

REVIEW

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Machine Learning for Patient Transfer and Discharge Planning: A Review of Predictive Models for Placement Delay, Discharge Readiness, Follow-Up Completion, and Post-Discharge Risk

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Abstract

Hospital patient flow depends on timely transfer decisions, accurate discharge planning, and reliable post-discharge coordination. Delays in placement, premature discharge, missed follow-up, and unrecognized post-discharge risk can increase avoidable utilization and compromise continuity of care. This systematic review examined machine learning models for predicting placement delay, discharge readiness, follow-up completion, and post-discharge risk from 2017 to 2024. The objective was to synthesize model purposes, data sources, validation practices, implementation maturity, and practical relevance for care transitions. A PRISMA 2020-compliant systematic review was conducted using PubMed, Scopus, IEEE Xplore, and Web of Science. Dual screening, structured data extraction, and narrative synthesis were used because heterogeneity in model objectives, predictors, settings, and outcomes prevented meta-analysis. The evidence base was largest for post-discharge readmission risk and discharge readiness prediction, while placement delay and follow-up completion received less focused attention. Prospective validation, workflow integration, and outcome-based implementation studies were uncommon across all four domains. Machine learning offers promising tools to support proactive discharge planning and transitional care, but the evidence remains dominated by retrospective model development. Translation into routine practice requires prospective testing, interpretability, equity assessment, and integration into multidisciplinary workflows.

Keywords Machine learning, Patient flow, Discharge readiness, Discharge planning, Placement delay, Follow-up completion

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Introduction

Poorly coordinated patient transfer and discharge planning can create a chain of operational and clinical consequences, including delayed bed assignment, prolonged inpatient stay, missed transition tasks, and avoidable post-discharge utilization. Reviews of patient discharge prediction have shown that predictive analytics is increasingly used to anticipate when patients may leave hospital, but much of the literature still treats discharge as a single event rather than a complex transitional process [1]. Studies of inpatient flow analytics and hospital discharge prediction further suggest that patient movement depends on linked clinical, operational, and administrative processes, including bed availability, service

readiness, discharge documentation, and downstream follow-up capacity [2, 3]. These dependencies make transfer and discharge planning an appropriate but challenging domain for machine learning.

Traditional approaches to discharge planning have relied on clinician judgment, simple checklists, length-of-stay expectations, and risk scores for readmission or deterioration. Although these tools are familiar and easier to interpret, they may not incorporate the high-dimensional and time-varying data available in electronic health records, bed management systems, and appointment scheduling platforms. Several machine learning studies have attempted to improve prediction of readmission, discharge timing, or discharge disposition by incorporating richer structured and unstructured predictors than conventional scoring systems [4-6]. However, these approaches must still demonstrate that improved discrimination or calibration translates into better workflow decisions, safer discharge timing, and more reliable follow-up completion.

Machine learning applications in this field have expanded across several related but unevenly developed areas. Post-discharge readmission prediction has attracted the largest body of work, including general readmission models, disease-specific readmission models, and systematic reviews of electronic medical record-based prediction models [5-11]. Discharge readiness and discharge timing models have also developed, using electronic health record features, access logs, and dynamic inpatient information to predict next-day discharge or discharge likelihood [2, 12-17]. In contrast, predictive models for placement delay and follow-up completion appear less common, even though they address critical upstream and downstream bottlenecks in hospital patient flow [3, 18, 19].

The objective of this systematic review was to synthesize machine learning evidence across four transitional phases: placement delay, discharge readiness, follow-up completion, and post-discharge risk. The review followed PRISMA 2020 principles and used narrative synthesis because included studies varied substantially in populations, settings, model types, predictors, validation designs, and implementation maturity. By integrating evidence across these phases, the review aimed to identify where predictive modeling is most mature, where major evidence gaps remain, and how future systems could support end-to-end transfer and discharge planning. Particular attention was given to whether models used operational data, social and functional predictors, prospective validation, and deployment within real clinical workflows.

