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Development and validation of the discharge severity index for post-emergency department hospital readmissions

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ABSTRACT

Introduction: Hospital readmissions often result from a combination of factors, including inadequate follow-up care, poor discharge planning, patient non-adherence, and social determinants of health (SDOH) that impact access to healthcare and follow-up resources, many of which are beyond provider control. Enhanced post-discharge strategies, including risk stratification, are essential. This study aims to develop and validate the Discharge Severity Index (DSI) to predict readmission risk and optimize resource allocation for effective follow-up care.

Methods: This single-center retrospective study analyzed ED visits from the Medical Information Mart for Intensive Care IV, dividing the data into derivation (75 %) and validation (25 %) cohorts. Univariate analyses were conducted on factors commonly available for most discharges, including patient age, the latest vital signs recorded, medical complexity, and ED length of stay (LOS). Multiple logistic regression (MLR) was employed to identify independent risk factors of patients revisiting the ED within a week and being subsequently admitted to the hospital. Adjusted parameter estimates from the MLR were used to develop a predictive model.

Results: Among 229,920 patients discharged from the ED, 1.92 % were readmitted. The analysis identified seven variables correlated with this outcome, with six significant risk factors pinpointed through MLR: age above 65, heart rate over 100, and oxygen saturation below 96 % (assigned 1 point each), along with having more than five active medications administered during the hospital stay or a LOS exceeding 3 h (assigned 2 points each). Using these scores, we categorized patients into five DSI groups, reflecting escalating readmission risk from DSI 5 (lowest risk) to DSI 1 (highest risk): DSI 5 (0; OR: 1.0), DSI 4 (1–2; OR: 3.49), DSI 3 (3–4; OR: 8.44), DSI 2 (5–6; OR: 11.65), and DSI 1 (>6; OR: 14.63). The seven-day readmission rates were comparable between the development and validation cohorts. For instance, for DSI 1, the rates were 5.16 % in the development cohort and 4.67 % in the validation cohort. For DSI 2, the rates were 4.16 % and 4.04 %, respectively.

Conclusion: This study seeks to develop and validate the DSI, proposing its effectiveness as a tool for healthcare providers to categorize patients by their risk of post-discharge admission from the ED. The utilization of this tool has the potential to lead to a more informed allocation of resources after discharge.

1. Introduction

Several factors enhance the risk of ED visits and hospital readmissions, including old age, lower income, multiple chronic conditions, e.g., COPD, and previous history of frequent hospitalizations. Living alone or requiring home care services increases the likelihood of hospital readmission among older adults [1,2]. Additionally, many patients discharged from the ED are scheduled to follow up with a primary care physician or specialist to continue the diagnostic process or address evolving conditions after an ED visit [3,4]. As emergency medicine (EM) continues to see improvements in medical care for patients who do not need acute hospitalization, the field has become increasingly reliant on follow-up care to ensure patients' full recovery. Follow-up care in EM

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has garnered significant attention, as about half of all malpractice claims against EM physicians are related to the quality or presence of follow-up care [5]. However, despite its growing importance, only about 26 %–56 % of patients adhere to the follow-up plan that an ED physician prescribes [6].

Patient non-adherence to follow-up plans is multifaceted, with many opting out of continued care due to perceived recovery [6]. Patients who do not fully understand their discharge instructions may fail to manage their conditions effectively post-discharge, leading to complications and readmission. Studies have shown that enhanced discharge education can significantly reduce readmissions [5,7]. Research conducted by Engel et al. [8] on patients recently discharged from U.S. emergency departments revealed that the most common parts of clinical care that patients do not fully understand and adhere to are home care and return care instructions. Beyond patients' adherence to follow-up plans, however, there is often a lack of clarity in the plans developed by EM physicians. Boockvar et al. [9] found that only 45 % of patients discharged from the ED received instructions about their post-discharge care. Due to a lack of clear patient-provider and provider-provider communication about follow-up care, many patients return to the ER due to worsening medical conditions, leading to readmission rates within 30 days post-discharge of around 14 % [10]. Establishing comprehensive and clear follow-up care plans can alleviate some of the pressures that EDs currently face due to overcrowding through decreasing readmissions to the ED.

