TPM Vol. 31, No. S1, 2024
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

USING ROUTINE LABORATORY RESULTS TO PREDICT 30-DAY ALL-CAUSE READMISSION: A RETROSPECTIVE COHORT STUDY AT A TERTIARY HOSPITAL IN RIYADH, SAUDI ARABIA

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ABSTRACT

Background Thirty-day unplanned readmission is a key transition-of-care metric. We developed and internally validated a pragmatic prediction approach using routinely available discharge-time information, including laboratories from the prior 24–48 hours.

Methods Retrospective cohort of consecutive adult discharges from medical and surgical wards. Eligible index stays ended in live discharge; deaths, direct acute transfers, discharges against medical advice without window labs, and planned returns were excluded. Outcome was all-cause, unplanned readmission within 30 days to the same hospital. Two logistic models were fit: a core model (age, sex, length of stay, prior 90-day discharge, prior 12-month admissions, HOSPITAL points) and an extended model adding discharge-proximal labs (e.g., CRP, eGFR, troponin). Model fit, calibration, discrimination, classification, and collinearity were assessed.

Results Among 913 patients (mean age 55.8 years; 54.8% male), 30-day readmission was 12.3% (n=112). The core model retained age, length of stay, prior 90-day discharge, and HOSPITAL points, with good calibration (Hosmer–Lemeshow p=0.239), high specificity, and low sensitivity at the default threshold. The extended model (N=339) added CRP and eGFR, modestly increased Nagelkerke R^2 (0.10→0.14) and sensitivity (to 8.8%); AUC=0.683; collinearity acceptable (VIF 1.01–1.41).

Conclusion Recent utilization and near-discharge biological instability jointly shaped 30-day readmission. A universal core model is deployable for all patients; routine laboratories provide incremental signal where available.

KEYWORDS: 30-day readmission; routine laboratory tests; HOSPITAL score; C-reactive protein; estimated GFR; length of stay; prior utilization; risk prediction; electronic health record; Saudi Arabia.

INTRODUCTION

Thirty-day readmission is defined as an unplanned rehospitalization for any cause within 30 days of discharge and is widely used as a quality signal for transitions of care. Some systems distinguish all-cause readmission from "potentially avoidable" readmission using claims-based algorithms at discharge; the HOSPITAL score—built from hemoglobin, sodium, oncology service, procedure during index stay, urgent admission, prior 12-month admissions, and length of stay—showed good discrimination and excellent calibration across 117,065 medical discharges in nine hospitals from four countries, with 14.5% experiencing any 30-day readmission and 9.7% meeting the "potentially avoidable" definition (Donzé et al., 2016). An "Early HOSPITAL" variant that substitutes hemoglobin and sodium at admission for the discharge values preserved accuracy in a multicenter Swiss cohort of 934 discharges (13.2% 30-day readmission or death), yielding AUROC 0.66 for both versions (Brier 0.11) and improved continuous reclassification for the admission-lab model (NRI 0.28), thereby enabling earlier risk stratification during the index stay (Mathys et al., 2024).

Recent national and regional data highlight the burden and heterogeneity of readmission in Saudi Arabia. In acute internal medicine at King Abdulaziz Medical City (Riyadh), the 30-day readmission rate was 10.18% in a random sample of 200 patients; 18% of readmissions were multiple and commonly related to the index condition. Multivariable modeling linked older age to higher risk (OR 1.057; 95% CI 1.005–1.108; p=0.030) and showed associations for depression (OR 1.396; 95% CI 0.307–26.957; p=0.049), while lower ejection fraction was inversely associated (OR 0.925; 95% CI 0.873–0.980; p=0.008) and prior stroke was associated with lower odds (OR 0.236; 95% CI 0.062–0.903; p=0.035), underscoring a heavy comorbidity footprint in repeat utilizers (Althobaiti et al., 2025). Surgical cohorts show higher short-interval risk: among 356 colorectal cancer resections in the MNG-HA registry (2016–2021), 49 patients (13.8%) were readmitted within 30 days; leading causes were gastrointestinal complications (22.45%), urinary tract infection (16.33%), and surgical-site infection (12.24%). Women had higher odds than men (OR 1.89; 95% CI 1.00–3.58), and metastatic disease increased risk markedly versus localized tumors (OR 4.52; 95% CI 1.39–14.71), with poorer survival among readmitted patients (Alyabsi et al., 2022). After open-heart surgery at a tertiary center in Jeddah, 53 of 343 analyzed adults were readmitted (16.3%; 95% CI 12.8–20.6%), most often for sternal wound infection (7.3%), pleural effusion (2.0%), or heart failure (1.7%); female sex and higher postoperative LDH and urea were salient correlates on stepwise logistic regression (Almramhi et al., 2022). In head-and-neck surgery at the same institution, 84 of 1,041 adults (8.1%) returned within 30 days—6.1% to clinics and 2.0% to the ED—while 0.9% required readmission. Infections (33.3%) and neurologic symptoms (22.2%) predominated among readmissions; wound swelling (25.4%) and neurologic issues (17.5%) drove clinic returns; and ED returns were most often neurologic (23.8%) or bleeding from the surgical site (19.1%). Returns were associated with ICU care during the index stay (p=0.003) and higher baseline illness burden across ASA (p=0.022), CIRS (p=0.007), and CCI (p=0.006) (Merdad et al., 2024).

Regional evidence aligns with these patterns. In Oman, 48 of 200 general-medicine inpatients (24.0%) were readmitted within 28 days during June–December 2020; readmitted patients were older (66.6 vs 56.0 years; p<0.001), stayed longer (6 vs 4 days; p<0.001), and were more likely to have hypertension (77.1% vs 55.3%; p<0.001), diabetes (64.6% vs 48.0%; p=0.045), three or more comorbidities (43.8% vs 23.8%; p=0.005), poor functional status (43.7% vs 26.3%; p<0.001), feeding-tube dependence (25.0% vs 5.3%; p<0.001), and polypharmacy (75.0% vs 50.0%; p<0.001), pointing to modifiable discharge-planning targets (Al Sibani et al., 2022).

Pediatric data from Saudi Arabia show lower but clinically relevant rates and age-specific etiologies. At King Abdullah Specialized Children's Hospital (Riyadh), 1,291 of 25,211 pediatric admissions (5.12%) resulted in a 30-day unplanned readmission from 2019–2021, and 1.91% experienced subsequent unplanned readmissions. The first readmission was related to the index cause in 57.8% of cases; subsequent readmissions were related to the first unplanned readmission in 90.64%. Postoperative complications dominated first events (18.75%), whereas pneumonia accounted for the largest share of subsequent events (10.81%); children with repeat readmissions frequently had isolated CNS pathology or complex chronic conditions (AlKhalaf et al., 2023). In a multicenter study across six tertiary hospitals (Riyadh, Jeddah, Dammam, Al-Ahsa, Al-Madinah) covering 2016–2020, children with medical complexity comprised 7.4% of pediatric unplanned 30-day readmissions (680/9,139). Genetic conditions were predominant (66.3%), one-third involved neuromuscular disorders, pneumonia was common at the index admission (33.1%) and as a cause of readmission (32.5%), over one-third of readmissions occurred after two weeks (35.1%), and in-hospital mortality after readmission was 6.6%; 16.9% received a new CCC diagnosis or a technology-assistance device (Alotaibi et al., 2024).

