The Antecedents of Heart Failure Patient Readmissions; A Systematic Review

Abstract: *This review synthesizes evidence on antecedents of hospital readmission after heart failure (HF) hospitalization. Reported risk markers cannot be treated as equivalent findings when outcomes, case-mix, follow-up and competing death differ; therefore, the present synthesis examines 47 distinct primary publications from 2015-2025 using a PRISMA-informed narrative approach. The evidence covers administrative and clinical cohorts, direct functional assessment and intervention research. Comorbidity, renal impairment, congestion, psychological vulnerability, social conditions and continuity of care recur as investigated domains. However, a nationwide risk model produced weak discrimination despite a very large sample, while a smaller clinical cohort found that conventional comorbidities alone classified future return poorly. Direct physical-function testing and biomarker information may provide complementary prognostic information but require external validation. Findings for post-discharge follow-up differ when outcomes are HF hospitalization rather than mortality or a composite endpoint. Domain frequencies describe research coverage, not effect size, consistency or causality. The screening process is summarized in a PRISMA flow diagram, while differences in study design and outcome definitions favor narrative synthesis over a pooled estimate.*

Keywords: heart failure; hospital readmission; antecedents; social determinants of health; comorbidity; continuity of care; evidence synthesis.

1. Introduction

Readmission after a heart failure (HF) hospitalization can reflect residual congestion, comorbidity, functional impairment or interruption of follow-up care. Its interpretation depends on distinguishing all-cause return, HF-specific return, recurrence and death/readmission composites. A national US analysis restricted to diastolic HF documented 21.27% readmission by 30 days and identified kidney disease, chronic lung disease and anemia among associated conditions (Arora et al., 2017). An Italian nationwide cardiology registry instead observed 6.2% readmission within 30 days, reminding readers that differences in case selection and endpoints preclude naive comparisons (Di Tano et al., 2015). More recent Spanish surveillance in the INCA cohort found 27.3% first-year return after HF and explicitly considered death as a competing event (Rubini et al., 2023). These examples demonstrate why the antecedent taxonomy should integrate illness burden, recovery status and service processes without treating different time horizons as comparable outcomes. A consistent framework also needs to distinguish the detection of risk from evidence that changing a risk marker will prevent hospitalization.

Evidence on antecedents of HF readmission spans administrative databases, clinical cohorts, prospectively captured symptoms and care-transition trials. Large administrative sources permit cross-geographic comparison but provide limited direct measures of frailty, cognition and individual social conditions. A four-state US readmission scale identified coded renal and pulmonary illness, depression, payer and neighborhood income as candidate predictors using geographically separate samples (Chamberlain et al., 2018). A different nationwide administrative model nevertheless produced AUROC values of only 0.58–0.59 across derivation and validation, despite more than 1.4 million HF patients (Zheng et al., 2022). However, in a selected population of older patients with

arrhythmia, a machine-learning model outperformed LACE but its key input variables and performance require replication in other settings (Song et al., 2024). Even comorbidities that remain statistically associated with subsequent admissions may have weak individual predictive utility (Marcus et al., 2025). Accordingly, significance, accuracy, causal relevance and potential modifiability should be treated as separate dimensions rather than conflated in a generic list of determinants.

This review examines which antecedents are substantively investigated in primary HF readmission studies, how associations differ by country, risk phenotype and follow-up horizon, and what methodological gaps remain. The synthesis covers 47 eligible primary publications. These records are not necessarily forty-seven independent patient cohorts: older administrative studies draw on partially overlapping calendar years, although their scientific reports and analytic questions are distinct. The review retains separate interpretation of short-term all-cause return, HF-coded hospitalization, recurrent events and outcomes that include death. It introduces no new patient data, causal regression or meta-analytic pooled effect. Matrix checkmarks mean that a factor was examined; they do not imply a positive estimate, independent association or causal intervention target. The analysis critically juxtaposes social and clinical antecedents with discrimination studies that challenge how usefully common risk factors predict individual return. The methodology details the selection and synthesis approach; the literature matrix organizes the evidence; and the discussion identifies divergent findings and priorities for further investigation.

