligible AMI readmissions. Of these, 54,859 cases were identified as 30-day readmissions, with the final analysis including 39,324 men and 25,535 women.

Table 1 provides a comparison of the demographic, clinical, and hospitalization characteristics of AMI patients who were readmitted within 30 days and those who were not, utilizing data from the NHISS claims database ($n = 204{,}825$). Of these, 26.8% were readmitted within 30 days. Higher LACE index scores predicted readmission, with 29.1% readmission in the ≥ 10 score group and 22.3% in the 0–4 score group ($p < 0.001$). Men had slightly higher readmission rates (36.6%) than women (27.8%) ($p = 0.008$), with older persons aged ≥ 65 years having the highest rate (30.4%). Health insurance type was also linked to different outcomes, with "Others" having the lowest readmission (17.8%) and employment-based coverage having the highest (28.1%) ($p < 0.001$), and geographic area having the highest (30.0%) readmission in Seoul and metropolitan areas compared to rural areas (22.0%) ($p < 0.001$).

The 30-day readmission rate was significantly influenced by the length of hospital stay, with a 3-day stay resulting in the highest readmission rate (55.0%) ($p = 0.043$), and the admission route, notably those admitted via the emergency room (35.2%) ($p = 0.017$). Patients with ≥ 3 comorbidities had a 34.4% readmission risk ($p < 0.001$), indicating a significant association between comorbidities as determined by the Charlson Comorbidity Index (CCI). A further major predictor was a previous emergency visit during the previous 6 months (36.8% vs. 25.5%, $p < 0.001$). Patients who were transferred to other facilities had a 31.5% readmission rate, compared to 25.1% for those who were released regularly ($p = 0.029$). Other lab results, like WBC count, platelets, creatinine, and cholesterol, did not show significant differences. Only hemoglobin did, with lower amounts linked to readmissions ($p < 0.001$).

Table 2 presents the odds ratios (ORs) derived from binary logistic regression model analysis identifying factors associated with 30-day hospital readmissionin AMI Patients. Patients with a LACE index score of 5–9 had significantly higher odds of 30-day readmission compared with those scoring 0–4 (aOR: 1.82; 95% CI: 1.15–2.88; $p = 0.011$). The risk was even greater for patients with scores ≥ 10 (aOR: 2.65; 95% CI: 1.68–4.19; $p < 0.001$). Middle-aged adults (35–64 years) were also at elevated risk (aOR: 3.42; 95% CI: 1.74–6.73; $p < 0.001$), whereas no significant association was observed among those aged ≥ 65 years (aOR: 0.89; 95% CI: 0.61–1.31; $p = 0.55$). Patients residing in metropolitan cities other than Seoul had reduced odds of readmission compared with those in Seoul/metropolitan areas (aOR: 0.63; 95% CI: 0.41–0.97; $p = 0.03$). No significant associations were identified for sex, health insurance status, length of stay, or admission route. Likewise, comorbidity burden (CCI ≥ 3: aOR: 1.11; 95% CI: 0.69–1.79; $p = 0.68$) and emergency transfers were not independently predictive.

Figure 2 illustrates the results of multiple linear regression analyses examining the association between laboratory parameters and the probability of 30-day readmission among AMI patients. Hemoglobin showed a statistically significant inverse relationship with readmission risk ($\beta = -0.02$, $p < 0.001$), indicating that lower hemoglobin levels were strongly associated with increased likelihood of readmission. Although creatinine ($\beta = 0.03$, $p = 0.06$), blood urea nitrogen ($\beta = 0.005$, $p = 0.08$), and estimated glomerular filtration rate (eGFR) ($\beta = -0.001$, $p = 0.09$) exhibited meaningful trends in expected directions, these associations did not reach statistical significance. Other variables, including potassium, sodium, total cholesterol, and triglycerides, showed weak or inconsistent relationships (all $p > 0.1$).

Figure 3 presents the Kaplan–Meier survival curves stratified by LACE index score categories, showing the probability of avoiding 30-day readmission. Patients with a LACE score ≥ 10 (red line) experienced the steepest decline in survival probability, dropping from 100% to approximately 70% by day 30. In contrast, patients with LACE scores of 4–9 (blue line) maintained a survival probability of around 88%, while those with scores < 4 (green line) had the highest probability of avoiding readmission, remaining above 95% throughout the 30-day period. These results highlight the strong predictive power of higher LACE scores for early hospital readmission.

3.1 | Subgroup Analysis

The ROC curve from a subgroup analysis evaluating the model's ability to predict 30-day hospital readmission within a specific patient subgroup (Supplementary Figure 2). The area under the curve (AUC) is 0.7533, indicating good discriminatory power of the

TABLE 2 | Association between the 30-days readmission and covariates of patients with AMI.