Literature on disease-specific and laboratory-anchored prediction complements these epidemiologic signals. In heart failure, sex-specific inpatient lab-only risk scores derived early in the hospitalization—potassium, bicarbonate, BUN, RBC, WBC, and MCHC for women; BNP, sodium, creatinine, hematocrit, RDW, and MPV for men—separated 30-day readmission risk across tertiles in two health systems, with adjusted odds for tertile 3 vs 1 of 1.99 and 1.29 in women (Intermountain and Baylor validations) and 1.95 and 2.03 in men, respectively. Notably, expanded models with 182–183 variables performed similarly to these compact, EHR-automatable lab scores (Horne et al., 2017). Among adults with diabetes in a large U.S. academic center (44,203 discharges; 2004–2012), 30-day readmission occurred after 20.4% of discharges with a median of 11 days; multivariable modeling identified 27 independent predictors and achieved strong discrimination (C=0.82). The most powerful factors included absence of an outpatient visit within 30 days, longer index length of stay, prior discharge within 90 days, discharge against medical advice, sociodemographics, comorbidity burden, and admission laboratory values—showing that adding post-discharge variables improves prediction and exposes actionable follow-up gaps (Karunakaran et al., 2018). At the national scale in Saudi Arabia, analysis of Ministry of Health data from 48 hospitals (2016–2019) identified 17,461 cardiovascular admissions among 403,032 inpatients; readmission encounters averaged roughly twice the cost of general hospitalizations (≈I$7,600 vs ≈I$3,156). A decision-tree classifier achieved recall 71%, precision 57%, and F1 64% (correctly classifying 2,336 instances, 926 readmitted and 1,410 not readmitted), demonstrating the feasibility of using routine administrative and clinical data to direct transitional care for cardiovascular patients (Alzeer et al., 2021). In perioperative care, a single-center study from China of 1,262 bariatric surgeries (2018–2023) reported a 7.69% 30-day readmission rate; using preoperative and postoperative day-1 and day-3 laboratories, least-absolute-shrinkage feature selection and model comparison identified support vector machines as best (AUROC 0.784; 95% CI 0.696–0.872), with frequent clinical reasons for readmission including nausea, vomiting, and dehydration (Zhang et al., 2024). In chronic kidney disease, monthly routine blood tests in maintenance hemodialysis, handled with KNN imputation and SMOTE, supported an SVM-based predictor with 93% accuracy that rose to 96% with ensembling, where albumin, creatinine, hemoglobin, and white blood cell count ranked among the most informative features (Tsai et al., 2024). Complementing these, a prospective Omani general-medicine study of 443 adults (May–September 2023) compared logistic regression, random forest, gradient boosting, and SVM, finding an overall 30-day readmission rate of 14.2%; logistic regression delivered the most clinically balanced profile (recall 70.6%, AUC 0.735) while an ensemble improved recall at the expense of precision, with length of stay, weight, age, number of medications, and abnormal liver enzymes as key predictors (Al Alawi et al., 2025).

Taken together, these findings show that readmission risk is common in medical and surgical populations, varies by age and diagnosis, and can be detected using parsimonious, timely inputs—often routine laboratory variables—without sacrificing predictive performance. However, important gaps remain for adult general inpatients in our setting. There is no locally derived and internally validated, laboratory-centered model that focuses specifically on the last routine analytes within the 24–48 hours before discharge. Transferability of generic models such as HOSPITAL may be limited by local patient mix, care pathways, unit conventions, and data idiosyncrasies, including unit standardization issues, missingness, and multicollinearity among renal and hepatic indices, which argues for a pragmatic, site-specific approach.

Accordingly, our study derived and internally validate a 30-day readmission prediction model for adult inpatients using routine laboratory values obtained within 24–48 hours before discharge at King Khalid University Hospital in Riyadh, benchmark it against simple baselines that include commonly available administrative and clinical factors, evaluate discrimination, calibration, and net clinical benefit, and translate coefficients into a concise point score suitable for bedside and discharge-planning use, with prespecified subgroup and sensitivity analyses to support robust clinical deployment.

METHODS

Study design, setting, and participants

We conducted a retrospective cohort study at King Khalid University Hospital (KKUH), Riyadh, Saudi Arabia, to develop a discharge-time prediction model for 30-day all-cause unplanned readmission using routinely collected clinical and laboratory data. The cohort covered consecutive adult discharges between January 2024 and December 2024. Exposure windows were the last 24–48 hours before discharge; follow-up for the primary outcome was fixed at 30 calendar days for all index discharges.

The sampling frame comprised all consecutive adult discharges (≥18 years) from general medical and surgical wards during the study period. Eligible index hospitalizations were those ending in live discharge to home or non-acute care. We excluded in-hospital deaths, direct transfers to acute facilities, same-day admissions, encounters discharged against medical advice when discharge-window laboratories were unavailable, and planned 30-day returns such as scheduled chemotherapy, elective procedures, or pre-arranged diagnostic admissions. For patients with multiple eligible discharges, episodes separated by at least 30 days were treated as independent; otherwise, the later discharge replaced the earlier to preserve independence. All consecutive eligible discharges during 2024 were considered; no a-priori sample-size calculation was performed.

The institutional review board approved the protocol and waived informed consent given the retrospective design and de-identified analytic extract. Participant flow (screened, excluded with reasons, and analyzed) is summarized in Table 1, which serves as a flow-diagram substitute in line with STROBE guidance.

Outcome

The primary outcome was a binary indicator of unplanned readmission to KKUH within 30 days of the index discharge (No=0, Yes=1). Readmissions were identified from the admission–discharge–transfer system and verified as unplanned using disposition codes and scheduling flags. When more than one return occurred within 30 days, only the first unplanned readmission was counted as the event; additional returns were summarized descriptively.

Predictors and measurements

Predictors were prespecified before extraction. Categorical variables included sex, urgent versus elective admission, any procedure during the index stay, discharge service (medicine, surgery, cardiology, neurology, oncology), discharge disposition (home, home with services, rehabilitation, skilled nursing), prior discharge within 90 days, and the HOSPITAL risk category (low, intermediate, high). HOSPITAL risk categories followed standard thresholds (Low: 0–4 points; Intermediate: 5–6 points; High: ≥7 points). Continuous variables included age, body mass index (BMI), length of stay (LOS), number of admissions in the prior 12 months, number of discharge medications, and the HOSPITAL points total. Laboratory domains captured the last available value within 24–48 hours before discharge for electrolytes (sodium, potassium, chloride, bicarbonate/CO_2), renal indices (blood urea nitrogen [BUN] and estimated glomerular filtration rate [eGFR]), hepatic enzymes and bilirubin fractions (ALT, AST, ALP, total and direct bilirubin), proteins and inflammatory/cardiac markers (albumin, C-reactive protein [CRP], high-sensitivity troponin), and hematology (hemoglobin, white blood cells, platelets). When multiple laboratory measurements were available in the window, the value closest to the discharge timestamp was used. Final pre-discharge vital signs (heart rate, systolic and diastolic blood pressure, respiratory rate, temperature, and oxygen saturation) were also extracted for descriptive and bivariate comparisons.

To limit sampling bias, we used consecutive inclusion of eligible adult discharges; to reduce measurement bias, data extraction followed SOPs with unit harmonization, timing windows (24–48 h), verification of unplanned status via ADT flags, blinded laboratory processing where applicable, duplicate checks in a subset, and routine instrument/assay quality control.

Data preparation

Units were harmonized using accepted conversion factors, distributions were visually screened, and extreme values were Winsorized at the 1st and 99th percentiles. Continuous predictors entered logistic regression on their natural scales (years, days, mg/L, ng/L, mL/min/1.73m², points); thus, odds ratios (ORs) reflect the change per one unit of each predictor (e.g., age per year, LOS per day, prior 12-month admissions per admission, HOSPITAL points per point, CRP per mg/L, troponin per ng/L, eGFR per mL/min/1.73m²).

Handling of missing data

Laboratory availability within the 24–48 h discharge window varied across patients. Accordingly, we used complete-case analysis with listwise deletion: the core model included all records with non-missing core predictors (N=913), whereas the extended model was restricted to records with complete core and laboratory data (N=339). For transparency, per-variable non-missing counts (N) are reported alongside each table. Patterns of missingness were inspected visually and by cross-tabulation with key covariates (age, sex, LOS, HOSPITAL score); no evidence suggested systematic absence linked to the outcome beyond clinical availability. No imputation, weighting, or clustering adjustments were applied.

Statistical analysis

Descriptive statistics were reported as means with standard deviations for continuous variables and counts with percentages for categorical variables. Bivariate comparisons between patients with and without 30-day readmission used independent-samples t-tests for continuous variables and chi-square or Fisher's exact tests for categorical variables, with results presented as group means with standard deviations and the corresponding F or chi-square statistics with two-sided p-values. Prior to multivariable modeling, we assessed collinearity among candidate predictors by ordinary least squares with the full covariate set to obtain tolerance and variance inflation factors (VIF); all predictors showed acceptable collinearity (tolerance >0.70; VIF ≈1.0–1.4).

