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Clinical Decision Rules for Heart Failure Management in Acute Emergency Department Settings

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Abstract

Background: Heart failure (HF) is the leading cause of ED visits, thus patients must immediately assess their risk to make informed treatment choices. Emergency heart failure treatment is increasingly using clinical decision rules (CDRs) like the HEART score. More study is needed on their ED efficacy.

Aim: This research examined how effectively CDRs predicted ED outcomes for HF patients. In the emergency room of King Hussein Medical Centre, this research examined how effectively and how frequently established CDRs treated acute HF. Planning for release and short-term problems was the emphasis.

Methods: This research reviewed all adult HF patients (age 18 or older) presented to the ED between January 2024 and June 2025 using electronic health records. HF patients with acute decompensation were included. No patients with missing data, non-cardiac dyspnoea, or terminal conditions were included. We collected patient data, vital signs, lab findings, CDR usage (HEART-like route, MEESSI score components), and events (hospital admission, 30-day return, and death). ROC curves and multivariable logistic regression let us identify separate adverse event factors and assess the CDR's prediction ability.

Results: The MEESSI-based rule accurately identified hospitalised patients (AUC=0.87, 95% CI: 0.85–0.89) and non-hospitalized patients (AUC=0.76, 95% CI: 0.73–0.79) in 1,420 patient interactions. The modified HEART-like circuit differentiated well at entrance (AUC=0.79) but not after 30 days (AUC=0.7). Multiple regression study indicated that high-acuity screening, qSOFA score, higher BNP, and ED crowds independently predicted admission. However, MEESSI high-risk categorisation, higher creatinine, and older age independently predicted the 30-day composite outcome.

Conclusion: Well-known CDRs, notably those based on the MEESSI score, accurately predicted clinical outcomes in Jordanian tertiary care emergency departments for severe HF patients. These techniques may assist standardise risk ranking, make decisions, and optimise resources.

Keywords: Heart failure; Clinical decision rules; Emergency department; HEART score; MEESSI score; Risk stratification; Disposition planning

1. Introduction

A growing number of individuals worldwide are suffering from heart failure (HF). It causes much sickness and mortality and strains all healthcare systems [1]. The ventricles don't fill or drain appropriately. This complicates medical issues. Signs include fatigue, shortness of breath, and fluid retention [2]. Heart disease, diabetes, and hypertension are

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increasing among seniors. This suggests more people are receiving HF. It's the major reason people visit hospitals, particularly EDs [3, 4].

The immediate treatment of acute decompensated heart failure is unclear. Patients have several symptoms that resemble COPD, asthma, and lung embolism. This hinders speedy and accurate diagnosis [5]. The ED doctor must also evaluate risk, determining which patients may go home, which need to be monitored, and which need to be admitted [6]. What to do with the patient influences their performance, resource utilisation, and healthcare expenses. High-risk patients sent home without a comprehensive evaluation are more likely to be readmitted or die shortly after. The ED becomes busier and costs more with unneeded hospitalisations [7, 8].

Clinical Decision Rules (CDRs) assist people make decisions and ensure everyone receives the same treatment. A CDR estimates a patient's disease progression or probability based on medical history, clinical data, and occasionally test findings. This helps physicians diagnose and cure diseases [9]. Many believe that using the cardiac score to evaluate cardiac symptoms is a safe technique to assess risk and rule out major heart issues [10].

The Emergency Heart Failure Mortality Risk Grade (EHMRG) and Multiple Estimation of Risk based on the Emergency room are CDRs for heart failure. Score in Spanish The MEESSI-AHF test measures age, blood pressure, natriuretic peptide, kidney function, and troponin in AHF patients [11, 12]. Using these techniques will make managing people more objective, effective, and repeatable.