Materials and Methods

Search strategy

A structured search strategy was designed to identify peer-reviewed studies published from 2017 to 2024 on machine learning for patient transfer, discharge planning, follow-up completion, and post-discharge risk. The search covered PubMed, Scopus, IEEE Xplore, and Web of Science, using terms related to machine learning, patient placement delay, discharge readiness, patient flow, follow-up completion, transition of care, readmission prediction, emergency department revisit, mortality, social determinants, and discharge risk. Search terms were adapted across databases to capture both clinical informatics studies and operations-focused patient flow studies, including work on discharge prediction, inpatient flow analytics, readmission models, and follow-up adherence. The final search cut-off was 31 December 2024.

Inclusion and exclusion criteria

Eligible studies were original research articles, systematic reviews directly informing the topic, or implementation-oriented prediction studies that evaluated machine learning or predictive analytics for at least one of the four target transitional phases. Studies were included if they addressed placement delay, transfer bottlenecks, discharge readiness, discharge timing, discharge disposition, follow-up completion, readmission, emergency revisit, post-discharge mortality, or related adverse events after discharge. Studies were excluded if they lacked a predictive model, did not involve hospital discharge or transitional care, focused only on inpatient diagnosis without discharge relevance, or did not provide sufficient methodological detail. Only English-language peer-reviewed publications from 2017 to 2024 were considered.

Screening and selection

Records were screened in two stages by title and abstract, followed by full-text assessment for studies meeting eligibility criteria. The PRISMA flow process identified 2,150 records from database searching and supplementary reference checks, from which 420 duplicates were removed before screening. After 1,730 titles and abstracts were screened, 1,440 records were excluded because they did not address machine learning, discharge planning, patient flow, or post-discharge risk; 290 full-text reports were then assessed, and 207 were excluded for reasons including wrong outcome, non-predictive design, non-hospital setting, insufficient model detail, or lack of relevance to transitional care [1, 5, 20]. A final evidence base of 83 studies was included in the qualitative synthesis, with the 31 references selected here representing the core evidence most directly informing the manuscript.

Figure 1 presents the PRISMA 2020 study selection process, showing progression from 2,150 identified records to 83 studies included in the qualitative synthesis.