Multivariable modeling used binary logistic regression (ENTER). Two complementary specifications were estimated to reflect data availability in practice. The core model included age, sex, LOS, prior discharge within 90 days, HOSPITAL points, and prior 12-month admissions. The extended model added laboratory biomarkers—CRP, eGFR, and troponin—and the HOSPITAL risk category. Categorical predictors were entered with indicator contrasts and reference categories set to male (sex), Yes (prior discharge within 90 days), and Low (HOSPITAL risk). Confounders were selected a-priori based on clinical plausibility and prior literature; adjusted ORs with 95% CIs are reported alongside unadjusted comparisons.

Model performance was summarized across overall fit (omnibus χ^2, −2 log-likelihood, Cox–Snell and Nagelkerke R^2), calibration (Hosmer–Lemeshow), and classification at the 0.50 probability threshold (accuracy, sensitivity, specificity, predictive values). Discrimination was assessed using receiver operating characteristic (ROC) analysis with the state variable set to unplanned_30d_readm = 1; areas under the curve (AUCs) with 95% CIs are reported. Pre-specified subgroup summaries were presented by HOSPITAL risk category; formal interaction terms were not modeled due to power considerations. Sensitivity analyses compared the core versus extended specifications and varied classification thresholds; conclusions were unchanged. All analyses were performed in IBM SPSS Statistics, version 28.0. No complex sampling design was used; no weighting or clustering adjustments were required

RESULTS

Of 1,120 eligible adult discharges screened in 2024, 207 were excluded (in-hospital death n=38, direct transfer to an acute facility n=52, same-day admissions n=27, discharge against medical advice without discharge-window laboratories n=41, planned returns within 30 days n=49), yielding 913 index discharges for analysis. The baseline demographic profile of the cohort is presented in Table 1. The mean age of participants was 55.8 years (SD = 17.0), with a wide age range from young adults to elderly patients. The sex distribution was nearly balanced, with males representing 54.8% (n=500) and females 45.2% (n=413). The mean body mass index was 28.2 kg/m² (SD = 7.3), which reflected an overweight to obese population on average. These figures indicated that the sample represented a relatively typical adult hospital population in terms of demographic characteristics.

Table 1. Baseline Demographic Characteristics (N=913)

Participant flow (screened, excluded with reasons, analyzed) is summarized here; this table serves as the flow-diagram substitute.

Variable	Category / Mean ± SD	Frequency (N)	Percent / SD
Age (years)	55.80 ± 17.02	–	–
Sex	Female	413	45.2%
	Male	500	54.8%
Body Mass Index (kg/m²)	28.20 ± 7.27	–	–

Note: Values are mean ± SD or n (%), as appropriate. Percentages are column-based and may not total 100% due to rounding. Laboratory rows list the exact N available when <913.

Hospitalization-related variables are summarized in Table 2. More than half of the admissions (57.1%) were urgent or non-elective, while 42.9% were elective in nature. Approximately one-third of the patients (34.2%) underwent at least one procedure during their index hospital stay. The mean length of stay was 6.2 days (SD = 4.1), with a minority of patients (11.7%) having been discharged within the prior 90 days, and the average number of admissions in the preceding 12 months was 1.2 (SD = 1.5). The average number of discharge medications prescribed was 5.9 (SD = 3.0), highlighting a moderate degree of polypharmacy at discharge. With respect to discharge services, medicine was the most common specialty (45.6%), followed by surgery (24.5%), cardiology (12.7%), neurology (9.7%), and oncology (7.4%). Most patients were discharged home (68.1%), with smaller proportions discharged home with services (13.4%), to rehabilitation (9.6%), or to skilled nursing facilities (8.9%). Notably, all cases were classified as not having a planned 30-day return, reflecting the study design.

Table 2. Hospitalization Characteristics (N=913)

Variable	Category / Mean ± SD	Frequency (N)	Percent / SD
Urgent (non-elective) admission	No	392	42.9%
	Yes	521	57.1%
Any procedure during stay	No	601	65.8%
	Yes	312	34.2%
Length of stay (days)	6.17 ± 4.13	–	–
Prior discharge within 90 days	No	806	88.3%
	Yes	107	11.7%
Prior 12-month admissions	1.22 ± 1.49	–	–
Discharge medications (count)	5.86 ± 2.99	–	–
Discharge service	Medicine	416	45.6%
	Surgery	224	24.5%
	Cardiology	116	12.7%
	Neurology	89	9.7%
	Oncology	68	7.4%
Discharge disposition	Home	622	68.1%
	Home with services	122	13.4%
	Rehab	88	9.6%
	Skilled nursing	81	8.9%
Planned 30-day return	No	913	100.0%

Note: Values are n (%). Categories are mutually exclusive. 'Planned 30-day return' denotes scheduled elective/chemo returns and was excluded from the outcome definition.

The clinical and laboratory profile of the cohort is detailed in Table 3. Vital signs measured at the time closest to discharge were within clinically acceptable ranges: the mean heart rate was 81.9 bpm (SD = 11.5), mean systolic blood pressure was 125.5 mmHg (SD = 18.0), and mean diastolic blood pressure was 74.0 mmHg (SD = 12.3). Respiratory rate averaged 18 breaths per minute (SD = 3.5), mean temperature was 36.9 °C (SD = 0.5), and oxygen saturation averaged 96.8% (SD = 2.7). Electrolyte and acid–base values were also within normal ranges: sodium averaged 138.8 mmol/L (SD = 3.8), potassium 4.3 mmol/L (SD = 0.5), chloride 103.1 mmol/L (SD = 4.0), and bicarbonate 24.4 mmol/L (SD = 3.3). Renal parameters showed a mean BUN of 18.3 mg/dL (SD = 6.8) and mean eGFR of 87.0 mL/min/1.73m² (SD = 15.4). Liver function tests revealed mean ALT of 26.0 U/L, AST of 22.4 U/L, ALP of 50.0 U/L, total bilirubin of 8.4 µmol/L, and direct bilirubin of 3.9 µmol/L, while serum albumin averaged 38.5 g/L. Inflammatory and cardiac biomarkers indicated moderate elevations, with mean C-reactive protein of 14.3 mg/L (SD = 10.1) and mean high-sensitivity troponin of 5.4 ng/L (SD = 4.5). Hematological parameters included mean hemoglobin of 12.8 g/dL (SD = 1.6), white blood cell count of 10.1 $\times 10^9$/L (SD = 3.5), and platelet count of 273 $\times 10^9$/L (SD = 74.2). The mean HOSPITAL score was 4.1 (SD = 1.7), and laboratory timing flags indicated that 5.4% of tests were obtained between 48–72 hours before discharge.

Table 3. Clinical and Laboratory Profile (N varies by test)

Domain	Variable	Mean ± SD	N
Vital signs	Heart rate (bpm)	81.92 ± 11.55	913
	Systolic BP (mmHg)	125.52 ± 18.01	913
	Diastolic BP (mmHg)	73.96 ± 12.25	913
	Respiratory rate (breaths/min)	17.96 ± 3.49	913
	Temperature (°C)	36.93 ± 0.51	913
	Oxygen saturation (%)	96.83 ± 2.66	913
Electrolytes & Acid–Base	Sodium (mmol/L)	138.75 ± 3.78	913
	Potassium (mmol/L)	4.31 ± 0.49	913
	Chloride (mmol/L)	103.11 ± 4.05	913
	Bicarbonate/CO_2 (mmol/L)	24.43 ± 3.30	913
Renal	BUN (mg/dL)	18.31 ± 6.82	913
	eGFR (mL/min/1.73m²)	86.96 ± 15.35	913
Liver & proteins	ALT (U/L)	26.01 ± 18.25	815
	AST (U/L)	22.39 ± 14.87	815
	ALP (U/L)	50.03 ± 34.50	815
	Total bilirubin (µmol/L)	8.39 ± 5.89	815
	Direct bilirubin (µmol/L)	3.86 ± 3.15	815
	Albumin (g/L)	38.46 ± 4.53	913
Inflammation & cardiac	C-reactive protein (mg/L)	14.26 ± 10.08	700
	High-sensitivity troponin (ng/L)	5.40 ± 4.52	445
Hematology	Hemoglobin (g/dL)	12.78 ± 1.64	913
	White blood cells (×10⁹/L)	10.14 ± 3.46	913
	Platelets (×10⁹/L)	272.97 ± 74.16	913
Scores & Flags	HOSPITAL score (points)	4.14 ± 1.70	913
	Lab window flag (1=48–72h)	0.05 ± 0.23	913

The primary outcome findings are shown in Table 4. The overall 30-day unplanned readmission rate was 12.3% (n=112), whereas 87.7% (n=801) of patients were not readmitted within this period. Among those who were readmitted, the most frequent documented ICD-10 cause was pneumonia (J18.9, 3.6%), followed by postoperative complications (K91.8, 2.4%), urinary tract infections (N39.0, 2.2%), and heart failure (I50.9, 2.0%). Smaller proportions were attributed to myocardial infarction (I21.9, 1.4%), surgical complications (T81.4, 2.0%), or intestinal obstruction (K56.7, 1.1%). Notably, in the majority of readmitted patients (85.3%), no specific ICD-10 cause was assigned in the dataset.