The proliferation of out-of-hospital tools has allowed for a greater capacity for post-discharge care. For example, remote monitoring has become an especially effective way to monitor patients after discharge through smartphone apps, tele-education, and teleconsultation [11]. However, there currently is no method to assign discharge priorities to these resources, and the quality of post-discharge care is ultimately limited by time and resource constraints [12]. Inspired by systems like the Emergency Severity Index (ESI), a triage tool widely used in the ED by 70 % of large hospitals in the US [13-15], there is significant potential to develop a comparable approach for post-discharge care, using an algorithm that utilizes risk stratification to allocate resources based on severity-based priorities. The objective of this study is to develop and validate the Discharge Severity Index (DSI), a tool designed to predict the risk of post-discharge readmissions and optimize the allocation of healthcare resources for follow-up care based on risk stratification.

2. Methods

2.1. Data and selection of participants

This retrospective cohort study analyzed clinical data from patients who visited the emergency department (ED) at Beth Israel Deaconess Medical Center, a Level I trauma center and academic medical institution in Boston, Massachusetts. We utilized data from the Medical Information Mart for Intensive Care IV (MIMIC-IV) public database [16], which spans from 2008 to 2019 and includes de-identified records of 425,087 ED visits. This database comprises data on patients aged 18 years and older. For our study, we included patients who were discharged home following their emergency department visit, which in the MIMIC-IV-ED dataset includes both those discharged directly and those who underwent an observation period before discharge. Patients who were admitted to the hospital, transferred to another facility, left without being seen, eloped, left against medical advice, or expired were excluded from the analysis. Admission in this study was defined as admission to any acute care unit within the same facility and did not include transfers to other facilities.

2.2. Risk factors

Our analysis selected risk factors and established thresholds for dichotomizing these variables. Included factors were patient age, the latest vital signs recorded, medical resource needs as reflected by the number of active medications a patient has been prescribed, and the length of stay (LOS) in the ED. The cutoffs for dichotomizing continuous variables were selected based on clinical significance, existing literature [14]. Age (65 years) aligns with the definition of older adults, who are more vulnerable to adverse outcomes (Maher et al., 2020) [17]. ED Length of Stay (LOS) 180 min reflects a meaningful marker of prolonged stay, as defined by Becker's Hospital review [18,19], who emphasized the importance of shorter benchmarks in analyzing ED operations. The threshold of five medications reflects polypharmacy as a proxy for medical resource needs and poorer outcomes (Liu et al., 2017) [20]. SBP of 120 mmHg was chosen as it indicates suboptimal hemodynamic status that could impact readmission risk. Our study had the same objectives as Wuerz et al. (2000) [14] and therefore used the same variables. The goal was to create a scoring system that stratifies patients based on their risk of adverse outcomes, such as ED return visits or readmissions, while maintaining clinical relevance and ease of use.

We chose not to include variables like race, gender, payor status, and laboratory or imaging data because we wanted to mimic ESI as a resource allocation tool without individual characteristics, to get the first version of DSI. Including variables like ESI level, laboratory abnormalities, or consultations could improve predictive accuracy but might limit generalizability and practicality, especially in resource-limited environments.

We chose to use the latest set of vital signs recorded prior to discharge as they reflect the patient's condition at the point of decision-making for discharge. This approach aligns with the clinical practice of ensuring that patients meet stability criteria before being discharged. While the most abnormal or concerning vital signs during the ED visit could provide valuable insights into a patient's overall severity of illness, our primary objective was to focus on data that is both consistent and directly relevant to the discharge decision-making process for later resource allocation. Additionally, including the most abnormal vital signs (only 17 % of the excluded data) could introduce variability and potential bias, as these values may not represent the patient's stabilized condition. Moreover, focusing on the last vital signs aligns with the study's goal of simplicity and generalizability, ensuring that the DSI remains practical and widely applicable.

For vital sign values that were out of range and not compatible with life, which was most likely due to coding errors, we excluded these values from the patient's visit record [21]. These exclusion criteria applied to any vital sign measurements that were less than zero, heart rates below 20 or above 250 beats per minute, systolic blood pressures under 50 or over 300 mmHg, instances where the diastolic blood pressure was recorded as higher than the systolic, body temperatures below 86 or above 113 degrees Fahrenheit, and oxygen saturation levels exceeding 100 % [22]. We excluded approximately 45 % of records due to these issues. This 45 % reflects the sum of all exclusions, including 33,621 visits (approximately 8 % of the initial dataset) that were excluded for having missing values or vital signs outside the predefined (and physiologically plausible) range and an additional 161,546 visits that were excluded due to dispositions other than discharge to home. The proportion of records excluded for this reason is roughly 8 % rather than 45 %.