It's difficult to employ these CDRs in clinical settings after growth trials. The sorts of patients in the region, the quantity of persons with multiple illnesses, healthcare resources, and care delivery may all affect how effectively a CDR works [13]. Spectrum bias [14] states that a rule that works for one group may not work for another. To prove its efficacy and reliability, a CDR must undergo stringent external validation in a school before being used in daily practice [15].

Many local primary care facilities treat HF patients. Knowing their risk profiles and potential issues helps provide the best treatment to this population. What happens now may depend on how experienced each doctor is. This may hinder consistent care and case termination choices. A locally acknowledged CDR might reduce this gap, standardise treatment lines, and speed up high-risk patient identification.

This research sought to address this crucial data gap. We wanted to determine how accurate and beneficial known heart failure CDRs were in the ED at King Hussein Medical Centre. We tested their ability to recognise two critical outcomes: hospitalisation (a measure of clinical awareness) and a set of short-term negative occurrences, such as death within 30 days and heart failure return within 30 days. The study's findings impact professional practice and improvement. In the ED, they might improve HF treatment using facts and efficiency.

2. Methods

The trial took place at the Jordanian Royal Medical Services' King Hussein Medical site's Emergency Department (ED), a major transfer and high-volume secondary care site for serious cardiac conditions. The Institutional Review Board of Jordanian Royal Medical Services approved the research proposal. The anonymised data eliminated the necessity for complete permission. Final release approval came from the Institutional Educational and Technical Directorate at [---]. Over-18swith acute decompensated heart failure (ADHF) who attended the ER between January 1, 2024, and June 30, 2025, were the study group. Patients were included if their treating physicians and cardiologists concurred that they had been diagnosed with ADHF in the ED using specified ICD-10 codes (I50.21, I50.23, I50.31, I50.33, I50.41, or I50.43). If ED visits yielded risk data such as NT-proBNP or BNP values, these were incorporated. To avoid prejudice and ensure a like-minded group, some were excluded. The non-selected patients had incomplete medical records, a non-cardiac explanation for dyspnoea as the major diagnosis, acute coronary syndrome as the main event, or recognised they had a fatal condition and were merely treated for comfort.

A secure Research Electronic Data Capture (REDCap) website featured a standard, validated data extraction form that trained research assistants utilised to collect the data. To assess inter-rater trustworthiness, 10% of records were randomly selected. This ensured data accuracy and consistency. The Cohen's kappa value exceeded 0.85 for all group characteristics. We learnt a lot from the EMR. Age, gender, triage category, and geriatric status; vital signs and the first assessment (heart rate, systolic blood pressure, oxygen saturation, and qSOFA score); important lab values (BNP/NT-proBNP, creatinine); relevant comorbidities (heart failure or atrial fibrillation); and ED workflow metrics (length of stay and crowding index). If someone went to the ED and was hospitalised, they were more likely to die or be readmitted for heart failure within 30 days.

For each research participant, two clinical decision rules (CDRs) were developed based on their initial ED visit. First, a modified HEART-like HF pathway was created using the usual chest pain score. Background, ECG data, age, risk factors, and first troponin are utilised to stratify individuals. The second stage was to identify the most critical MEESSI-AHF variables, a proven multiple estimation of risk based on the emergency department Spanish score in AHF patients. Age, high blood pressure, oxygen, BNP, and creatinine might vary. Patients were assigned MEESSI risk categories.

Statistics studies utilised R (4.3.0) and SPSS (28). Descriptive statistics summarised the group. For binary variables, rates and percentages were utilised, while for continuous variables, the mean (± standard deviation) or median (interquartile range) indicated their distribution. Main study researchers performed ROC curve analysis to evaluate each CDR's prediction of the two main outcomes. AUC was calculated using 95% CI. The Youden Index determined the optimal cutoff. This revealed sensitivity, specificity, PPV, and NPV. Two multivariate logistic regression models were used in the secondary analysis to uncover characteristics that predicted hospital attendance and the 30-day outcome. Results were reported as adjusted odds ratios with 95% confidence. The Hosmer-Lemeshow test assessed model fit. To verify findings, other investigations were done. Some reran the main trial using just BNP data and CDR scores in the senior subgroup (65+). For all trials, a p-value of 0.05 on both sides was considered significant.