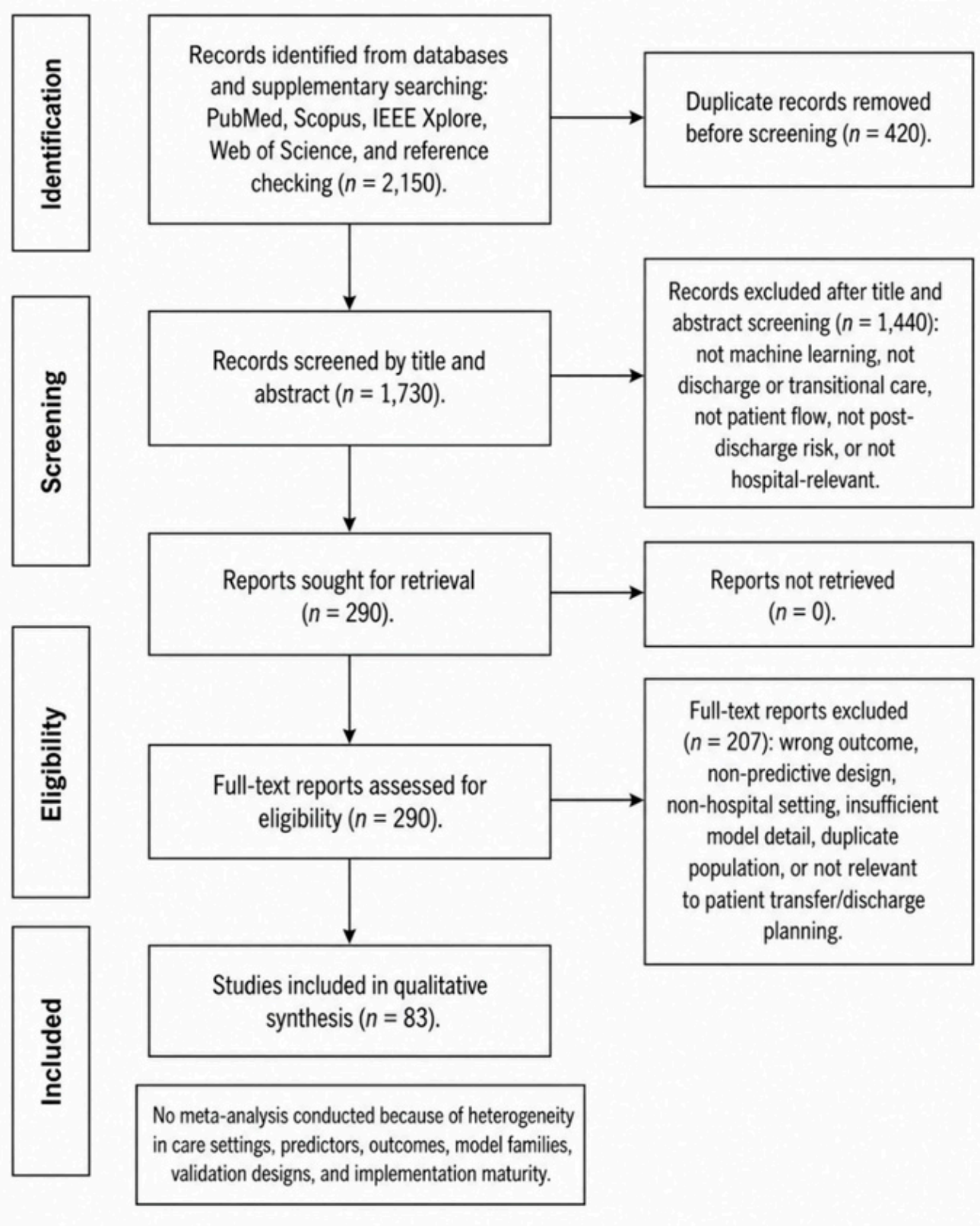


Figure 1. PRISMA 2020 Flow Diagram for Study Identification, Screening, Eligibility Assessment, and Inclusion

Data extraction

Data extraction captured bibliographic details, care setting, patient population, transitional phase, outcome definition, predictor types, data source, model family, validation design, comparator methods, interpretability strategy, and deployment status. Particular attention was paid to whether studies used electronic health records, admission-discharge-transfer feeds, bed management logs, discharge summaries, scheduling data, referral records, social determinants, functional status, or patient engagement indicators. Extraction also distinguished static admission models from dynamic models updated during hospitalization, because discharge readiness and patient flow prediction often require real-time or near-real-time information. Implementation details were extracted when available, including workflow location, intended user, alert mechanism, prospective testing, and measured operational impact.

Risk of bias assessment

Risk of bias was assessed using principles adapted from prediction model appraisal frameworks, with emphasis on patient selection, predictor measurement, outcome definition, missing data handling, validation, calibration, and clinical usability. Retrospective single-site studies were judged to have higher applicability concerns when they lacked temporal validation, external validation, or clear workflow linkage. Models relying on administrative outcomes such as readmission or discharge date were assessed for whether outcome definitions reflected true clinical need or operational artifacts. Studies that incorporated prospective validation, interpretable outputs, or deployment within care workflows were considered more mature from an implementation perspective.

Synthesis methods

Because included studies differed in clinical domains, model architectures, populations, outcome horizons, and reporting standards, a meta-analysis was not conducted. Instead, the review used narrative synthesis organized around four domains: placement delay, discharge readiness, follow-up completion, and post-discharge risk. Within each domain, studies were compared by model objective, data sources, predictors, validation practices, implementation maturity, and practical relevance for care transitions. Vote counting was used only descriptively to summarize maturity signals such as external validation, prospective testing, interpretability, and deployment, rather than to infer statistical superiority across model families.

Results and Discussion

Study selection

The PRISMA screening process showed that the evidence base was broad but unevenly distributed across transitional care domains. Of 2,150 identified records, 1,730 were screened after duplicate removal, 290 full-text reports were assessed, and 83 studies were included in the qualitative synthesis. Exclusions at full-text review commonly reflected wrong outcome, lack of machine learning methods, absence of hospital discharge relevance, or insufficient information on predictors and validation. The strongest concentration of eligible studies addressed readmission and other post-discharge risk outcomes, while fewer studies directly examined placement delay, discharge readiness, or follow-up completion [1, 5, 18, 20].