We carefully considered additional variables, such as recent hospital discharges, the number of recent ED visits, and measures of complexity based on past medical history. However, these were not included in the final model due to a combination of factors. For instance, some variables were excluded due to data unavailability or inconsistency across the dataset, while others were tested but did not show significant predictive value during model development. We prioritized variables consistently recorded across hospital discharges and supported by prior literature as strong predictors of readmissions, as reflected in Table 1.

2.3. Outcome measures

We selected the likelihood of patients returning to the ED within a week of discharge and the subsequent need for hospital

Table 1
Characteristics of the derivation cohort.

	Revisit with Admission	No Revisit	*P* value
	N = 3347	*N* = 169,093	
Age, median (IQR)	50 (36–67)	42 (28–58)	<0.001
Age, No. (%)			<0.001
> 65	1002 (29.94)	28,812 (17.04)	
≤ 65	2345 (70.06)	140,281 (82.96)	
Vital signs			
SBP, median (IQR)	129 (117–142)	126 (114–139)	<0.001
SBP, No. (%)			0.002
> 120	2091 (62.47)	101,173 (59.83)	
≤ 120	1256 (37.53)	67,910 (40.16)	
Heart rate, median (IQR)	77 (69–87)	75 (67–85)	<0.001
Heart rate, No. (%)			<0.001
> 100	223 (6.66)	7001 (4.14)	
≤ 100	3124 (93.34)	162,092 (95.86)	
SO2, median (IQR)	98 (96–99)	99 (97–100)	<0.001
SO2, No. (%)			<0.001
≥ 96	2749 (82.13)	146,180 (86.45)	
< 96	598 (17.87)	22,913 (13.55)	
LOS (minutes), median (IQR)	403 (278,618)	296 (192,462)	<0.001
LOS, No. (%)			<0.001
> 180 min	3102 (92.68)	131,894 (78.00)	
≤ 180 min	245 (7.32)	37,199 (22.00)	
Number of Active Medications, median (IQR)	7 (3−12)	4 (1–7)	<0.001
Number of Active Medications, No. (%)			<0.001
> 5	1957 (58.47)	54,111 (32.00)	
≤ 5	1390 (41.53)	114,982 (68.00)	

Abbreviations: SD, standard deviation; No., numbers; SBP, systolic blood pressure; SBP, systolic blood pressure; SO2, oxygen saturation; LOS, length of stay; IQR, interquartile range.

admission as indicators of the necessity of critical follow-up. The primary outcome of this study was to identify independent risk factors contributing to this scenario and to develop the DSI score accordingly. We opted for a seven-day observation period rather than the conventional 72 h. This longer time frame allows for a more comprehensive capture of potential complications that could occur once patients are back home [23], thus enabling the allocation of more targeted and effective healthcare resources for post-discharge follow-up.

2.4. Statistical analysis

The data was randomly divided into derivation and validation cohorts, comprising 75 % and 25 % of the total. We analyzed the statistical significance ($p < 0.05$) of commonly available variables between patients who revisited and were admitted and those who did not, using Pearson's chi-square test. Variables found to be significant were subsequently included in the logistic regression analysis for developing the predictive model. This analysis helped determine the odds ratios (OR) with 95 % confidence intervals (CI) and *p*-values for each predictor. The statistically significant variables were then normalized by dividing them by the lowest variable odds ratio to create weighted scores, and standard rounding was applied to assign integer values. These scores were incorporated into the logistic regression model to develop the scoring model. Predictive scores were categorized into five DSI levels by evaluating the distribution of total risk scores and their associated odds ratios from the logistic regression model. We selected cut-points to ensure that each category reflected a meaningful and progressive increase in readmission risk while maintaining sufficient sample sizes within each group to preserve statistical power and clinical interpretability. Finally, we calculated the prediction probabilities for each DSI category. All statistical analyses were carried out in Stata version 18.0.

3. Results

3.1. Characteristics of study subjects

The initial dataset for the study included a total of 425,087 ED visits. Of these, 33,621 visits were excluded due to missing values and vital signs falling outside the predefined range, and an additional 161,546 visits were excluded owing to dispositions other than discharge to home. Consequently, the refined dataset comprised 229,920 visits that met the eligibility criteria for inclusion in this study. These visits were subsequently stratified into a derivation cohort consisting of 172,440 visits for DSI development and a validation cohort encompassing 57,480 visits to test the DSI. Within these cohorts, the percentages of patients who revisited and were admitted within a 7-day window were 1.94 % and 1.86 %, respectively (Fig. 1).