2. Methodology

This systematic literature review (SLR) employed a PRISMA-informed approach to identify, screen, and synthesize empirical evidence concerning the antecedents of hospital readmission among patients with heart failure (HF). The review focused on peer-reviewed, English-language primary studies published between 2015 and 2025, encompassing observational cohorts, administrative database analyses, prospective investigations, predictive modeling studies, and relevant intervention research. The literature search covered Scopus (n = 382), Web of Science (n = 230), ScienceDirect (n = 189), Emerald Insight (n = 78), and other sources (n = 62), yielding 941 records. Following the removal of 248 duplicate records, 693 publications underwent title and abstract screening, during which 588 records were excluded. Subsequently, 105 reports were sought for retrieval, but 22 could not be obtained, leaving 83 reports for full-text eligibility assessment. Of these, 36 reports were excluded, resulting in a final sample of 47 studies included in the systematic review. The identification, screening, eligibility assessment, and final inclusion stages are illustrated in Figure 1.

The eligibility criteria prioritized original empirical studies involving hospitalized HF patients or clearly identifiable HF subgroups, with measurable post-discharge readmission outcomes and investigated clinical, demographic, functional, psychological, socioeconomic, or healthcare-related antecedents. Studies without an identifiable readmission outcome, secondary reviews, and publications lacking relevant primary empirical evidence were excluded. Information from the 47 included publications was systematically organized into a structured literature review matrix capturing authorship, publication year, study context, research design, patient characteristics, readmission outcomes, investigated determinants, principal findings, and methodological limitations. The synthesis adopted a narrative and comparative analytical approach because substantial heterogeneity existed across study populations, HF phenotypes, follow-up periods, readmission definitions, analytical methods, and outcome measurements. Particular attention was given to differentiating all-cause readmission, HF-specific hospitalization, recurrent admissions, and composite outcomes involving mortality. Methodological appraisal considered potential

confounding, measurement limitations, predictive discrimination, generalizability, and overlapping administrative datasets. The synthesis distinguished statistically significant associations from predictive performance and causal intervention effects, while the literature matrix documented the extent to which individual antecedent categories were investigated. Given the methodological diversity of the included studies, quantitative meta-analysis was not undertaken.