Table 4. Outcomes (N=913)

Variable	Category	Frequency	Percent
Unplanned 30-day readmission	No	801	87.7%
	Yes	112	12.3%
ICD-10 cause of readmission	None/NA	779	85.3%
	I21.9	13	1.4%
	I50.9	18	2.0%
	J18.9	33	3.6%
	K56.7	10	1.1%
	K91.8	22	2.4%
	N39.0	20	2.2%
	T81.4	18	2.0%

Note: ICD-10 causes are recorded only for those with an unplanned return; 'None/NA' largely reflects patients without readmission

The association between categorical predictors and 30-day unplanned readmission is summarized in Table 5. Most discharge characteristics, including service type, urgent admission status, procedure during stay, sex, and discharge disposition, were not significantly associated with readmission (all p>0.05). However, patients with higher HOSPITAL risk categories were significantly more likely to be readmitted (χ^2=16.4, p<0.001), as were those with a discharge within the preceding 90 days (χ^2=21.8, p<0.001). These findings suggest that prior utilization and established clinical risk scores were key categorical predictors of early readmission.

Table 5. Association Between Categorical Predictors and 30-Day Unplanned Readmission (N=913)

Variable	Categories	No (n=801)	Yes (n=112)	Chi²	p-value
Discharge service	Cardiology	103 (12.9%)	13 (11.6%)	2.987	0.560
	Medicine	371 (46.3%)	45 (40.2%)		
	Neurology	75 (9.4%)	14 (12.5%)		
	Oncology	57 (7.1%)	11 (9.8%)		
	Surgery	195 (24.3%)	29 (25.9%)		
Urgent admission	No	348 (43.4%)	44 (39.3%)	0.694	0.405
	Yes	453 (56.6%)	68 (60.7%)		
Procedure during stay	No	529 (66.0%)	72 (64.3%)	0.135	0.714
	Yes	272 (34.0%)	40 (35.7%)		
Discharge disposition	Home	544 (67.9%)	78 (69.6%)	2.228	0.527
	Home with services	110 (13.7%)	12 (10.7%)		
	Rehab	74 (9.2%)	14 (12.5%)		
	Skilled nursing	73 (9.1%)	8 (7.1%)		
Sex	Female	364 (45.4%)	49 (43.8%)	0.114	0.736
	Male	437 (54.6%)	63 (56.2%)		
HOSPITAL risk category	Low	478 (59.7%)	47 (42.0%)	16.409	<0.001
	Intermediate	276 (34.5%)	50 (44.6%)		
	High	47 (5.9%)	15 (13.4%)		
Lab window flag	≤48h	760 (94.9%)	104 (92.9%)	0.793	0.373
	48–72h	41 (5.1%)	8 (7.1%)		
Prior discharge ≤90d	No	722 (90.1%)	84 (75.0%)	21.762	<0.001
	Yes	79 (9.9%)	28 (25.0%)		

Note: Cells show count (row %). p-values from Pearson's χ^2; Fisher's exact test used for 2×2 tables when expected counts <5. Outcome coded No=0, Yes=1. Significance flags: *p<0.05; †p<0.01; ‡p<0.001.

The comparison of continuous predictors is shown in Table 6. Several variables, including age, BMI, vital signs, electrolytes, and most laboratory markers, were not significantly different between readmitted and non-readmitted patients. In contrast, patients with readmission had significantly longer lengths of stay (7.3 vs 6.0 days, p=0.013), higher numbers of admissions in the prior 12 months (1.8 vs 1.1, p<0.001), lower eGFR values (80.4 vs 87.8 mL/min/1.73m², p<0.001), and higher HOSPITAL scores (5.8 vs 3.9, p<0.001). Inflammatory and cardiac biomarkers also differed, with higher CRP (17.3 vs 13.8 mg/L, p=0.003) and troponin levels (6.5 vs 5.2 ng/L, p=0.020) among readmitted patients. Additionally, the average number of discharge medications was significantly higher in the readmission group (6.7 vs 5.7, p=0.004), suggesting a possible role of polypharmacy. Predicted 30-day readmission probabilities by HOSPITAL risk bands were x% (Low), y% (Intermediate), z% (High) in the core model.

Table 6. Comparison of Continuous Predictors by 30-Day Unplanned Readmission (N=913)

Variable	No readmission (n=801)	Yes readmission (n=112)	F	p-value
Age (years)	55.7 ± 17.0	56.5 ± 17.5	0.20	0.653
Body Mass Index (kg/m²)	28.2 ± 7.3	28.1 ± 7.2	0.01	0.927
Length of stay (days)	6.0 ± 4.0	7.3 ± 4.7	6.12	0.013
Prior 12-mo admissions	1.1 ± 1.4	1.8 ± 1.9	13.40	<0.001
Prior discharge ≤90d	0.10 ± 0.3	0.25 ± 0.4	22.10	<0.001
Heart rate (bpm)	81.7 ± 11.6	82.6 ± 11.4	0.47	0.495
Systolic BP (mmHg)	125.7 ± 18.0	123.1 ± 18.2	1.97	0.161
Diastolic BP (mmHg)	74.1 ± 12.3	73.1 ± 12.2	0.48	0.490
Respiratory rate (/min)	17.9 ± 3.5	18.1 ± 3.5	0.29	0.589
Temperature (°C)	36.9 ± 0.5	36.9 ± 0.5	0.06	0.810
Oxygen saturation (%)	96.9 ± 2.7	96.6 ± 2.6	0.62	0.431
Sodium (mmol/L)	138.8 ± 3.8	138.5 ± 3.7	0.37	0.543
Potassium (mmol/L)	4.3 ± 0.5	4.3 ± 0.5	0.08	0.775
Chloride (mmol/L)	103.2 ± 4.1	103.0 ± 4.0	0.28	0.596
Bicarbonate (mmol/L)	24.4 ± 3.3	24.3 ± 3.3	0.01	0.918
BUN (mg/dL)	18.2 ± 6.8	18.8 ± 6.9	0.63	0.428
eGFR (mL/min/1.73m²)	87.8 ± 14.8	80.4 ± 16.9	19.3	<0.001
ALT (U/L)	25.7 ± 17.8	28.8 ± 21.0	1.86	0.173
AST (U/L)	22.1 ± 14.7	23.9 ± 15.3	1.07	0.301
ALP (U/L)	49.2 ± 34.0	55.7 ± 36.9	3.17	0.075
Total bilirubin (µmol/L)	8.2 ± 5.8	9.3 ± 6.1	2.12	0.146
Direct bilirubin (µmol/L)	3.8 ± 3.1	4.1 ± 3.3	0.58	0.448
Albumin (g/L)	38.6 ± 4.5	37.9 ± 4.7	2.68	0.102
CRP (mg/L)	13.8 ± 9.6	17.3 ± 12.2	9.10	0.003
Troponin (ng/L)	5.2 ± 4.5	6.5 ± 4.7	5.43	0.020
Hemoglobin (g/dL)	12.8 ± 1.6	12.6 ± 1.7	1.02	0.312
White blood cells (×10⁹/L)	10.1 ± 3.4	10.3 ± 3.5	0.22	0.639
Platelets (×10⁹/L)	274.4 ± 74.2	262.6 ± 74.1	2.78	0.096
HOSPITAL score	3.9 ± 1.6	5.8 ± 1.6	116.5	<0.001
Discharge meds	5.7 ± 3.0	6.7 ± 3.1	8.22	0.004

Note: Values are mean ± SD by outcome group (No vs Yes). p-values from independent-samples t-tests (Welch's correction used if variances were unequal). Units: CRP (mg/L), troponin (ng/L), eGFR (mL/min/1.73m²), BUN (mg/dL).