Characteristics of the study subjects, as detailed in Table 1, show notable differences based on their subsequent ED outcomes. Patients who revisited and were subsequently admitted had an average age of 53 years, significantly higher than those who did not revisit, who averaged 45 years. There was a marked disparity in the length of stay (LOS) in the ED; the median LOS for revisited patients was 403 min, considerably longer than the 296 min for those not revisited. Furthermore, the revisited patients had an average of 9 active medications, in contrast to 5 in the not revisited group.

3.2. Main results

Table 2 presents the derivation of the risk scores based on the logistic regression models developed in the study. In this model, the scoring system ranges depending on specific risk factors. The lowest possible score assigned to a patient was 0, which applies to those without identified risk factors. Conversely, the highest possible score accumulated from all risk factors could be 7, achieved when all the identified risk factors are present in a patient. The factors contributing to the score include age over 65, a history of more than five active medications, a pulse rate above 100 beats per minute at discharge, an oxygen saturation level below 96 % at discharge, and an ED length of stay from triage to discharge exceeding 3 h. Each of these factors contributes to the cumulative risk score, which assesses the likelihood of a patient revisiting the ED within seven days and being subsequently admitted. Further details on the logistic regression model utilizing weighted scores, including odds ratios, are demonstrated in Table 3.

Table 4 introduces the final model with five DSI categories central to the predictive scoring tool developed in the study. These categories range from DSI 5 (representing a reference group with a predictive score of 0) to DSI 1 (indicating the highest risk group with a predictive score greater than 5). The odds ratio (OR) for each DSI category escalates with increasing predictive risk scores.

The DSI score was evaluated using a validation cohort, as demonstrated in Table 5. The findings revealed that the percentage of patients who revisited the ED within seven days and were subsequently admitted was comparable between the derivation and validation cohorts. Around 46 % of discharged patients in both cohorts were categorized as DSI 4, followed by those under DSI 3.

To evaluate the discriminative ability of the DSI model, we compared the area under the receiver operating characteristic (ROC) curve (AUC) between the full logistic regression model and the DSI score. The AUC was 0.67 (95 % CI: 0.66–0.68) for the logistic regression model and 0.64 (95 % CI: 0.63–0.65) for the DSI score. The ROC curve is provided in Appendix X. This result indicates that the simplified integer-based DSI maintained comparable discriminative power to the original model.

4. Discussion

The development and validation of the DSI in this study represent a significant step in enhancing post-discharge patient care management,

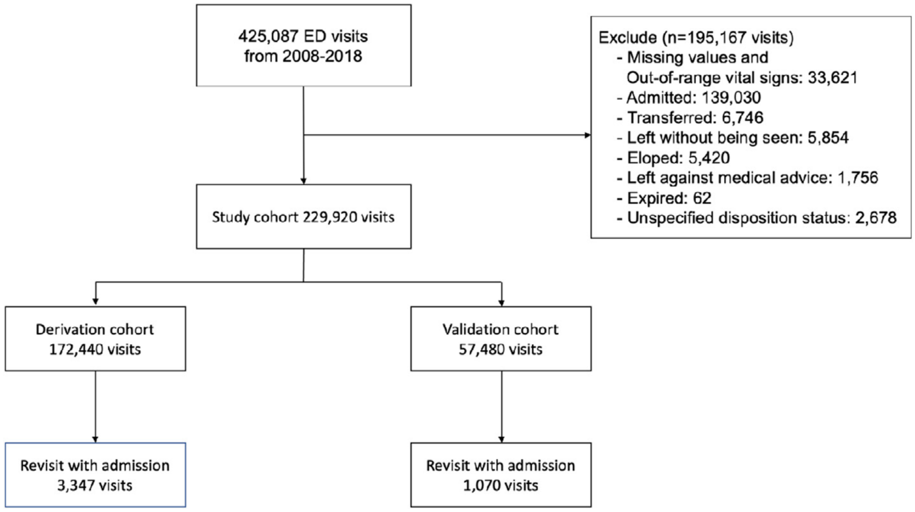


Fig. 1. Data Flow Chart.

Table 2
Risk scores.