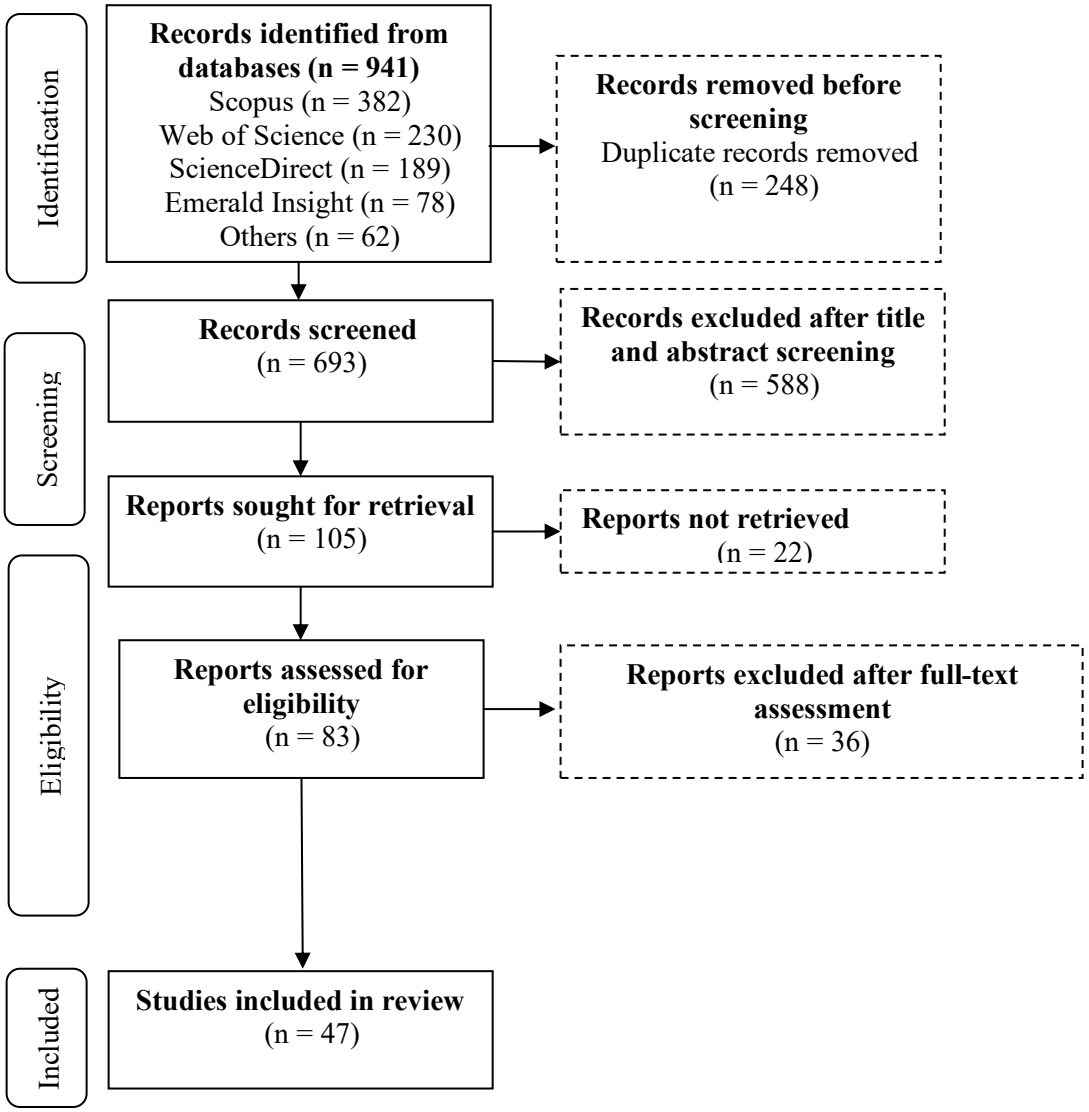


Figure 1: The Systematic Review Process

3. Thematic Synthesis of Readmission Antecedents

Clinical predictors center on illness burden, renal dysfunction, hemodynamic status, residual congestion and treatment history. The US diastolic-HF administrative analysis connected multiple chronic conditions and discharge to a facility with 30-day return, but its coding-defined HF phenotype and patient-year structure constrain interpretation (Arora et al., 2017). A Spanish competing-risk

cohort likewise associated kidney and pulmonary disease, diabetes, anemia and prior ischemic illness with first-year readmissions, while acknowledging changes in care across two decades (Rubini et al., 2023). These positive associations should not be mistaken for strong individual-level prognosis. In a national US study with more than 1.4 million patients, a model combining utilization, demographic and coded medical factors yielded validation discrimination of only 0.59 (Zheng et al., 2022). An Israeli cohort made the distinction especially explicit: kidney disease, diabetes, ischemic illness and anemia showed associations, yet the best four-comorbidity combination achieved only 0.555 AUROC for 30-day return (Marcus et al., 2025). The evidence distinguishes chronic vulnerability from acute discharge physiology. Across settings, a diagnosis recorded at admission may describe underlying disease burden but not the discharge state that triggers an early return.

Frailty, psychiatric illness, health literacy and patient-reported function represent potentially distinct pathways into readmission. A nationwide Medicare analysis found elevated 30-day risk among older HF admissions with high claims-derived frailty, but diagnosis codes are not a substitute for direct assessment (Kundi et al., 2019). Prospective Japanese evidence linked low short physical performance battery scores with increased 90-day readmission alongside high BNP, illustrating how physical function and cardiovascular congestion could jointly characterize vulnerability (Nonaka et al., 2023). Its combination-specific hazard ratio was large, but the very wide confidence interval and only 25 outcome events strongly limit generalization. Administrative depression research has also reported a contrast between increased all-cause and non-significant cardiovascular-specific return (N. Patel et al., 2020). A separate four-state US risk model identified coded depression and insurance markers, yet historical administrative variables cannot establish whether intervening on either risk marker changes an individual outcome (Chamberlain et al., 2018). Such heterogeneity argues against a single unqualified psychosocial score. It also supports prospective work that combines directly assessed physical capacity, mental health, treatment literacy and social support with serial congestion measurements, using harmonized outcome periods and pre-specified adjustment. Nutritional status, physical function and depression should remain separately operationalized in data extraction: a shared label such as vulnerability can mask different assessment tools and causal pathways.