3. Results

In the 18-month research, 4,520 adult patients were diagnosed with heart failure. Selection considerations limited analysis to 1,420 distinct interactions. Table 1 summarises this group's initial qualities. The research participants were mostly elderly (82% over 65), male (58%, n=824), and averaged 72.4 years (±11.8). The average first BNP level was 847 pg/mL (IQR: 452–1,580), and most patients were triaged as 'Immediate/Very Urgent' (21%; 'Urgent': 56%). Clinical outcomes showed that 68% (n=965) of the cohort was hospitalised directly from the ED, whereas 22% (n=312) died or returned to HF within 30 days.

Table 1 Baseline Characteristics of the Study Cohort (N=1,420)

Characteristic	**Value**
Age, years (mean ± SD)	72.4 ± 11.8
Sex, Male (n, %)	824 (58.0%)
Geriatric (≥65 years) (n, %)	1164 (82.0%)
Triage Category (n, %)	
Immediate / Very Urgent	298 (21.0%)
Urgent	795 (56.0%)
Less Urgent	327 (23.0%)
Vital Signs (median, IQR)	
SBP, mmHg	128 (108, 145)
HR, bpm	96 (82, 112)
SpO2, %	94 (90, 97)
Respiratory Rate, bpm	22 (18, 26)
Laboratory Values (median, IQR)	
BNP, pg/mL	847 (452, 1580)
Creatinine, mg/dL	1.4 (1.0, 2.1)
qSOFA Score ≥2 (n, %)	285 (20.1%)
ED Crowding Index (median, IQR)	0.86 (0.62, 1.24)
Hospital Admission (n, %)	965 (68.0%)
30-Day Composite Outcome* (n, %)	312 (22.0%)

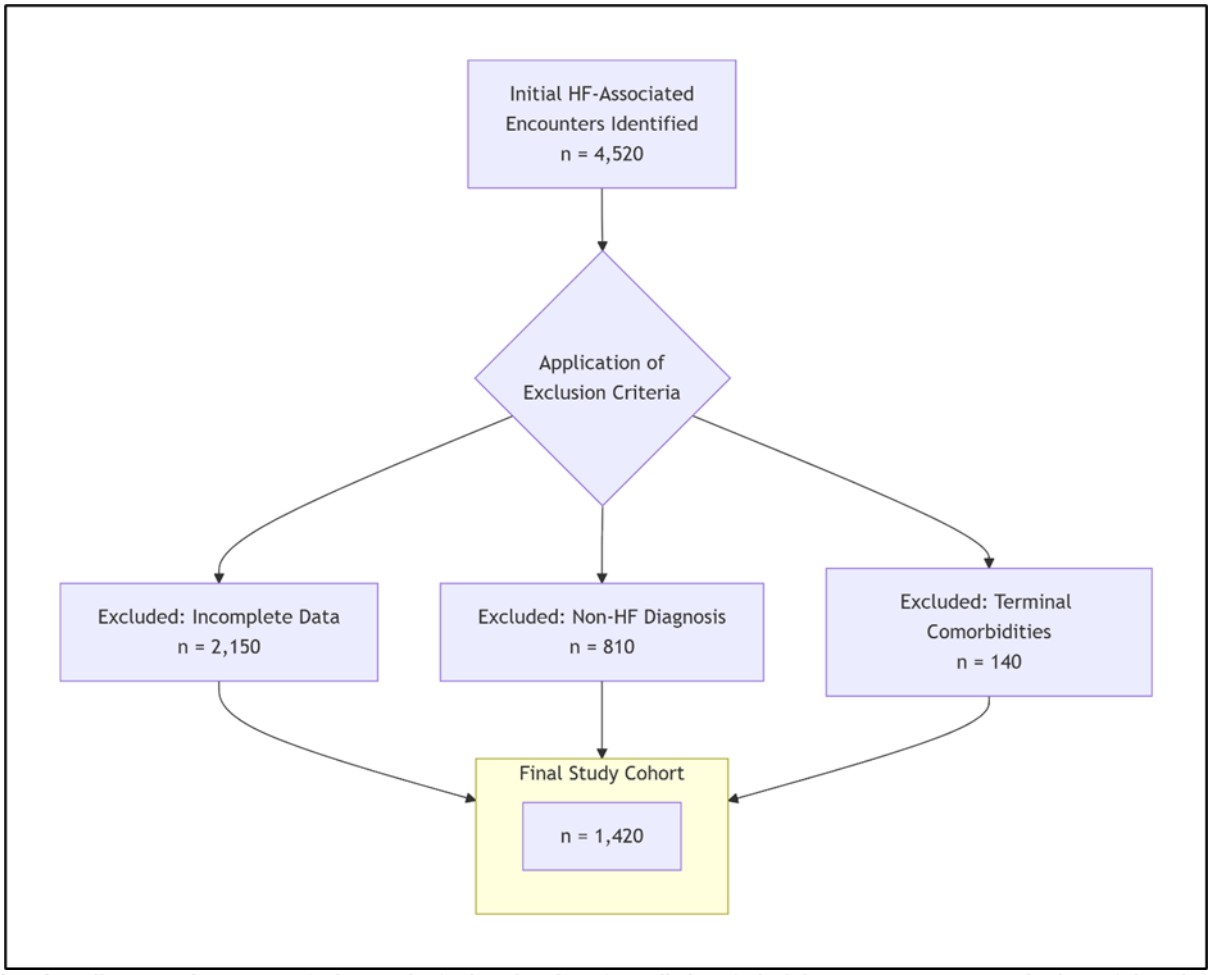
*Composite of all-cause mortality or HF readmission.