Predictive score	OR	SE	z	*P* values	95 % CI for OR		Score (OR/1.29)
					Lower	Upper	
Age > 65	1.29	0.50	6.1	< 0.001	1.19	1.40	1
Active medications >5	2.65	0.10	25.27	< 0.001	2.46	2.86	2
Heart rate at discharge >100	1.67	0.12	7.01	< 0.001	1.45	1.92	1
Systolic blood pressure < 120	1.06	0.04	1.62	0.11	0.99	1.45	–
Oxygen saturation at discharge <96	1.36	0.07	6.35	<0.001	1.23	1.49	1
LOS from triage to discharge >3 h	2.87	0.19	15.67	<0.001	2.51	3.27	2

Abbreviations: LOS, length of stay; OR, odds ratio; CI, confidence interval; SE, standard error.

particularly for patients discharged from the ED. The DSI, derived from a comprehensive analysis of 229,920 patient discharges, offers a nuanced approach to risk stratification, facilitating targeted allocation of post-discharge resources. This tool categorizes patients into five risk groups based on factors commonly available for most discharges, such as age, heart rate, oxygen saturation, active medication history, and length of stay in the ED.

The decision to use five categories for the Discharge Severity Index (DSI) was made to capture a broader spectrum of patient risk levels, thereby enhancing the granularity and sensitivity of the tool. By creating five categories, we were able to better stratify patients according to their risk of readmission, rather than grouping them into broader risk bands like low, moderate, and high. The DSI provides a framework which may help to identify patients who may require more immediate follow-up care. Additionally, we tried to mimic the resource allocation model of the Emergency Severity Index (ESI), which also uses five categories. While a three-category system may simplify the model, it could potentially overlook important differences in patient risk that are critical for clinical decision-making.

In this study, we define active medications as the number of medications patients were prescribed at the time of their admission to the ED and reconcile them with patient charts, as documented in the MIMIC-IV database. These include all medications such as antibiotics, antihistamines, H2 blockers, non-narcotic pain relievers, and others. Non-prescription medications were not included unless explicitly recorded as part of the administered medications during the hospital stay. The number of medications served as a proxy for assessing medical resource needs. This approach is based on prior literature suggesting that polypharmacy is associated with increased healthcare utilization. [24].

In our model, two risk factors were assigned with higher weight: a length of stay in the ED exceeding 180 min and having more than five active medications, each contributing 2 points to the overall risk score.

Table 3
Logistic regression model using weighted score.

Predictive score	OR	SE	z	P values	95 % CI for OR		Number of patients (N)
					Lower	Upper	
1	2.55	0.59	4.04	< 0.001	1.62	4.01	3929
2	3.52	0.36	12.2	< 0.001	2.88	4.31	28,683
3	6.38	0.72	16.41	< 0.001	5.12	7.97	24,603
4	9.44	0.98	21.71	< 0.001	7.71	11.56	72,675
5	11.65	1.22	23.38	< 0.001	9.48	14.31	23,422
6	14.70	1.97	20.1	< 0.001	11.31	19.11	2081
7	12.21	7.31	4.18	< 0.001	3.78	39.46	35
Constant	0.00	0.00	- 56.94	< 0.001	0.00	0.00	

Abbreviations: OR, odds ratio; CI, confidence interval; SE, standard error.

Table 4
Final model presenting 5 DSI categories derived from the derivation cohort.

DSI	Predictive score	OR	SE	z	P values	95 % CI for OR	
						Lower	Upper
5	0	Ref					
4	1–2	3.49	0.36	12.13	< 0.001	2.85	4.28
3	3–4	8.44	0.86	20.88	< 0.001	6.91	10.31
2	5	11.65	1.22	23.38	0.01	9.48	14.31
1	>5	14.63	1.95	20.17	< 0.001	11.28	18.99

Abbreviations: DSI, Discharge Severity Index; OR, odds ratio; CI, confidence interval; SE, standard error.