	Variable	OR	95% CI
LACE index	Score 0–4	1.00	
	Score 5–9	1.02	0.99–1.05
	Score ≥ 10	1.28	1.25–1.31**
Age (Years)	19–44	1.00	
	45–64	1.02	0.99–1.06
	≥ 65	1.36	1.33–1.42*
Sex	Female	1.00	
	Male	2.66	2.6–2.73**
Health insurance	NHI	1.00	
	Medicare	1.10	0.72–1.13
	Others	0.67	0.64–0.71*
Residence	Seoul and capital cities		
	Other cities	0.67	0.65–0.69**
	Rural	0.84	0.48–1.42
Length of stay	≥ 2	1.00	
	3	1.88	1.15–2.91**
	4	2.01	1.93–2.06*
	5	0.94	0.91–0.97
	6	1.39	0.79–2.48
	≥ 7	0.73	0.71–0.75**
Admission route	ER	1.00	
	OP	1.69	1.65–1.74**
	Transfer	1.44	1.36–1.52**
Comorbidities	CCI 1	1.00	
	CCI 2	0.82	0.79–0.84*
	CCI ≥ 3	1.63	1.59–1.68**
Emergency visits	Yes	1.00	
	No	1.36	1.32–1.43*
Discharge	Normal	1.00	
	Others	1.44	1.4–1.48*

Abbreviations: CCI, Charson index; ER, Emergency; NHI, National Health Insurance.
*$p < 0.05$; **$p < 0.001$.

model in distinguishing between readmitted and non-readmitted patients in this subgroup. The model performs substantially better than chance (AUC = 0.5), suggesting its utility for targeted prediction and risk stratification in this patient population.

Supplementary Figure 3 displays a calibration plot evaluating the performance of the predictive model for 30-day hospital readmission in another subgroup. The Loess fit curve remains closely aligned with the 45-degree diagonal line, indicating strong agreement between predicted and observed readmission probabilities. The Spiegelhalter z-test statistic ($z = 0.1101$, $p = 0.9123$) further confirms good calibration, with no statistically significant deviation from perfect model fit in this subgroup.

4 | Discussion

This study examined 30-day hospital readmission among patients with AMI using data from the Korean NHISS cohort, with a particular focus on the utility of the LACE index. The temporal trend revealed a decline in readmission rates between 2011 and 2019, consistent with broader improvements in discharge planning and care coordination efforts seen internationally [24]. A sharp reduction to 5.5% was observed in 2020, likely reflecting the impact of the COVID-19 pandemic on healthcare utilization and hospital readmissions. [25].

The study findings revealed that higher proportion of patients with elevated LACE scores were readmitted within 30 days compared to those with lower scores, supporting the index's role as a valuable predictor. This finding aligns with prior studies [13], who originally developed the LACE index, and Rajaguru et al. [22, 23, 26], who demonstrated its predictive strength across various conditions. However, some research has shown modest performance of the LACE index in cardiovascular populations, indicating that while it is useful, it should be supplemented with clinical judgment and additional predictors [16, 17, 27, 28]. The age distribution further revealed that the majority of readmissions occurred among older adults, a finding consistent with prior literature highlighting the association between aging, comorbidity, and hospital utilization [26, 29].

Our findings confirmed that patients with higher LACE scores had significantly associated with 30-days readmission. Interestingly, middle-aged adults were also at elevated risk, which contrasts with the typical focus on geriatric patients in readmission literature and may suggest underrecognized care gaps in this demographic [26, 27, 30–32]. Additionally, patients residing in nonmetropolitan cities showed lower odds of readmission. This may be partially explained by different discharge practices, availability of local services, or reduced access to tertiary facilities factors reported in earlier Australian and US studies [33, 34].

Laboratory findings are highlighted hemoglobin as the only statistically significant laboratory predictor of readmission, supporting existing evidence that anemia is a key marker of adverse outcomes post-AMI [18, 35, 36]. In contrast, other variables such as creatinine, GFR, and cholesterol did not show significant associations in our regression model. This is notable, as prior research has found these markers to predict long-term outcomes but not necessarily short-term readmission, highlighting a discrepancy between different time horizons for risk prediction [37–39].