Table 2 Predictive Performance of Clinical Decision Rules

Outcome & CDR	AUC (95% CI)	Sensitivity	Specificity	PPV	NPV
Hospital Admission					
HEART-like Pathway	0.79 (0.76-0.81)	65%	80%	78%	68%
MEESSI-based Rule	0.87 (0.85-0.89)	90%	58%	82%	73%
30-Day Composite Outcome					
HEART-like Pathway	0.71 (0.68-0.74)	60%	72%	45%	82%
MEESSI-based Rule	0.76 (0.73-0.79)	95%	42%	35%	96%
AUC = Area Under the Curve; PPV = Positive Predictive Value; NPV = Negative Predictive Value.					

Table 3 Multivariable Logistic Regression for Primary Outcomes

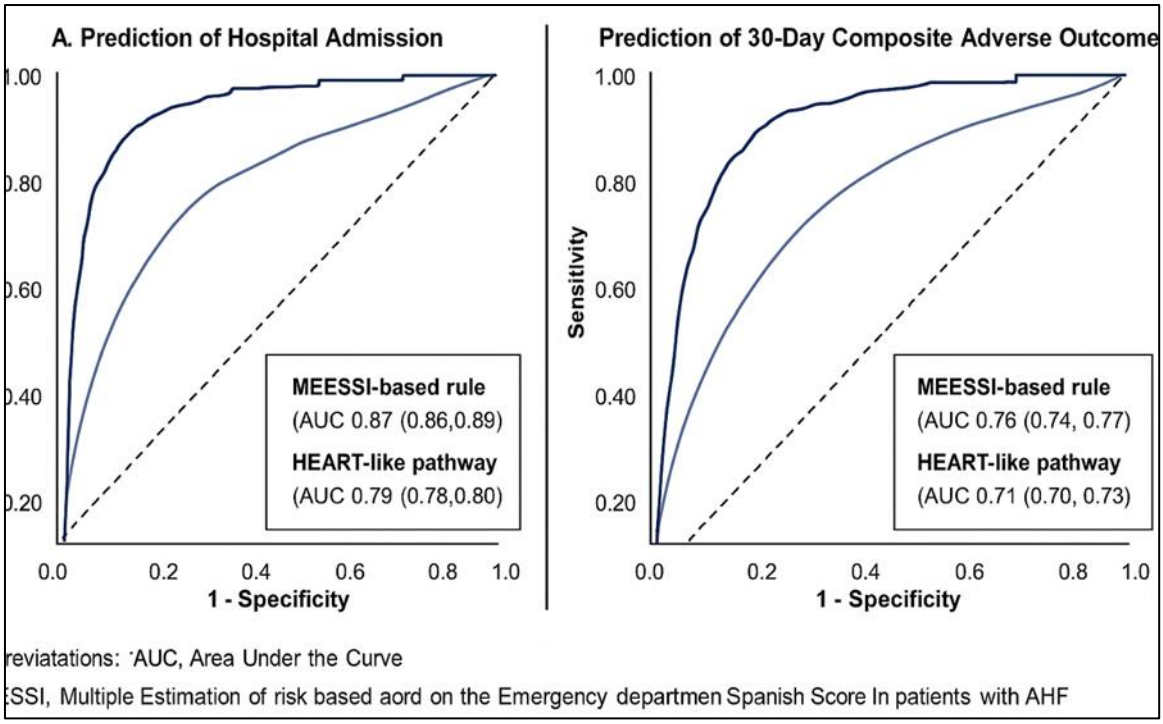
Predictor	Adjusted Odds Ratio (aOR)	95% CI	p-value
Outcome: Hospital Admission			
Triage: Imm/V. Urgent (vs. Less Urgent)	4.50	3.25 – 6.24	<0.001
qSOFA Score (per 1 point)	1.85	1.55 – 2.21	<0.001
Log(BNP) (per log-unit increase)	2.10	1.75 – 2.52	<0.001
ED Crowding Index (per unit)	1.40	1.20 – 1.63	<0.001