Interestingly, we found that the median length of stay in the ED was 403 min for patients who were subsequently readmitted, compared to 296 min for those who were not. This pattern suggests that shorter ED stays, significantly below the median duration, were associated with a reduced risk of readmission. The correlation between more extended ED visits and an increased likelihood of adverse outcomes could indicate more complex or severe medical issues among these patients [25,26]. Additionally, research by Wessman et al. underscores the significant impact of extended ED-LOS on short-term mortality, particularly for patients with triage levels 2 to 4 who were not admitted to hospital care. This indicates that patients who are not in immediate life-threatening conditions but still require timely care may experience worse outcomes due to delays associated with longer ED stays [19]. This underscores the importance of prioritizing patients who might benefit from enhanced follow-up resources to mitigate risks associated with prolonged ED stays. While our analysis suggests a correlation between prolonged ED Length of Stay (LOS) and increased risk of readmission, it is important to acknowledge that LOS can be influenced by various factors beyond medical complexity. Extended ED stays may also be a surrogate for ED overcrowding, delays in care, and operational inefficiencies, such as staffing shortages or lack of inpatient beds. These factors may contribute to longer LOS, making it a multifaceted variable that should not be interpreted solely as an indicator of patient complexity. For example, a study by Sartini et al. (2022) [27] indicates that operational inefficiencies, such as inadequate inpatient capacity and boarding, contribute to prolonged ED stays, negatively impacting patient outcomes. Similarly, A study by Pines et al. (2009) [28] explores how ED crowding delays care initiation, contributing to longer boarding times and increased length of stay (LOS). Future studies could explore the interplay between these operational variables and LOS to better understand their combined impact on patient outcomes.

Additionally, in our model, the number of different medications a patient has been prescribed serves as an indicator of their medical resource needs. This aspect is especially pertinent as it highlights that patients with similar types of comorbidities may have varying levels of disease severity, as reflected by the number of medications they require [29,30]. The allocation of points for medication history within the model highlights the necessity of considering a patient's extensive medical history rather than focusing solely on their current underlying disease. This approach emphasizes a more holistic view of patient health, acknowledging that their past medical interventions are crucial to understanding their health status.

Several studies have shown that abnormal vital signs at ED discharge, such as hypotension, tachycardia, fever, and hypoxia, are significant predictors of adverse outcomes, including ED recidivism and unplanned returns to the hospital [31]. For instance, a study [32] showcased that hypotension at discharge is associated with the highest odds of adverse events, and tachycardia is a key predictor that ED clinicians may easily miss. These findings emphasize the importance of monitoring vital signs at discharge to identify high-risk patients who may benefit from targeted interventions to prevent readmission. Our study builds on this work by introducing the Discharge Severity Index (DSI). This novel tool incorporates not only vital signs but also other clinical factors to predict the likelihood of an ED revisit. Unlike prior studies that primarily focus on vital sign abnormalities, our DSI provides a more comprehensive risk assessment, offering new insights into how multifaceted discharge factors can be used to improve post-discharge care and resource allocation.

The validation of the score against the validation cohort successfully highlights the potential for stratified post-discharge resource allocation based on DSI categories, as shown in the data analysis from Table 5 of the study. DSI 4, which includes the majority of patients (46.41 % in the derivation cohort and 46.64 % in the validation cohort), exhibited a lower revisit rate (1.28 % and 1.13 %, respectively), suggesting these patients might require fewer resources post-discharge. Conversely, DSI 1 and DSI 2, despite representing a smaller fraction of the patient population, show higher revisit rates and could necessitate more intensive follow-up and resources. Employing this stratification to inform discharge planning could enable hospitals to tailor their resource distribution more effectively, potentially enhancing the quality of patient care. Farias et al. (2020) depicted the effectiveness of remote patient monitoring tools in managing these high-risk (DSI 1 and 2) patients. Their systematic review [9] highlights the benefits of using wearable devices for continuous vital sign tracking and early intervention, supporting the role of these technologies in improving patient outcomes and reducing readmissions.

The DSI is different from commonly used tools like the LACE and HOSPITAL scores. The LACE score [33] incorporates length of stay, acuity of admission, comorbidities, and discharge disposition, and the HOSPITAL score includes factors such as cancer history, admission type, and electrolyte disturbances. While these tools are widely used for predicting readmissions, the DSI is designed to address the needs for post-discharge resource allocation, such as home care, nursing follow-ups, telehealth services, and timely primary care visits. By integrating variables such as vital signs, patient demographics, and ED length of stay, the DSI provides a framework for stratifying patients based on discharge risk, which may help guide resource allocation. Future studies are needed to evaluate its impact on post-discharge care and patient outcomes. In a subsequent phase, we plan to evaluate the

Table 5
Predicted vs. Observed Risk for inpatient admission within seven days of discharge from ED. The comparison in Table 5 between DSI and ESI scores is observational and does not imply a direct correlation between the two scoring systems.