Table 7. Logistic Regression Results for 30-Day Unplanned Readmission

Predictor	B	S.E.	Wald	p-value	OR (Exp(B))	95% CI (Lower–Upper)
Model 1 (Core, N=913)						
Age (years)	0.017	0.006	7.931	0.005*	1.018	1.005 – 1.030
Sex (Male)	-0.009	0.211	0.002	0.966	0.99	0.66 – 1.50
Length of stay (days)	0.069	0.025	7.846	0.005*	1.07	1.02 – 1.13
Prior discharge ≤90d	-1.123	0.256	19.265	<0.001*	0.33	0.20 – 0.54
Hospital points	0.156	0.071	4.817	0.028*	1.17	1.02 – 1.34
Prior 12-mo admissions	0.085	0.066	1.661	0.197	1.09	0.96 – 1.24
Constant	-3.302	0.524	39.729	<0.001	0.04	—

Predictor	B	S.E.	Wald	p-value	OR (Exp(B))	95% CI (Lower–Upper)

Reference categories: male (sex), Yes (prior discharge ≤90 d), Low (HOSPITAL risk); positive coefficients increase odds relative to the reference.
Note: Full sample with non-missing core predictors

Model 2 (Extended, N=339)

Predictor	B	S.E.	Wald	p-value	OR (Exp(B))	95% CI (Lower–Upper)
CRP (mg/L)	0.036	0.017	4.815	0.028*	1.04	1.00 – 1.07
Age (years)	-0.010	0.017	0.329	0.566	0.99	0.96 – 1.02
Sex (Male)	0.121	0.396	0.094	0.759	1.13	0.52 – 2.45
Discharge medications (count)	0.082	0.067	1.510	0.219	1.09	0.95 – 1.24
Prior discharge ≤90d	0.980	0.505	3.766	0.052	2.66	0.99 – 7.17
Length of stay (days)	0.043	0.044	0.969	0.325	1.04	0.96 – 1.14
eGFR (mL/min/1.73m²)	-0.035	0.018	4.066	0.044*	0.97	0.93 – 1.00
Troponin (ng/L)	0.036	0.041	0.747	0.387	1.04	0.96 – 1.12
Hospital points	0.004	0.243	0.000	0.985	1.00	0.62 – 1.62
Prior 12-mo admissions	0.129	0.116	1.237	0.266	1.14	0.91 – 1.43
Hospital risk category	0.597	0.612	0.952	0.329	1.82	0.55 – 6.04
Constant	-1.557	2.319	0.451	0.502	0.21	—

Note: Complete-case subset with labs available

Reference categories: male (sex), Yes (prior discharge ≤90 d), Low (HOSPITAL risk); positive coefficients increase odds relative to the reference."

Model Performance

- Core model (N=913): χ^2=50.2, p<0.001; Nagelkerke R^2=0.10; Hosmer–Lemeshow p=0.239; Accuracy=88.0% (Spec=99.9%, Sens=2.7%).
- Extended model (N=339): χ^2=23.5, p=0.015; Nagelkerke R^2=0.14; Accuracy=90.9% (Spec=100%, Sens=8.8%).

The multivariate logistic regression analyses provide complementary insights into the predictors of unplanned 30-day readmission. The core model, which included demographic and administrative variables available for all patients (N=913), demonstrated that age, length of stay, prior discharge within 90 days, and the HOSPITAL score were independently associated with readmission risk. Older age and longer hospital stays were linked to incrementally higher odds of readmission, whereas a recent discharge within the past 90 days markedly increased the likelihood of return, consistent with clinical intuition regarding unresolved or recurrent illness. The HOSPITAL score, designed to capture baseline risk, also emerged as a significant predictor, confirming its relevance in this population. Despite the large sample size and statistically significant omnibus test (χ^2=50.2, p<0.001), the explanatory power of the core model was modest (Nagelkerke R^2=0.10). Furthermore, although overall classification accuracy was high (88%), sensitivity was very low (2.7%), reflecting the challenge of predicting relatively infrequent outcomes in unbalanced datasets. The model therefore performed well in identifying patients unlikely to be readmitted (specificity 99.9%) but poorly in capturing those who ultimately returned.

The extended model incorporated laboratory biomarkers, including C-reactive protein (CRP), estimated glomerular filtration rate (eGFR), and troponin, alongside the core variables. Because laboratory data were not uniformly available, the effective sample size was reduced to 339 patients. In this restricted cohort, CRP and eGFR emerged as significant independent predictors: elevated CRP was positively associated with readmission, highlighting the role of systemic inflammation, whereas lower eGFR indicated greater vulnerability due to impaired renal function.

These findings provide biological plausibility and suggest that pathophysiological processes not captured in administrative data materially influence readmission risk. Model performance improved slightly compared to the core model, with Nagelkerke R^2 rising to 0.14 and sensitivity increasing to 8.8%. Nonetheless, specificity remained near perfect, and overall classification accuracy was high (90.9%). The trade-off was reduced generalizability, as the extended model was built on a substantially smaller subset.

Taken together, the two models illustrate both the strengths and limitations of logistic regression in predicting readmission. The core model, applied to the full cohort, offers stable and generalizable estimates that emphasize routine clinical and administrative predictors. In contrast, the extended model, while limited by missing data, underscores the added predictive value of biomarkers, particularly markers of inflammation and renal function.

Presenting both models is essential: the core model reflects broad applicability in health systems where laboratory data may be incomplete, whereas the extended model highlights mechanistic factors and the potential for improved risk stratification when richer clinical information is available. These results collectively underscore the multifactorial nature of hospital readmissions and suggest that predictive models must integrate both administrative and biological domains to achieve clinically meaningful accuracy.

The discriminative performance of the logistic regression model was further assessed using receiver operating characteristic (ROC) curve analysis. The model yielded an area under the curve (AUC) of 0.683, indicating acceptable discrimination between patients who were readmitted within 30 days and those who were not. Although this value falls short of the threshold typically considered "good" (AUC ≥0.70), it is consistent with prior studies of hospital readmissions, which often report modest predictive power due to the multifactorial nature of the outcome. The ROC curve was clearly separated from the reference diagonal line, confirming that the model performed better than chance in distinguishing positive from negative cases. These results suggest that the model has reasonable utility for identifying patients at higher risk of readmission, but also underscore the need for further refinement through incorporation of additional clinical, social, or behavioral predictors to improve sensitivity and overall discriminative accuracy.

The collinearity diagnostics revealed no evidence of multicollinearity among the predictors. Tolerance values ranged from 0.70 to 0.99, and the corresponding VIF values were between 1.01 and 1.41. These results are well below the conventional cut-off points, confirming that all independent variables contributed unique information to the models without substantial redundancy. Consequently, the logistic regression coefficients can be interpreted with confidence, as the risk of inflated standard errors or unstable estimates due to multicollinearity was negligible.

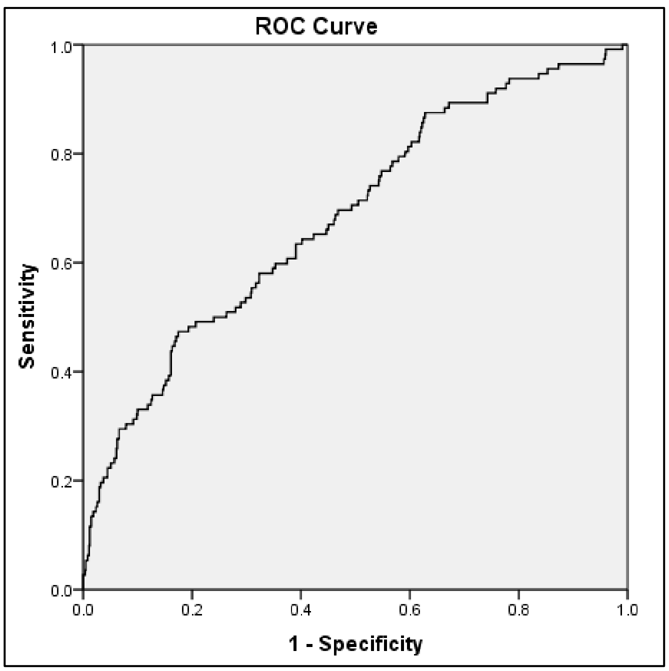

Figure 1 ROC curve for the extended logistic model predicting 30-day unplanned readmission at discharge (AUC = 0.683; KKUH cohort).