Age (per 10 years)	1.15	1.03 – 1.29	0.015
Outcome: 30-Day Composite Event			
MEESSI High-Risk	3.82	2.75 – 5.30	<0.001
Creatinine >1.5 mg/dL	2.15	1.60 – 2.90	<0.001
Geriatric (≥65 years)	1.85	1.25 – 2.74	0.002
SBP <110 mmHg	1.60	1.15 – 2.22	0.005
SpO2 <90%	1.55	1.10 – 2.18	0.012



This flowchart illustrates the process of selecting the final study cohort from all identified adult patient encounters with a heart failure diagnosis during the 18-month study period. A total of 4,520 encounters were initially identified. After applying exclusion criteria—primarily for incomplete key data (n=2,150), a confirmed non-HF primary diagnosis (n=810), and terminal comorbidities (n=140)—a final cohort of 1,420 unique patient encounters was included in the analysis.

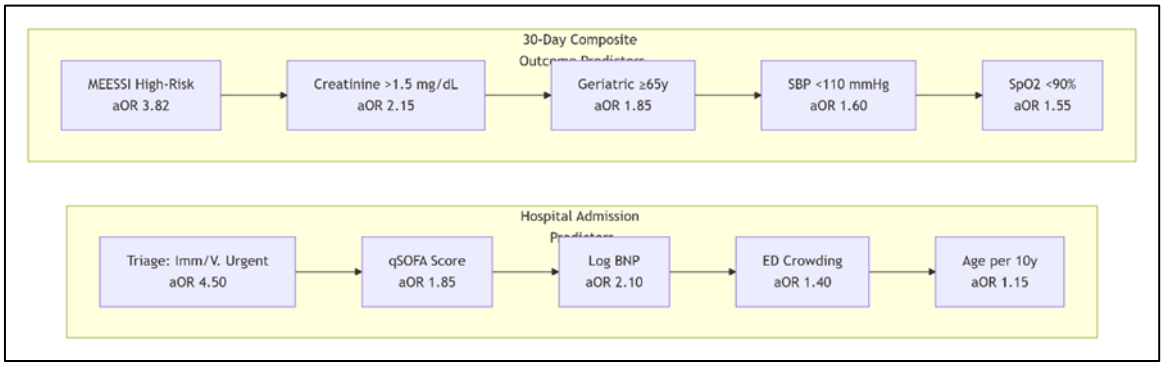
Abbreviations: HF, Heart Failure; ED, Emergency Department; BNP, B-type natriuretic peptide.