Scoring algorithm	Derivation cohort		Validation cohort		Scoring algorithm	Validation cohort	
	% of revisit	% of patients in the category	% of revisit	% of patients in the category		% of revisit	% of patients in the category
DSI 1	5.16	1.47	4.67	1.38	ESI 1	2.43	1.85
DSI 2	4.16	10.56	4.04	10.36	ESI 2	2.32	23.02
DSI 3	3.04	25.29	3.11	25.35	ESI 3	1.93	63.33
DSI 4	1.28	46.41	1.13	46.64	ESI 4	0.51	11.33
DSI 5	0.37	16.26	0.39	16.27	ESI 5	0	0.42

Abbreviations: DSI, Discharge Severity Index; OR, odds ratio; CI, confidence interval; SE, standard error; ESI, emergency Severity Index.

DSI side by side with LACE and HOSPITAL using ROC metrics, which will help clarify relative performance and practical utility. This study is already underway.

4.1. Limitations

However, this study has limitations, including its retrospective design, reliance on a non-data-driven approach to threshold selection, and use of data from a single academic medical center, which may not fully capture patient care variations across different settings. A high data exclusion rate (45 %) may impact the generalizability of the study. We plan to implement a more systematic approach in future to missing data in subsequent work, possibly including multiple imputation or additional inclusion criteria, to evaluate any bias introduced by these exclusions. A notable constraint is our method's focus on commonly recorded variables like vital signs, medical complexity and LOS, which, while facilitating ease of use and broader implementation, might not capture the entire complexity of patient care. For instance, LOS is influenced by numerous factors, including patient complexity, ED overcrowding, operational inefficiencies, and systemic healthcare dynamics. The study does not distinguish between these contributing factors, limiting the specificity of LOS as a predictor. This simplification trades off potential accuracy for practicality, possibly overlooking detailed data such as laboratory tests, imaging results, and prescribed medications that could enhance predictive precision. A significant limitation is that our study does not propose specific actions based on the DSI scores. Similar to how the Emergency Severity Index (ESI) is a descriptive scale that does not prescribe specific actions based on its 1–5 scale, the DSI is also intended as a descriptive tool rather than a prescriptive one. We propose that each medical center develop its evolving follow-up plan tailored to the different levels of DSI and based on its resources, acknowledging that the DSI is designed to guide rather than dictate clinical actions.

We acknowledge that the number of medications may not always perfectly reflect future resource utilization risk, as it does not account for nuances such as treatment optimization or disease control. For instance, patients with well-managed chronic conditions due to lifestyle changes or treatment adjustments may require fewer resources than those with poorly controlled conditions, even if both groups have similar medication counts. Additionally, the specific indications for medications, their therapeutic impact, and patient adherence to treatment regimens play a significant role in resource needs. Moreover, this study does not account for the reasons behind medication changes (e.g., switching from one class of medication to another or discontinuing medications due to lifestyle improvements), which may not reflect resource utilization. However, this study used the number of medications as a surrogate marker for future resource utilization risk due to its availability in most ED discharge records and its demonstrated correlation with adverse outcomes in prior studies [18,20,24]. In developing this approach, we also aimed to mimic the resource allocation model of the Emergency Severity Index (ESI). We acknowledge the limitations of this approach, and future models should incorporate measures such as disease control, medication adherence, and transitions in treatment regimens to better assess resource utilization needs.

This study acknowledges the absence of Social Determinants of Health (SDOH) variables. SDOH, such as housing instability, access to healthcare, employment status, and socioeconomic factors, play a critical role in shaping frequent ED utilization patterns, particularly among high-risk patient populations. Their inclusion could enhance the implication of the Discharge Severity Index (DSI) by capturing risks that extend beyond clinical parameters. We acknowledge the limitations of splitting the dataset into derivation (75 %) and validation (25 %), a standard approach in retrospective studies to ensure sufficient data for both training and validation within the available dataset. However, we recognize that using an entirely independent dataset for validation would enhance the robustness of our findings. In addition, a temporal split—using the most recent data for validation—could further assess the model's stability over time and detect potential temporal drift. Although we prioritized balanced sample sizes for this initial development, we acknowledge this limitation and plan to incorporate temporal validation in future studies. As a step forward, we plan to address this limitation by incorporating external validation in future studies, enabling us to assess the generalizability of the predictive model across diverse populations and settings. Hence, future research could benefit from incorporating a more comprehensive range of data to validate and refine the DSI's utility.