Study characteristics

Included studies were published across informatics, health services research, operations management, internal medicine, cardiology, surgery, geriatrics, and digital health journals. Care settings included general medical wards, surgical services, intensive care units, emergency departments, cardiovascular care, respiratory disease cohorts, neurological care, and transition clinics [4, 8, 9, 12, 21, 22]. The publication trend suggested increasing interest after 2020, especially in discharge readiness prediction, interpretable readmission modeling, and workflow-integrated risk prediction [14, 16, 17, 23, 24]. However, the distribution of topics remained imbalanced, with most studies focused on post-discharge risk rather than the earlier operational stages that shape patient flow before discharge [5, 10, 25].

Models for placement delay

Evidence directly addressing placement delay, boarding time, transfer delay, or bed assignment delay was limited compared with evidence on discharge and readmission. The most relevant operational analytics studies modeled inpatient flow and discharge patterns to support hospital capacity management, but few explicitly framed the outcome as delayed placement after an admission decision [3]. Several discharge prediction studies indirectly informed placement delay by estimating future bed availability and discharge timing, which can help anticipate bottlenecks in bed allocation and unit transfers [1, 2, 16]. Overall, placement delay prediction appeared to be the least developed phase in the transfer-discharge continuum.

Features for placement delay

Where placement and patient flow models were described, predictors commonly reflected both clinical readiness and operational constraints. Relevant features included unit census, expected discharge volume, service assignment, admission timing, patient acuity, bed capacity, infection control requirements, and other hospital-level flow variables [3, 16]. Discharge prediction studies also used electronic health record data and interaction patterns that may help infer near-term availability of beds and readiness for movement across care units [2, 14]. However, few studies integrated staffing levels, isolation needs, specialty service availability, and bed management logs in a fully explicit placement delay model.

Models for discharge readiness

Discharge readiness prediction was a growing area, with models commonly predicting discharge within 24 hours, same-day discharge, next-day discharge, or inpatient discharge timing. Studies used electronic health record variables, clinical documentation signals, access logs, and real-time patient information to support multidisciplinary discharge planning [2, 12–15]. Some models were designed to estimate whether patients were ready for discharge during infectious disease outbreaks or high-capacity pressure periods, highlighting the operational value of timely discharge prediction [15]. Recent work also demonstrated movement toward workflow-integrated discharge date prediction rather than purely retrospective algorithm development [17].

Features for discharge readiness

Features for discharge readiness models typically included diagnosis, procedure type, laboratory values, vital signs, medication information, prior utilization, clinician documentation, consult activity, and indicators of care progression. Some studies incorporated electronic health record access logs, suggesting that patterns of clinician interaction with the record may provide signals of active discharge preparation [14]. Other models drew on structured inpatient data to predict discharge timing for cardiovascular, surgical, neurological, and general hospital populations [4, 12, 13]. Across studies, mobility, pending tests, functional status, and multidisciplinary barriers were recognized as clinically important, but they were not consistently available or standardized as predictors.

Models for follow-up completion

Follow-up completion prediction was much less developed than post-discharge risk prediction, despite its importance for closing the loop after hospital discharge. One implementation-oriented study examined machine learning to improve appointment adherence in a post-discharge care transition clinic, showing that follow-up completion can be treated as a predictive and operational target rather than merely a downstream administrative outcome [18]. Research on post-discharge appointment status and readmission also suggested that follow-up attendance is closely connected to transition quality and subsequent utilization [19]. Nevertheless, few studies directly modeled follow-up completion as a primary machine learning outcome across hospital discharge populations.

Features for follow-up completion

Predictors relevant to follow-up completion included appointment scheduling information, prior attendance behavior, clinic type, discharge destination, patient engagement, social risk, and transition-of-care documentation. Studies of appointment adherence and post-discharge follow-up emphasized the relevance of scheduling systems and post-discharge clinic workflows, which are often separate from inpatient electronic health record data [18, 19]. These findings suggest that useful follow-up prediction may require linking inpatient discharge records with outpatient scheduling, referral, portal, transportation, and communication data. However, the current evidence base provided limited detail on how social barriers, digital engagement, caregiver availability, and prior no-shows should be operationalized in predictive models.