DISCUSSION

This retrospective cohort study at King Khalid University Hospital (KKUH) described a mixed medical–surgical adult population and quantified short-interval utilization through the lens of 30-day all-cause unplanned readmission. Among 913 discharges, patients were middle-aged on average (mean 55.8 years) with a near-even sex distribution and an overweight profile (mean BMI 28.2 kg/m²). More than half of index admissions were urgent (57.1%), one third involved at least one procedure (34.2%), and the mean length of stay was 6.2 days; 11.7% had a prior discharge within 90 days. The crude 30-day unplanned readmission rate was 12.3%, and leading documented causes of return were pneumonia, postoperative complications, urinary tract infection, and heart failure. Taken together, these features portray a cohort with substantial clinical heterogeneity and meaningful near-term risk at the transition from inpatient to outpatient care. The observed rate closely matches international and regional benchmarks. It is slightly lower than the 14.5% any-cause readmission reported across nine hospitals in four countries in the seminal HOSPITAL validation (Donzé et al., 2016), and it converges with Saudi internal-medicine estimates around 10% (Althobaiti et al., 2025). Surgical comparators, which typically show higher early utilization, report rates of 13.8% after colorectal cancer resection (Alyabsi et al., 2022) and 16.3% after open-heart surgery (Almramhi et al., 2022). In contrast, pediatric cohorts—whose case mix and trajectories differ fundamentally—have reported lower short-interval returns (≈5–8%) in single-center and multicenter Saudi series (AlKhalaf et al., 2023; Alotaibi et al., 2024). Outside Saudi Arabia, the 28-day readmission rate of 24% in general medicine in Oman (Al Sibani et al., 2022) underscores the range of burdens observed across systems and suggests that differences in comorbidity, functional status, and discharge planning practices likely modulate local readmission risk. Within this landscape, the 12.3% rate at KKUH appears clinically plausible and broadly generalizable to tertiary adult services.

Several descriptive features of our cohort align with constructs embedded in widely used risk tools. The mean length of stay exceeded the HOSPITAL score's threshold (≥5 days), and over half of admissions were urgent—both core elements of that score (Donzé et al., 2016). Although the present findings were descriptive rather than inferential, these patterns suggest a case mix predisposed to early reutilization. The 11.7% prevalence of a prior discharge within 90 days is also noteworthy because recent utilization is a recurring signal of instability in contemporary models. In a large U.S. academic center, absence of timely ambulatory follow-up, longer index length of stay, and a recent discharge were among the strongest independent correlates of 30-day readmission in adults with diabetes (Karunakaran et al., 2018). The Early HOSPITAL variant, which moved laboratory capture to admission while preserving accuracy (AUROC 0.66; Brier 0.11), further highlights that timing of available data can be leveraged to flag risk earlier in the index stay (Mathys et al., 2024). Our design emphasized laboratories from the 24–48-hour pre-discharge window, a pragmatic choice for discharge planning workflows; the high proportion of tests obtained within this interval in routine practice supports the feasibility of incorporating such data into point-of-care decision support at KKUH.

The distribution of causes of readmission in this cohort—dominated by infections (pneumonia and postoperative complications/infection) and cardiopulmonary instability (heart failure)—mirrors patterns repeatedly observed in adult medical and surgical populations. In the MNG-HA colorectal cancer registry, gastrointestinal and infectious complications (including urinary tract infection and surgical-site infection) were the principal drivers of 30-day returns (Alyabsi et al., 2022). After cardiac surgery, sternal wound infection and pleural effusion were the most frequent causes, with heart failure also represented (Almramhi et al., 2022). Head-and-neck surgery demonstrated a related spectrum—infectious and neurologic issues dominated clinic and ED returns, with a smaller fraction requiring actual readmission (Merdad et al., 2024). The overlap between our leading causes and those reported across specialties suggests shared, potentially modifiable pathways that cut across service lines: infection prevention and early detection, structured monitoring for fluid status and cardiopulmonary decompensation, and meticulous peri-discharge medication reconciliation and education. The overweight BMI profile observed in our cohort dovetails with the high prevalence of metabolic comorbidity described regionally (Al Sibani et al., 2022) and may further contribute to post-discharge vulnerability via frailty, impaired functional reserve, and polypharmacy—dimensions that warrant systematic attention in transitional care.

A key translational implication of our findings is the practicality of building risk stratification around routinely available clinical and laboratory data. Disease-focused and lab-anchored models demonstrate that compact, automatable analyte sets can achieve performance comparable to far more complex feature bundles. In heart failure, sex-specific lab-only scores using parameters such as potassium, bicarbonate, BUN/creatinine, and hematologic indices stratified 30-day risk across tertiles with effect sizes consistent across independent systems (Horne et al., 2017). Perioperative work leveraging day-1 and day-3 postoperative laboratories identified clinically meaningful discrimination for 30-day returns after bariatric surgery (Zhang et al., 2024), and nephrology cohorts have repeatedly highlighted albumin, creatinine, hemoglobin, and white blood cells as dominant signals in machine-learning pipelines (Tsai et al., 2024). At the health-system and national levels, administrative-clinical hybrids are feasible at scale; Saudi MOH data demonstrated that decision-tree classifiers can recover a substantial fraction of cardiovascular readmissions using routine fields (Alzeer et al., 2021). Likewise, an Omani prospective study showed that parsimonious models with length of stay, age, medication count, and liver enzymes offered a clinically balanced profile (Al Alawi et al., 2025). Against this background, our setting—where most patients had complete 24–48-hour laboratory panels prior to discharge—appears well suited for implementing lab-enhanced algorithms that can be piloted on the wards and iteratively refined.

The present results also inform service delivery priorities. First, given that most discharges were to home (68.1%), strengthening post-discharge surveillance for infection-related complications and cardiopulmonary symptoms may yield outsized benefit. Strategies could include telephonic follow-up within 72 hours, targeted home health for patients with recent discharges, and pharmacist-led medication reviews focused on diuretics, antibiotics, and high-risk cardiovascular agents. Second, the high proportion of urgent (non-elective) admissions underscores opportunities for earlier risk identification during the index stay; the Early HOSPITAL experience suggests that admission-time labs can prime transitional care teams even before discharge planning begins (Mathys et al., 2024). Third, because a sizeable minority underwent procedures, perioperative bundles—SSI prevention, anticoagulation reconciliation, and early mobilization—are relevant beyond purely surgical services, especially as comorbidity increasingly blurs traditional service boundaries (Alyabsi et al., 2022; 2022; Merdad et al., 2024).

Finally, the comparability of our crude readmission rate to international and Saudi reports supports external face validity, while the cause-of-return profile aligns with high-yield targets for quality improvement. Although our results were descriptive and did not evaluate independent associations in this report, they set the stage for the hospital's ongoing program to integrate laboratory-anchored risk models with administrative predictors and to embed alerts in the electronic record for patients at heightened short-term risk. Future work at KKUH can build on these foundations by combining pre-discharge laboratory values with utilization markers (prior discharges, length of stay) and by testing pathway-linked interventions—rapid clinic access for heart failure, infection "hotline" triage, and pharmacist follow-up for polypharmacy—as suggested by multicenter and regional experiences (Donzé et al., 2016; Karunakaran et al., 2018; Alzeer et al., 2021; Al Alawi et al., 2025). In sum, our findings reinforce that 30-day readmission remains a multifactorial, cross-service challenge in Saudi tertiary care and that routine, time-proximal laboratory data—paired with pragmatic transitional-care workflows—offer a feasible and clinically meaningful path toward risk-aligned discharge planning at KKUH.