5. Conclusion

In conclusion, this study seeks to develop and validate the DSI. It proposes its effectiveness as a tool for healthcare providers to categorize patients by their risk of post-discharge admission from the ED. Utilizing this tool has the potential to enable a more informed allocation of follow-up resources after discharge from ED. In future iterations of the DSI, incorporating individual characteristics such as race, gender, payor status, and laboratory or imaging data could enhance its predictive accuracy. Future efforts could focus on leveraging machine learning (ML) approaches to enhance the predictive capabilities of the DSI. By incorporating additional variables such as socioeconomic factors, dynamic patient data from wearable technology, or real-time clinical metrics, an ML-based model could identify more nuanced predictors of readmission. Additionally, exploring the integration of DSI into electronic health record systems could facilitate real-time decision support for clinicians, enabling proactive interventions at the point of care. Prospective validation across diverse healthcare settings and populations would also ensure the generalizability of the tool. Assessing the impact of implementing the DSI on clinical workflows, patient outcomes, and healthcare costs would provide valuable insights into its practical application and sustainability in routine care. Lastly, future iterations of the DSI could explore integrating SDOH variables through partnerships with community health organizations, public health databases, or patient-reported measures. Incorporating these factors would allow for a more holistic assessment of patient needs and potentially improve the tool's predictive accuracy.

CRediT authorship contribution statement

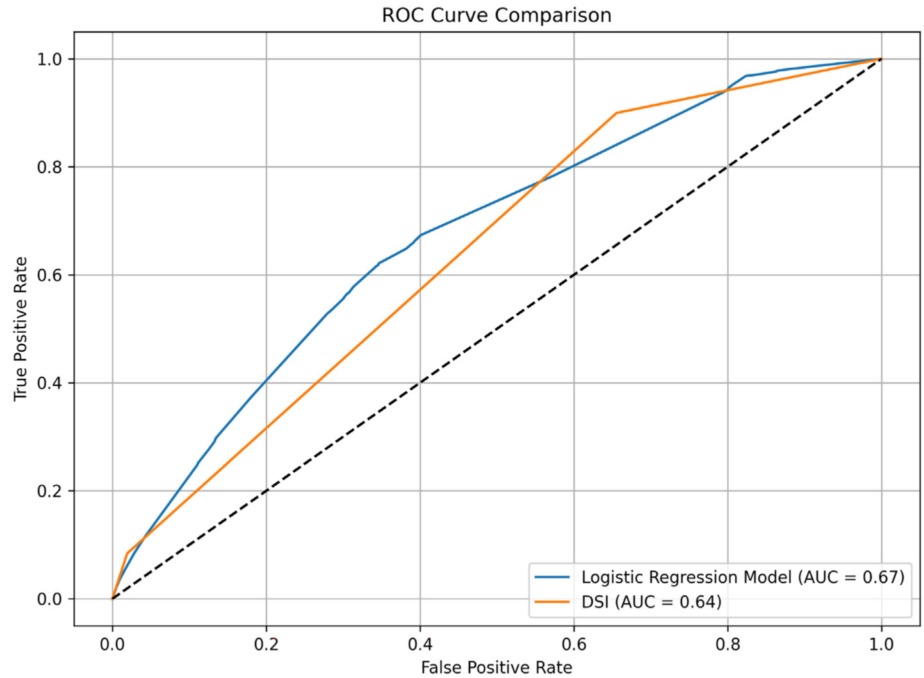
Norawit Kijpaisalratana: Writing – original draft, Methodology, Data curation, Conceptualization. **Abdel Badih El Ariss:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Adi Balk:** Writing – original draft, Methodology, Formal analysis. **Suhanee Mitragotri:** Writing – original draft. **Kian D. Samadian:** Methodology, Investigation, Formal analysis. **Barry J. Hahn:** Methodology, Formal analysis. **Adriana Coleska:** Methodology, Investigation, Formal analysis. **Joshua J. Baugh:** Writing – original draft, Project administration. **Ahmad Hassan:** Writing – original draft, Project administration, Data curation. **Jarone Lee:** Methodology. **Ali S. Raja:** Formal analysis. **Shuhan He:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

None.

Appendix A. Appendix

We have now compared the AUCs of the original logistic regression and the integer-based model.



Logistic Regression AUC 95 % CI: 0.66–0.68.
DSI Score AUC 95 % CI: 0.63–0.65.

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