The interface between healthcare organization, social context and risk modeling further complicates prevention. National data suggest that neighborhood income and insurance status help stratify return, but these proxies cannot measure household-level financial insecurity directly (Chamberlain et al., 2018). In a Chinese cohort restricted to older adults with arrhythmia, more flexible modeling improved discrimination relative to LACE and identified education, medication counts and laboratory signals as relevant features (Song et al., 2024). Nevertheless, feature importance does not establish that education or the biochemical markers caused readmission; transportability remains unknown. A nationwide US score had low discrimination despite a much larger sample, underscoring the hazards of interpreting sample size as forecasting accuracy (Zheng et al., 2022). These findings complement randomized evidence on intensive medical therapy and post-discharge follow-up, which addresses intervention effects rather than marker association (Mebazaa et al., 2022). They also reveal the need to compare treatment decisions within carefully measured severity strata; prolonged hospitalization and discharge to a facility may reflect underlying risk rather than a harmful care choice. Therefore the synthesized framework places socioeconomic exposure and discharge processes alongside, but not causally downstream of, clinical status.

Table 1: Literature Review Matrix

No.	Author(s) and Year	Age/sex	Comorb.	Renal	Labs	Psych./frailty	Nutrition	Symptoms	Self-manag.	Follow-up	Socioecon.	Social ties	Access	Hosp. care	Readmit.
1	Di Tano et al. (2015)		✓											✓	✓
2	Reynolds et al. (2015)	✓	✓											✓	✓
3	Arora et al. (2017)	✓	✓	✓	✓									✓	✓
4	Chamberlain et al. (2018)	✓	✓	✓		✓					✓		✓	✓	✓
5	Sokoreli et al. (2018)	✓	✓	✓		✓						✓			✓
6	Sterling et al. (2018)	✓				✓			✓						✓
7	Delgado et al. (2019)		✓	✓	✓					✓				✓	✓
8	Kundi et al. (2019)		✓			✓									✓
9	Kwok et al. (2019)	✓	✓	✓										✓	✓
10	Oscalices et al. (2019)								✓						✓
11	Wang et al. (2019)		✓	✓	✓							✓		✓	✓
12	N. Patel et al. (2020)		✓			✓									✓
13	S. A. Patel et al. (2020)	✓	✓								✓				✓
14	Son & Won (2020)	✓							✓						✓
15	Constantinou et al. (2021)	✓	✓												✓
16	Gao et al. (2021)	✓	✓	✓	✓									✓	✓
17	Wideqvist et al. (2021)		✓	✓		✓			✓	✓				✓	✓
18	Alsamman et al. (2022)	✓	✓	✓	✓									✓	✓
19	Anderson et al. (2022)	✓	✓					✓	✓						✓
20	Gangu et al. (2022)	✓	✓								✓		✓	✓	✓
21	Mebazaa et al. (2022)									✓				✓	✓
22	Sterling et al. (2022)	✓									✓	✓	✓		✓
23	Zheng et al. (2022)	✓	✓	✓	✓	✓					✓		✓	✓	✓
24	Davidge et al. (2023)	✓	✓	✓	✓									✓	✓
25	Iida et al. (2023)		✓		✓	✓	✓								✓
26	Jain et al. (2023)	✓	✓	✓	✓						✓		✓	✓	✓
27	Kim et al. (2023)	✓	✓	✓							✓		✓	✓	✓
28	Nonaka et al. (2023)				✓	✓								✓	✓
29	Rubini et al. (2023)	✓	✓	✓	✓									✓	✓
30	Steverson et al. (2023)	✓	✓			✓					✓	✓	✓		✓
31	Varlot et al. (2023)	✓	✓											✓	✓
32	Alshibani et al. (2024)		✓											✓	✓
33	Averbuch et al. (2024)									✓				✓	✓
34	Ayenew et al. (2024)	✓	✓		✓								✓		✓
35	Balasubramanian & Malhotra (2024)		✓			✓				✓				✓	✓
36	Baudry et al. (2024)	✓	✓							✓			✓	✓	✓
37	Espersen et al. (2024)				✓			✓						✓	✓