Our findings of survival curves showed stratified risk by LACE score, underlining its usefulness in clinical triage and decision-making and also confirmed good model calibration, consistent with validation efforts from the studies [40, 41], who emphasized that predictive tools should not only discriminate but also align well with actual outcomes. While our findings strongly support the LACE index's utility, the variability in readmission causes and timing calls for incorporating social, behavioral, and functional metrics into future risk prediction frameworks [30, 42]. Subgroup analysis in ROC analysis further validates our regression model's discriminatory ability, consistent with

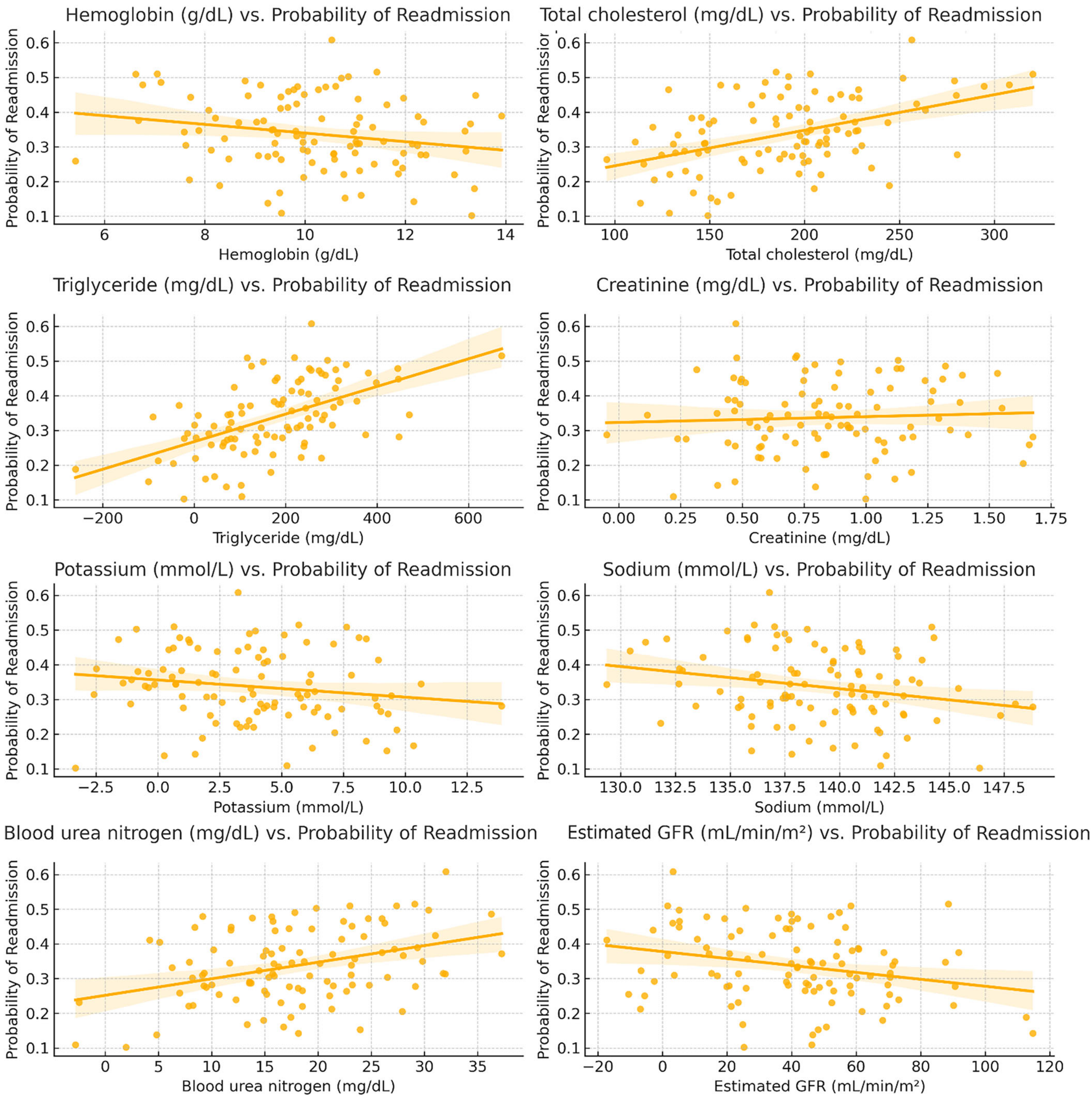

FIGURE 2 | Multiple linear regression analyses examining the association between laboratory parameters and the probability of 30-day readmission.

Desai et al. [15] and Donzé et al. [41], though others have argued that the LACE index alone may not be sufficient in high-risk cardiac populations [12]. Thus, integrating the LACE index with enriched clinical and contextual data may yield greater precision in preventing 30-days readmissions among AMI patients.