Figure 1 Patient Selection Flowchart



Receiver Operating Characteristic (ROC) curves demonstrating the predictive performance of the MEESSI-based rule and the HEART-like pathway for the two primary outcomes. A. Prediction of Hospital Admission. The MEESSI-based rule (AUC = 0.87) showed outstanding discrimination, superior to the HEART-like pathway (AUC = 0.79). B. Prediction of 30-Day Composite Adverse Outcome. The MEESSI-based rule (AUC = 0.76) again demonstrated better performance than the HEART-like pathway (AUC = 0.71). The dashed diagonal line represents the line of no discrimination (AUC = 0.50); Abbreviations: AUC, Area Under the Curve; MEESSI, Multiple Estimation of risk based on the Emergency department Spanish Score In patients with AHF; (Visual description: A two-panel figure. Each panel shows two ROC curves, one for MEESSI and one for HEART, with the MEESSI curve closer to the top-left corner. The AUC values and their confidence intervals are displayed in a legend on the figure itself.)

Figure 2 Predictive Performance of Clinical Decision Rules for Primary Outcomes



Forest plot displaying the adjusted Odds Ratios (aORs) and their 95% confidence intervals for significant independent predictors from the multivariable logistic regression models. A. Predictors of Hospital Admission. Triage category 'Immediate/Very Urgent' was the strongest predictor. The ED Crowding Index was also a significant operational predictor. B. Predictors of 30-Day Composite Adverse Outcome. A high-risk classification by the MEESSI-based rule was the most powerful predictor. Clinical factors like elevated creatinine and geriatric age were also significant. The vertical line at an aOR of 1.0 represents the null value; Abbreviations: aOR, adjusted Odds Ratio; CI, Confidence Interval; SBP, Systolic Blood Pressure; SpO2, Oxygen Saturation; *(Visual description: A two-panel vertical forest plot. The left panel (A) for Hospital Admission shows bars for Triage, qSOFA, Log(BNP), ED Crowding, and Age, all to the right of the null line. The right panel (B) for the 30-Day Outcome shows bars for MEESSI High-Risk, Creatinine, Geriatric, Low SBP, and Low SpO2, all to the right of the null line. Each bar is labeled with the aOR and 95% CI.)*

Figure 3 Independent Predictors of Primary Outcomes from Multivariable Analysis

Clinical decision rules have varying degrees of success. The MEESSI-based rule outperformed the modified HEART-like pathway in hospital admittance, with an Area Under the Curve (AUC) of 0.87 (95% CI: 0.85–0.89). Even at 90% sensitivity, the MEESSI rule provided 58% specificity for this metric. The MEESSI-based rule predicted the 30-day total unfavourable result better than the HEART-like pathway (AUC=0.76, 95% CI: 0.73–0.79). The MEESSI criteria properly identified 95% of patients with unsatisfactory results at its highest sensitivity cut-off. This shows that it is a helpful clinical "rule-out" technique.