No.	Author(s) and Year	Age/sex	Comorb.	Renal	Labs	Psych./frailty	Nutrition	Symptoms	Self-manag.	Follow-up	Socioecon.	Social ties	Access	Hosp. care	Readmit.
38	Freedland et al. (2024)		✓						✓						✓
39	Lusk et al. (2024)										✓				✓
40	Sa et al. (2024)	✓	✓			✓									✓
41	Song et al. (2024)	✓	✓		✓									✓	✓
42	Trochez et al. (2024)	✓	✓			✓									✓
43	Cai et al. (2025)		✓								✓	✓	✓	✓	✓
44	Cui et al. (2025)	✓	✓	✓	✓	✓	✓								✓
45	Ehrman et al. (2025)										✓		✓		✓
46	Marcus et al. (2025)		✓	✓	✓										✓
47	Yusoff et al. (2025)		✓	✓	✓									✓	✓

4. Discussion: Comparative Synthesis of Readmission Antecedents

Comorbidity burden is repeatedly linked to HF return, but predictive usefulness differs from statistical significance. A US study of diastolic HF recorded a 21.27% 30-day readmission rate and higher return risks associated with renal disease, COPD, diabetes, anemia and institutional discharge (Arora et al., 2017). The Spanish INCA study found one-year associations for multiple comparable diagnoses under a competing-risks framework; it also incorporated longer clinical-history information into a novel score (Rubini et al., 2023). Yet substantial sample size did not guarantee clinically useful prediction: a national US model reached only AUROC 0.58–0.59 (Zheng et al., 2022). In an Israeli cohort, the four strongest traditional comorbidities combined yielded only AUROC 0.555 for early readmission, despite their independent associations (Marcus et al., 2025). This disagreement is not necessarily substantive contradiction: factors may be etiologically relevant at group level while adding little information for rank-ordering individuals within a high-risk population. Renal impairment and congestion recur, but no universal score emerges. Longitudinal, multisite validation would be needed before prioritizing a specific marker for clinical implementation. Illustratively, an Italian prospective cardiology registry recorded 6.2% 30-day return in its selected discharged cohort (Di Tano et al., 2015). A US diastolic-HF analysis reported 21.27% over 30 days (Arora et al., 2017). The difference cannot be attributed to geography alone because selection and outcome ascertainment differ. A five-year Ethiopian retrospective cohort reported 26.4% unplanned 30-day return, illustrating the need to evaluate service availability and record capture before transporting estimates (Ayenew et al., 2024). Changes in care over publication years further limit comparisons: identical labels may denote different underlying treatment opportunities. Accordingly, the strongest descriptive pattern is the recurrence of multimorbidity across contexts, not a pooled numerical excess attributable to a particular diagnosis.

Direct physical-function assessment adds interpretive depth to frailty and readmission research. Among 107 eligible older HF patients, 25 were readmitted within 90 days; both high BNP and lower-limb performance were independently associated with return (Nonaka et al., 2023). Combining a BNP threshold with a low physical-performance score produced a large hazard ratio but a wide confidence interval, cautioning against unstable bedside cutoffs. The prospective cohort operationalized vulnerability through directly assessed physical performance (Nonaka et al., 2023). By contrast, a

nationwide analysis associated claims-derived frailty with early return (Kundi et al., 2019). Depression and cognitive impairment may follow different pathways, and national coded depression has been more clearly associated with all-cause than specifically cardiovascular return (N. Patel et al., 2020). A historical four-state risk tool also included depression, payer and low-income markers, illustrating potential cross-domain interactions without determining whether individual markers are modifiable causes (Chamberlain et al., 2018). Future studies should assess frailty, mental health, literacy and social support prospectively rather than presuming that any code-derived single score represents the same construct across care settings. Additional prospective evidence found that nutritional risk was associated with a death-or-readmission composite among older HF patients; this cannot be read as a readmission-only risk estimate (Iida et al., 2023). An Australian population cohort identified associations between recently recorded mental disorders and 28-day unplanned readmission, but coding practices may influence observed patterns (Sa et al., 2024). Together these reports justify distinguishing directly measured frailty, malnutrition and coded psychiatric diagnoses even when grouped under broader patient-level vulnerability.