The LACE index provides clinicians with a simple and efficient tool to estimate an individual's risk of 30-day readmission, facilitating better care coordination and targeted interventions for high-risk patients. Reducing readmissions not only lowers healthcare costs but, more importantly, improves patient outcomes and satisfaction. Because readmissions expose patients to additional risks, such as hospital-acquired infections, their prevention is a critical goal. Our findings support the use of the LACE index to guide clinical decision-making regarding treatment intensity, discharge timing, and post-discharge follow-up, particularly for patients at elevated risk of early readmission.

Our findings underscore the importance of integrating readmission risk stratification tools such as the LACE index into discharge planning processes in national health systems. Given the tool's simplicity and predictive ability, it could be routinely implemented in both tertiary and community hospitals to identify high-risk AMI patients. Health policymakers should consider incentivizing the use of such tools by

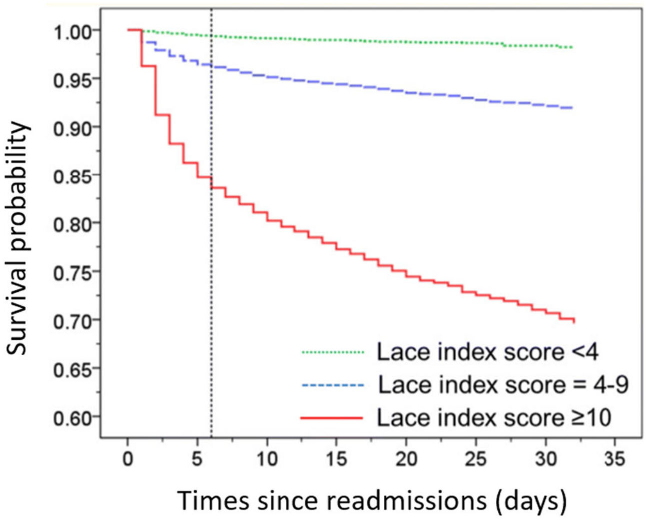

FIGURE 3 | Kaplan–Meier survival curves stratified by LACE index score categories, showing the probability of 30-day readmission.

embedding them into electronic medical record (EMR) systems and aligning them with value-based care models. Furthermore, targeted interventions, such as enhanced transitional care or home-based follow-up programs, could be prioritized for individuals with elevated LACE scores to reduce the burden of potentially avoidable readmissions.

This study has several limitations. First, it relied on administrative claims data, which may lack clinical granularity and diagnostic accuracy compared to prospective registries. Second, the exclusion of patients who were transferred or not admitted through the emergency department may limit generalizability. Third, although we examined a large and nationally representative cohort, we could not include behavioral, psychosocial, or socioeconomic variables, which are known contributors to readmission. Fourth, this study analyzed a large patient cohort, providing strong statistical power and enabling validation of the LACE index in a population comparable to that in which it was originally developed. However, readmission rates may have been underestimated, as readmissions to other hospitals and post-discharge deaths were not captured in the data set. Lastly, the study focused on short-term (30-day) readmissions and may not capture long-term outcomes or rehospitalizations driven by noncardiac causes.

5 | Conclusion

The LACE index demonstrates strong predictive value for identifying patients at risk of 30-day hospital readmission following AMI, with elevated scores correlating with increased odds of readmission. Hemoglobin emerged as a significant clinical predictor, suggesting that combining simple clinical and administrative indicators may improve risk assessment. This study supports the routine use of the LACE index within clinical workflows to guide post-discharge interventions. Furthermore, our findings have important policy implications given the growing importance of cost containment and quality of care in healthcare systems, along with the increasing growth in the elderly population. Future research should explore the integration of additional patient-level data to enhance predictive accuracy and broaden applicability across diverse healthcare settings.

Author Contributions

T.H.K. and S.G.L. designed the study. V.R. planned the data collection and analysis, with input from S.Y.J. and J.S. as needed. V.R. and W.H. drafted and revised the paper and is the guarantors for the work. T.H.K. and V.R. critically revised the paper for intellectual content. All the authors gave final approval of the manuscript and are accountable for all aspects of the accuracy and integrity of the work.

Ethics Statement

Ethical approval was obtained from the Bio-Ethical Committee of Severance hopsital, Yonsei University.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings will be available in [Korean National Health Insurance Service (NHIS)] at [https://nhiss.nhis.or.kr/] following an embargo from the date of publication to allow for commercialization of research findings.

The data can be accessed on the National Health Insurance Data Sharing Service homepage of the NHIS (http://nhiss.nhis.or.kr). Applications to use the NHIS-HEALS data will be reviewed by the inquiry committee of research support and once approved, raw data will be provided to the applicant with a fee. Although the data are coded in English and numbers, use of individual data is allowed only for Korean researchers at the moment, but it would be possible for researchers outside the country to gain access to the data by conducting a joint study with Korean researchers.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Supplementary file.