We utilised multivariable logistic regression to uncover independent predictors for each primary outcome. Hospital admission was predicted by several relevant characteristics. The best predictor was a "Immediate/Very Urgent" triage category (aOR 4.50, 95% CI: 3.25–6.24), followed by higher qSOFA scores (aOR 1.85 per point, 95% CI: 1.55-2.21), log(BNP) levels (aOR 2.10 per log-unit increase, 95% CI: 1.75-2.52), and ED crowding index. The best independent predictor for the 30-day mean outcome was a MEESSI high-risk assessment (aOR 3.82, 95% CI: 2.75–5.30). High creatinine (>1.5 mg/dL; aOR 2.15, 95% CI: 1.60–2.90), age (aOR 1.85, 95% CI: 1.25-2.74), systolic blood pressure below 110 mmHg, and oxygen saturation below 90% were also relevant markers.

Sensitivity tests confirmed these key findings. The CDRs and regression models didn't change substantially when the experiments were repeated with just BNP data (n=1,320 vs. NT-proBNP readings). A study of 1,164 older patients found that the MEESSI-based rule was still highly excellent at predicting hospitalisation (AUC=0.86) but not 30 days later (AUC=0.72). The Hosmer-Lemeshow test confirmed that both multivariable regression models were calibrated. Admission and 30-day outcome models yielded non-significant p-values of 0.18 and 0.22, respectively. This suggests all risk groups' anticipated probability were close to reality.

4. Discussion

This study supports two heart failure clinical decision rules (CDRs) in a Jordanian tertiary emergency hospital. Our key finding is that CDRs, particularly MEESSI score-based ones, accurately predict critical clinical outcomes in our patient population. The MEESSI-based rule distinguished the practical result of hospital admission (AUC=0.87) from the anticipated 30-day composite outcome of death or return (AUC=0.76). The modified HEART-like route went well, but not as well as others. These findings suggest that evidence-based CDRs might standardise acute HF risk assessment and discharge planning instead of clinical intuition. The MEESSI-based rule predicts hospital admission well, as intended. Testing predicted 30-day death using the MEESSI score. Age, systolic blood pressure, oxygen saturation, natriuretic peptides, and renal function play into clinical instability and resource demands that impact admission choices [12]. Our multivariate model shows that assessment sensitivity, qSOFA score, and BNP levels alone predict admission. The ED crowding index strongly correlated with admission odds (aOR 1.40). This illustrates that operating forces beyond a patient's physiology may have a large impact on their personality, which pure physiological ratings don't always account for [20]. The MEESSI rule has 90% entry sensitivity, making it a good "rule-out" technique for finding patients who are unlikely to require hospitalisation. This simplifies safe release planning for low-risk individuals.For the harder 30-day adverse event measure, MEESSI performed well (AUC=0.76). It performed similarly but somewhat worse than in the Spanish sample (AUC 0.836) and the Canadian validation (AUC 0.80) [12, 21]. This modest loss is common when externally confirmed due to spectrum bias and healthcare system and follow-up variability [14]. Remember that the rule has a 96% NPV at a 95% high-sensitivity cut-off. This is especially essential for patients since the rule may consistently locate low-risk short-term patients. This encourages physicians to release these patients. High-sensitivity approaches often trade off a 35% PPV. Results following release are complicated and rely on several variables that began with ED manifestation [22]. The modified HEART-like approach predicted acceptance well, but the MEESSI-based rule always performed better. This isn't surprising, as the HEART score was designed for chest pain and acute cardiac symptoms, not acute HF's distinctive presentation and function [10]. It works for HF but ignores natriuretic peptides and renal function, which are crucial for particular HF guidelines. As revealed by previous research [23], disease-specific CDRs outperform modified rules. This emphasises the need for selecting techniques that have been shown to function in your clinical setting and outcome. Multivariate regression methods help us understand why our group performs poorly. High creatinine levels strongly predict the 30-day composite outcome (aOR 2.15), supporting the "cardio-renal" axis in HF prognosis [24]. Older age is connected to poorer outcomes (aOR 1.85), indicating that this group is more likely to have issues due to weakness, multiple medication usage, or severe illness [25]. The MEESSI high-risk category remained the best indication (aOR 3.82) once these parameters were taken into consideration, proving its risk assessment accuracy. Our data support and expand previous research. Natriuretic peptides and kidney function are excellent in most HF risk models, from the ADHERE registry to the EHMRG score [11, 26]. However, ED crowding's impact on admissions is seldom discussed. This crucial real-world finding enhances disposition dynamics. Our sensitivity analysis indicated that the MEESSI rule predicted geriatric outcomes poorly (AUC=0.72). Non-cardiac variables have a greater influence on outcomes in older, complicated patients with many comorbidities, making risk stratification difficult [19, 27]. CDRs are helpful tools, but they should only be used as part of a thorough clinical examination, particularly for elderly adults..