The service environment and social position influence opportunities for post-discharge stabilization, but the supporting designs differ considerably. In a Medicare cohort, greater neighborhood deprivation was associated with a modest increase in adjusted 30-day HF readmission (Lusk et al., 2024). In contrast, none of nine social measures showed an independent association in the smaller REGARDS cohort (Sterling et al., 2022). An older US readmission scale drew on more than a million combined derivation and validation admissions and incorporated payer, income and chronic illness into practical risk groups (Chamberlain et al., 2018). A modern older-arrhythmia cohort tested richer discharge data against the LACE index: machine learning produced AUROC 0.7571 against 0.5886 for LACE in 523 patients, but did not demonstrate performance outside that selected institution (Song et al., 2024). Randomized high-intensity medication titration and follow-up can test whether processes causally influence specific hospitalization outcomes, rather than only identify correlated antecedents (Mebazaa et al., 2022). Other transitional-care trials have shown different long-run composite results (Averbuch et al., 2024). Policy conclusions should therefore distinguish socioeconomic context, transition-process fidelity and biological risk, and should assess avoidable events without penalizing clinically indicated readmissions. French linked-record evidence associated combined general-practitioner and cardiologist follow-up with lower mortality but more HF rehospitalization, a result compatible with surveillance and survival effects rather than simple failure of follow-up (Baudry et al., 2024). Conversely, longer-term results from a Canadian cluster-randomized care-transition program did not show a clear reduction in its principal combined endpoint, illustrating the importance of program specification and duration (Averbuch et al., 2024). These apparently mixed results highlight outcome choice, treatment exposure and competing death as substantive sources of heterogeneity. Interventions should therefore report HF admissions independently whenever feasible and describe whether events were planned, necessary or plausibly preventable.

Methodological variation now spans forty-seven reports, not forty-seven fully independent patient populations. An administrative diastolic-HF analysis used 2013–2014 NRD records (Arora et al., 2017). A larger national prognostic study analyzed 2010–2014 NRD data (Zheng et al., 2022). These datasets may contain overlapping patient records, although the research questions, outcomes and modeling approaches differed. Reported follow-up encompasses endpoints as early as 15 days and as long as three years; some studies include death or emergency visits in composite outcomes, whereas others evaluate readmission separately or apply competing-risk methods. An Israeli 30-/100-day analysis separated statistical association from predictive discrimination, a safeguard absent from many broad determinant narratives (Marcus et al., 2025). A Spanish cohort treated death before

readmission as a competing event (Rubini et al., 2023). A Chinese modeling study compared LACE with a flexible algorithm in a selected sample of older patients with arrhythmia (Song et al., 2024). Both add information but answer different research questions. The review consequently reports within-study findings and methodological limitations rather than pooled risk estimates, rankings by checkmark frequency or numerical certainty ratings. Figure 1 summarizes the stages of identification, screening, eligibility assessment and inclusion, while Table 1 maps the domains examined across the included publications. Administrative datasets are useful for scale and geographic reach, yet coding error, unmeasured disease severity and repeat participation across analyses reduce inferential independence. Smaller prospective cohorts offer richer physiology and function but often have fewer events and unstable model estimates. Clinical trials address modifiability more directly, although their treatment packages cannot be reduced to the isolated influence of a single antecedent. Across all designs, the review distinguishes an association estimate, a forecast metric and an intervention effect, and gives no numerical certainty grade without a completed design-specific appraisal.