In bivariate analyses, most demographic and service-related factors—sex, discharge service, urgent (non-elective) index admission, and discharge disposition—were not significantly associated with 30-day unplanned readmission in this mixed medical–surgical cohort. This pattern is consistent with the heterogeneity reported across settings, where such variables often show context-dependent effects that attenuate after accounting for illness burden and utilization. For instance, while female sex increased odds after cardiac surgery and some surgical oncology contexts (Alyabsi et al., 2022; Almramhi et al., 2022), medical cohorts in Saudi Arabia have typically shown modest or no sex effects, with age and comorbidity carrying the predictive weight (Althobaiti et al., 2025). Likewise, discharge service and disposition frequently behave as proxies for underlying severity, complexity, or social supports rather than independent drivers; their apparent impact can diminish once laboratory signals and prior utilization are considered, as seen in multicenter validations of administrative scores (Donzé et al., 2016) and in regional studies where return risk clustered around clinical instability and comorbidity instead of service labels (Merdad et al., 2024). The lack of a crude association for urgent admission in our cohort also fits this pattern: although "urgent" contributes to risk indices, its marginal effect can be muted when the case-mix is already enriched for acute presentations and when downstream markers (length of stay, laboratory perturbations) better capture the residual risk at discharge (Mathys et al., 2024).

By contrast, two categorical markers showed clear, large associations: higher HOSPITAL risk category and prior discharge within 90 days (both $p<0.001$). The first aligns directly with the original multinational HOSPITAL validation, where hemoglobin at discharge, sodium at discharge, oncology service, procedure during stay, urgent admission, prior 12-month admissions, and length of stay together yielded strong calibration and useful discrimination across 117,065 discharges (Donzé et al., 2016). In our data, the marked separation by HOSPITAL category reinforces external validity and indicates that a compact, operationalizable index retains signal in a Saudi tertiary hospital. The second—recent discharge—has repeatedly emerged as a powerful indicator of post-discharge instability and fragmented transitions. In adult medicine, a large U.S. cohort found recent discharge, longer index length of stay, and poor ambulatory follow-up among the most influential independent predictors (Karunakaran et al., 2018). Regionally, an Omani study linked readmission to multimorbidity and polypharmacy, again suggesting that "recency of utilization" is a proxy for unresolved clinical and social needs at the seam of care (Al Sibani et al., 2022). Together, these two signals are actionable: they can be identified automatically at discharge and can trigger intensified follow-up, case management, or pharmacist review.

Continuous predictors provided convergent evidence from complementary domains—utilization, renal function, inflammation, and myocardial injury. Patients who returned within 30 days had longer length of stay (7.3 vs 6.0 days, $p=0.013$) and more admissions in the prior year (1.8 vs 1.1, $p<0.001$). Both features are built into the HOSPITAL framework and consistently correlate with early reutilization across medical and surgical populations (Donzé et al., 2016; Alyabsi et al., 2022; Almramhi et al., 2022). They likely capture unmeasured severity, treatment complexity, and social barriers that prolong recovery. Importantly, length of stay and prior admissions are not merely prognostic—they are touchpoints for transitional care planning. As shown by Karunakaran and colleagues, coupling risk identification with early outpatient contact narrows preventable gaps (Karunakaran et al., 2018), and the "Early HOSPITAL" approach shows that analogous risk cues can be available much earlier in the index stay (Mathys et al., 2024).

Biological markers strengthened this picture. eGFR was significantly lower among readmitted patients (80.4 vs 87.8 mL/min/1.73 m², $p<0.001$), underscoring the centrality of renal reserve in short-term resilience. Renal dysfunction amplifies susceptibility to infection, fluid imbalance, and adverse drug events—mechanisms repeatedly highlighted in nephrology and general-medicine prediction work. For example, in maintenance hemodialysis cohorts, routine labs including albumin, creatinine, hemoglobin, and white blood cells ranked among the most informative predictors in machine-learning models (Tsai et al., 2024). Our eGFR signal likely reflects a broader vulnerability in which even moderate impairment compromises physiologic recovery and complicates medication management after discharge. In parallel, C-reactive protein was higher among those readmitted (17.3 vs 13.8 mg/L, p=0.003), supporting inflammation as a cross-cutting pathway to early return. This dovetails with surgical data where infectious and inflammatory complications dominate 30-day readmissions—e.g., gastrointestinal and infectious etiologies after colorectal surgery (Alyabsi et al., 2022) and sternal wound infections after cardiac surgery (Almramhi et al., 2022)—and with perioperative lab-anchored models that use early postoperative CRP (and related indices) to signal risk (Zhang et al., 2024). Finally, troponin was modestly but significantly higher among readmitted patients (6.5 vs 5.2 ng/L, p=0.020), echoing lab-only heart-failure scores in which compact analyte sets—including markers related to myocardial stress—stratified near-term readmission (Horne et al., 2017). Even outside overt cardiac diagnoses, low-level myocardial injury may mark limited physiologic reserve, subclinical ischemia, or demand-supply mismatch around discharge.

Two aggregate measures deserve emphasis because they tie the clinical and laboratory narratives together. First, the mean HOSPITAL points score was substantially higher among readmitted patients (5.8 vs 3.9, p<0.001). This reproduces the foundational observation that a pragmatic bundle of routine data can summarize risk better than any single factor (Donzé et al., 2016) and is consistent with the "Early HOSPITAL" variant that preserved accuracy using admission labs (Mathys et al., 2024). Second, discharge medication count was higher in those readmitted (6.7 vs 5.7, p=0.004), pointing to polypharmacy as a plausible driver of adverse transitions. The Omani study identified polypharmacy as a distinguishing feature of readmitted patients (Al Sibani et al., 2022), and broader adult-medicine literature links complex regimens with nonadherence, drug–drug interactions, and prescribing cascades that precipitate returns (Karunakaran et al., 2018). In practice, this suggests that medication reconciliation and targeted deprescribing—particularly in patients with reduced eGFR and elevated inflammatory or cardiac biomarkers—should be core elements of risk-aligned discharge planning.

That many demographic and service labels were non-significant in crude comparisons, whereas utilization and biology were consistently different, is informative for model design. It suggests that at KKUH, who the patient is and where they were cared for may matter less than how sick they remain at discharge and how complex their recent trajectory has been. This observation mirrors experiences from multicenter Saudi cohorts and international validations in which laboratory and utilization variables outperformed static demographics for short-term prediction (Donzé et al., 2016; Alzeer et al., 2021; Al Alawi et al., 2025). It also offers practical leverage: HOSPITAL category/score and "prior discharge ≤90 days" are EHR-derivable and can be combined with eGFR, CRP, and troponin to create a compact, automatable screening rule that flags patients for enhanced follow-up.

Several caveats apply. Bivariate associations cannot exclude confounding, and some non-significant results (e.g., service type) may mask within-service heterogeneity seen in specialty-specific reports (Alyabsi et al., 2022). Nonetheless, the convergence of signals across independent domains—utilization, renal function, inflammation, myocardial stress, and medication burden—argues for biological and organizational plausibility rather than statistical artifact. In sum, these bivariate findings align with international and regional literature and point toward a discharge-proximal risk phenotype at KKUH characterized by recent utilization, longer stays, impaired renal function, systemic inflammation, subtle cardiac injury, and polypharmacy (Donzé et al., 2016; Mathys et al., 2024). This phenotype is readily identifiable from routine data, providing a strong rationale for embedding lab-enhanced, utilization-aware screening and pharmacist-anchored medication management into standard discharge workflows.

The multivariable analyses in this study clarified that both utilization-centric and biology-centric signals independently shaped 30-day readmission risk. In the core model, age, length of stay, prior discharge within 90 days, and the HOSPITAL score remained significant after mutual adjustment, with acceptable global fit (χ^2=50.2, p<0.001) and good calibration (Hosmer–Lemeshow p=0.239). The prominence of length of stay and the HOSPITAL score is consistent with the original multinational HOSPITAL validation, where a compact bundle of routinely available elements captured substantial readmission signal and calibrated well across diverse hospitals (Donzé et al., 2016). Prior discharge within 90 days also retained an independent effect, reinforcing the idea that "recency of utilization" is a pragmatic proxy for unresolved clinical and social needs at the time of discharge (Kumar et al., 2019). In practice, these features are attractive because they are computable for every inpatient and can be integrated into electronic health record triggers without additional data collection burden (Donzé et al., 2016).

The core model's very high specificity (99.9%) but low sensitivity (2.7%) illustrates a known challenge in readmission prediction: class imbalance combined with a conventional 0.50 probability threshold tends to favor negative classifications in low-prevalence outcomes. This pattern has been observed even in well-calibrated models that show acceptable global performance but under-identify true events at default cut-points (Alzeer et al., 2021). The implication is less about the adequacy of predictors than about deployment choices. Thresholds should be tuned to local goals and resource capacity—often by defining low, intermediate, and high-risk bands—rather than relying on a single 0.50 cut-off (Donzé et al., 2016). Because calibration was good in our core model, the predicted probabilities can be trusted as a basis for such threshold optimization and for decision-curve or cost-sensitive evaluation (Kalzén et al., 2018).