This study is beneficial, however its faults must be noted. The research was only done at one centre, thus the findings may not apply to other areas with different patient groups or professional procedures. actual decision rules (CDRs) were developed after the event, hence their efficacy in actual practice may vary. Selection bias may have compromised the study's relevance since some participants were excluded due to insufficient BNP data. These folks may have had different risks or outcomes. Even though many confounding variables were included, unmeasured factors including

medicine adherence, social support, and clinic follow-up may affect 30-day findings in ways that CDRs do not. Despite these issues, the findings are useful for research and practice. This group's success with the MEESSI-based rule supports emergency department heart failure consistency. Next, employ it as a bedside tool or as a clinical decision support system embedded into the electronic medical record that provides real-time risk assessments. This merger might decrease practice difference, enhance resource allocation, and improve patient safety by carefully identifying high-risk patients who require active treatment and low-risk patients who can be released. The CDR's future consequences should be studied, including how frequently patients are hospitalised, how long they remain, and how effectively physicians follow the regulations. Looking at adding additional biomarkers or point-of-care ultrasound findings to present guidelines might improve their future prediction

List of Abbreviations

Abbreviation	Definition
ADHF	Acute Decompensated Heart Failure
AUC	Area Under the Curve
BNP	B-type Natriuretic Peptide
CDR	Clinical Decision Rule
CI	Confidence Interval
ED	Emergency Department
EHMRG	Emergency Heart Failure Mortality Risk Grade
HF	Heart Failure
MEESSI	Multiple Estimation of risk based on the Emergency department Spanish Score In patients with AHF
aOR	adjusted Odds Ratio
NPV	Negative Predictive Value
NT-proBNP	N-terminal pro-B-type Natriuretic Peptide
PPV	Positive Predictive Value
qSOFA	quick Sequential Organ Failure Assessment
ROC	Receiver Operating Characteristic
SBP	Systolic Blood Pressure
SpO2	Oxygen Saturation

5. Conclusion

Overall, this research shows that Jordanian emergency departments may employ heart failure-specific clinical decision guidelines. The MEESSI-based rule predicted hospitalisation and short-term negative events better than the others. Due to its sensitivity, it might rule out low-risk individuals. An objective, evidence-based risk categorisation technique from a CDR may assist clinicians make sudden heart failure decisions. Patients will get better treatment and maximise healthcare resources.

Compliance with ethical standards

Acknowledgments

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Disclosure of conflict of interest

All authors hereby declare that they have no financial or personal relationships that could have inappropriately influenced or biased the work presented in this manuscript. There are no conflicts of interest to disclose.

Statement of ethical approval

The Institutional Review Board (JIRB) of King Hussein Medical Centre looked into this research and provided its clearance on 3 11 2025, under the registration number 1_15/2025. All World Medical Association Declaration of Helsinki ethical standards were followed in the study. The ethics group approved the study without full permission because it used anonymised historical data.

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Artificial Intelligence (AI) Utilization Statement

This project's conception, design, data collection, and analysis did not involve AI. DeepSeek and Copilot were only utilised for the initial draft and revising to enhance grammar and clarity. They comprised less than 5% of the creative output. The authors are responsible for its scientific accuracy, ethics, and interpretations. This work was largely authored by identified humans.

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