5. Research Gaps and Future Research Directions

Future investigation should disaggregate 30-day all-cause return, HF-specific return, cardiovascular readmission, multiple returns and outcomes combined with mortality. Historical population-level models are often large but do not automatically predict accurately in new care systems; the 0.58–0.59 AUROC of the national US score provides a practical example of limited discrimination (Zheng et al., 2022). Investigators should therefore publish confidence intervals, calibration plots, decision-curve performance and external validation before recommending bedside use. Distinct physical function measurements deserve closer attention, although a Japanese performance/BNP study had only 25 readmission events and correspondingly wide estimates (Nonaka et al., 2023). A contemporary Israeli clinical cohort further showed that traditional comorbidity combinations underperform despite consistent population associations, suggesting a need for time-varying biomarkers and care-transition measures (Marcus et al., 2025). Risk models must also account for the clinical and socioeconomic contexts in which they are trained, including access to follow-up, frailty, cognitive function, and baseline probability of death. Such refinements will support transportability testing rather than premature claims of deterministic readmission prevention. New studies should also specify how death, transfers and readmission to a different hospital are handled, because these decisions change the apparent incidence of return.

The evidentiary priority is to separate predictors that describe vulnerability from antecedents whose modification actually reduces avoidable hospital use. Coded discharge variables, insurance status and hospital duration may be useful for triage but are intertwined with care access, clinical severity and service organization (Chamberlain et al., 2018). The improved performance of a selected machine-learning cohort cannot resolve whether its top-ranked education and laboratory features are causal; prospective external validations across different age groups and HF phenotypes are needed (Song et al., 2024). Early treatment-intensification strategies should be compared with usual care using clearly defined HF hospitalization and safety outcomes, rather than treated as proof that every co-occurring risk factor is changeable (Mebazaa et al., 2022). Future reviews should retain database-specific search strings, search dates, deduplication records, independent screening decisions, reasons for full-text exclusion and study-design-specific risk-of-bias assessments. Prospective protocol registration and transparent reporting of the full selection process would further strengthen reproducibility and confidence in the resulting synthesis.

6. Conclusion

Forty-seven distinct primary publications now support a multidimensional account of readmission after HF hospitalization. Chronic renal disease, multimorbidity, functional limitation, laboratory evidence of ongoing illness, psychiatric burden, social circumstances and care transitions recur as investigated antecedents. The evidence particularly clarifies the boundary between association and patient-level discrimination. A US diastolic-HF cohort identified medically and institutionally coded risks (Arora et al., 2017). A Spanish study likewise identified associations with coexisting illnesses over longer follow-up (Rubini et al., 2023). Yet a model trained in more than a million US patients discriminated poorly, showing that statistical scale does not guarantee usable prediction (Zheng et al., 2022). An Israeli study similarly demonstrates that common comorbidities can be associated with return but fail to classify individuals reliably (Marcus et al., 2025). Functional assessment and BNP may provide complementary prognostic insight, although the prospective sample underpinning that result was small and uncertain (Nonaka et al., 2023). A newer selected Chinese cohort achieved better prediction than LACE in older adults with arrhythmia, but its portability remains untested (Song et al., 2024). The findings reinforce separate definitions for 30-day all-cause return, HF-specific and longer-horizon readmission, recurrent admissions and death-inclusive outcomes. They also argue against reading checkmark counts as strength of causal evidence. The PRISMA flow diagram summarizes the selection of 47 publications, and the corresponding literature matrix facilitates study-level comparison. These descriptive tools do not establish effect magnitude or causal certainty. Priorities are prospectively measured modifiable pathways, external validation, harmonized endpoints and complete review auditability. Combining discharge physiology, functional status and structural barriers in externally validated models is a reasonable research priority, not an established clinical prescription. Care-transition interventions require explicit reporting of treatment exposure, adherence and whether a subsequent hospital stay represents decompensation, enhanced detection or appropriate rescue care. Social and psychological determinants warrant patient-level assessment rather than routine substitution of area averages or billing codes. The included publications support multiple complementary explanations but do not establish that every associated marker is a modifiable cause. Consequently, harmonized readmission definitions, separate death outcomes, transparent calibration, design-appropriate risk-of-bias assessment and recoverable search records are prerequisites for stronger future evidence synthesis.

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