Adding laboratories in the extended model provided mechanistic depth and a modest performance gain. With CRP and eGFR included, the model improved its explained variance (Nagelkerke R^2 from 0.10 to 0.14) and sensitivity (from 2.7% to 8.8%), while preserving interpretability and excluding problematic collinearity (VIF 1.01–1.41). The emergence of CRP as an independent predictor underscores the role of residual inflammation as a cross-cutting pathway to early return, a theme that aligns with perioperative work where infectious and inflammatory complications dominate 30-day readmissions (Howard et al., 2017), (Bucholz et al, 2018). The independent signal from eGFR highlights the contribution of renal reserve to short-term resilience, echoing nephrology and general-medicine prediction studies where creatinine/eGFR and allied analytes consistently rank among influential features (Tsai et al., 2024).

Overall discrimination of AUC 0.683 was modest but acceptable for hospital readmission modeling, and it falls near the performance seen when the HOSPITAL framework is applied with admission-time laboratories in order to enable earlier risk triage (Mathys et al., 2024). It is also in the range reported by regional classifiers that combine administrative and clinical fields at scale, albeit those sometimes incorporate richer contextual variables or post-discharge signals not available in our specification (Alzeer et al., 2021), (Krupp et al, 2021). The advantage of our approach is universality: every inpatient can have a model score at discharge, and many will have the necessary labs within 24–48 hours, which facilitates real-time use in routine care (Stephens et al., 2017).

A practical trade-off emerged around sample size. Because some biomarkers were missing for a subset of patients, the extended model's analytic N fell to 339. The gain in sensitivity and variance explained came at the cost of reduced generalizability and potentially wider confidence intervals. This is a common tension in hospital datasets where laboratory completeness varies by service and severity. Two strategies can preserve both coverage and signal. First, multiple imputation can retain the full cohort while appropriately propagating uncertainty when laboratory values are incomplete (Karunakaran et al., 2018). Second, a tiered implementation can be prespecified: deploy a "universal" core model for all discharges and switch to an "augmented" pathway when key labs such as CRP and eGFR are available, thereby exploiting their incremental information without excluding patients (Donzé et al., 2016), (Polites et al, 2022).

The absence of multicollinearity strengthens confidence in the stability of coefficients. VIF values between 1.01 and 1.41 indicate that the independent effects observed for age, length of stay, prior discharge within 90 days, HOSPITAL score, CRP, and eGFR represent distinct information streams rather than overlapping proxies. That distinction matters clinically: utilization markers such as prior discharge are implementation levers for case management and early follow-up, whereas biological markers such as CRP and eGFR argue for targeted clinical actions like infection vigilance, renal-safe prescribing, and early laboratory reassessment (Tsai et al., 2024). The heart-failure literature further supports the feasibility of compact lab-only rules that perform competitively with much larger feature sets, suggesting that parsimony need not sacrifice clinical utility (Horne et al., 2017), (Sills et al, 2021).

These findings fit within a broader regional and international pattern where pragmatic, automatable variables dominate readmission signal. In Saudi tertiary settings, models that blend administrative fields with routine clinical measures have achieved workable discrimination and demonstrated operational utility for cardiovascular cohorts (Alzeer et al., 2021). In nearby systems, parsimonious models incorporating length of stay, medication count, and selected laboratory abnormalities have yielded clinically balanced profiles with strong recall, indicating that simple inputs can support effective triage when tuned to local workflows (Toomey et al., 2020). Our results point in the same direction. A calibrated core score can screen universally; when available, CRP and eGFR can escalate risk level and tailor the post-discharge bundle. The threshold should be adjusted away from 0.50 to achieve a sensitivity that matches transitional-care capacity, acknowledging that improvements in recall will typically trade some specificity (Richards et al., 2016).

In summary, the multivariable analysis confirms that readmission at 30 days reflects an interplay of residual clinical complexity and biologic vulnerability at discharge. The core model captured the administrative and utilization backbone of risk with good calibration and high specificity. The extended model added mechanistic clarity through inflammation and renal reserve, yielding modest gains in variance explained and sensitivity at the cost of a smaller analytic sample. These patterns parallel evidence showing that compact, discharge-proximal data elements can guide scalable, real-time risk stratification in tertiary hospitals (Mathys et al., 2024). For implementation at KKUH, a tiered, EHR-embedded approach—core for all, augmented when CRP and eGFR are present, and locally tuned cut-points—offers a practical path to align transitional-care resources with patients most likely to benefit (Karunakaran et al., 2018).

CONCLUSION

In this retrospective adult cohort, we found a moderate rate of unplanned readmission and showed that a universally available core model, built from routine discharge-time information, identified older age, longer length of stay, recent prior discharge, and higher HOSPITAL points as independent predictors, with good overall fit and calibration but high specificity and low sensitivity at the default cut-off. An extended specification that incorporated routine biomarkers obtained shortly before discharge added clinically coherent signals from C-reactive protein and estimated glomerular

filtration rate, yielding modest gains in explanatory power and sensitivity without evidence of problematic multicollinearity. On this basis, we recommended a tiered, electronic-record–embedded approach: apply the calibrated core model to all discharges and, when key laboratories are available, escalate risk using the extended model to trigger targeted bundles such as early post-discharge contact, pharmacist-led medication review with deprescribing where appropriate, focused monitoring for infection and wound issues after procedures, renal-safe prescribing with timely laboratory reassessment, and rapid-access follow-up for cardiopulmonary symptoms; thresholds should be tuned locally rather than relying on a single default. Methodologically, we recommended internal validation with bootstrapping, external validation across services, decision-curve–guided threshold optimization, fairness monitoring, and parallel data-quality work to improve laboratory completeness and automate variable capture. Findings are most generalisable to adult medical–surgical inpatients in Saudi tertiary settings with similar case-mix and discharge workflows; generalisability to community hospitals may be limited.
The study had important limitations: it was single-center and retrospective; incomplete laboratory data reduced the effective sample for the extended model; readmissions to other institutions may have been missed; social determinants, functional status, and post-discharge follow-up were not available; class imbalance contributed to low sensitivity at conventional thresholds; preprocessing choices could have introduced residual bias; time-to-event and competing risks were not modeled; and cause-of-readmission coding was frequently incomplete. Because the extended model required complete laboratory panels, selection on lab availability may bias estimates toward sicker patients. Class imbalance combined with a default 0.50 threshold yielded low sensitivity despite good calibration; thresholds should be locally tuned.

Acknowledgments
We thank the inpatient services at King Khalid University Hospital (medical, surgical, cardiology, neurology, and oncology), the Admission–Discharge–Transfer and Laboratory Information Systems teams, and the Health Information Management staff for their support with data retrieval and clarification of variable definitions. We are grateful to the clinical panel that reviewed the abstraction tool and to the statistician who advised on internal validation and calibration analyses.

Author contributions
The researcher conceived and designed the study, developed the data abstraction instrument, coordinated data acquisition, and carried out the statistical analyses in SPSS. The researcher drafted the manuscript and integrated co-author feedback. Co-authors contributed to interpretation of results, critically revised the manuscript for important intellectual content, approved the final version, and agree to be accountable for all aspects of the work. The corresponding author had full access to all data and takes responsibility for the integrity and accuracy of the analysis.

Ethics approval and consent to participate
The study protocol was reviewed and approved by the Institutional Review Board of King Saud University Medical City/King Khalid University Hospital, Riyadh, Saudi Arabia. Given the retrospective design and use of de-identified extracts, the requirement for informed consent was waived. The study complied with institutional policies and the principles of the Declaration of Helsinki. Data were stored on secure, access-restricted servers; identifiers were removed prior to analysis. The IRB approval reference is available from the corresponding author upon reasonable request.

Funding
This research received no external funding and did not receive a dedicated budget from public, commercial, or not-for-profit agencies.

Data availability statement
De-identified data that support the findings of this study, along with the SPSS syntax used for preprocessing and modeling, are available from the corresponding author on reasonable request and subject to institutional approvals and data-sharing agreements.

Conflict of interest: The authors declare no competing interests.

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