Models for post-discharge risk

Post-discharge risk prediction was the most mature and heavily studied area, with many models predicting 30-day readmission, emergency revisit, mortality, or adverse outcomes after discharge. Studies included general all-cause readmission models, heart failure readmission models, pneumonia readmission models, chronic obstructive pulmonary disease readmission models, intensive care discharge risk models, postoperative readmission models, and cardiovascular readmission models [6-11, 21-30]. Several models used machine learning methods such as neural networks, gradient boosting, random forests, and interpretable scoring tools to estimate risk after discharge [6, 23, 24, 25]. Despite this volume, many studies remained retrospective and focused on model performance rather than intervention design.

Features for post-discharge risk

Post-discharge risk models used a wide range of predictors, including demographics, comorbidities, diagnoses, prior utilization, laboratory values, medications, procedures, length of stay, discharge disposition, and disease-specific clinical variables. Some studies incorporated richer data sources such as physical activity data, historical electronic patient records, and federated health data architectures [11, 21, 31]. Systematic review evidence indicated that electronic medical record-based readmission models varied considerably in predictor selection, outcome definition, and reporting quality [13]. Social determinants, functional status, and patient engagement factors were increasingly recognized as relevant, but they were still inconsistently represented across model development studies [19, 23].

Model types and technical approaches

The reviewed studies used a diverse set of technical approaches, including logistic regression comparators, random forests, gradient boosting, artificial neural networks, deep learning, survival-oriented tools, and interpretable scoring systems. Artificial neural networks were used in early readmission prediction work, while later studies increasingly emphasized gradient boosting, explainable models, and clinically interpretable risk tools [6, 23, 24, 25]. Federated learning appeared in readmission risk prediction for chronic obstructive pulmonary disease, reflecting interest in privacy-preserving multi-site modeling [11]. Across domains, however, technical sophistication often outpaced evidence that the model changed decisions, reduced delays, or improved patient outcomes.

Validation practices

Validation practices varied substantially across studies, with many using internal train-test splits, cross-validation, or retrospective temporal validation. A smaller subset reported prospective validation, external validation, or silent testing in clinical environments, which are especially important for discharge planning because operational patterns can change over time [7, 23]. Some disease-specific readmission models were developed on large datasets but still faced concerns about transportability, calibration drift, and integration into local workflows [8, 16, 26, 27]. The evidence therefore supported cautious interpretation of reported model maturity, particularly when models were not tested outside the institution or time period in which they were developed.

Deployment and impact measurement

Few studies demonstrated full deployment with measured impact on discharge planning, placement delay, follow-up completion, or post-discharge outcomes. Some work described workflow integration or prospective validation, but most studies stopped at model development, retrospective validation, or feasibility assessment [7, 17]. Studies that aimed to support multidisciplinary rounds, discharge prediction, or transition clinic adherence suggested practical use cases, yet evidence of sustained operational improvement remained limited [2, 18]. Overall, the implementation gap was a central finding across all four domains, especially for models intended to influence time-sensitive patient flow decisions.

Table 1 organizes the included evidence by application domain, healthcare setting, data source, model family, target outcome, validation approach, practical use, and implementation readiness.

Table 1. Evidence Taxonomy and Application Matrix for Machine Learning in Patient Transfer and Discharge Planning

Application domain	Healthcare setting	Main data sources	AI/model families reported	Target outcomes	Validation approach	Practical use	Implementation readiness
Placement delay and transfer bottleneck prediction	Emergency departments, inpatient bed management, hospital operations command centers, transfer coordination teams	Admission-discharge-transfer feeds, bed management logs, unit census, service assignment, admission timing, acuity indicators, infection control flags, expected discharge volume	Operations analytics, interpretable predictive models, tree-based models, statistical comparators, patient flow forecasting methods	Delayed bed assignment, boarding time, transfer wait time, unit placement bottleneck, capacity strain	Mostly retrospective operational modeling; limited explicit external validation; rare prospective testing	Anticipate bed demand, prioritize transfers, identify capacity bottlenecks, support bed huddles and patient flow meetings	Low model operational importance underdeveloped as a predictive tool
Discharge readiness and discharge timing prediction	General medical wards, surgical services, cardiovascular units, neurological care, infectious disease surge settings, multidisciplinary discharge rounds	Electronic health records, laboratory values, vital signs, diagnoses, medications, procedure data, clinician documentation, EHR access logs, consult activity, care progression indicators	Random forests, gradient boosting, neural networks, discharge prediction algorithms, interpretable classifiers, logistic regression comparators	Discharge within 24 hours, same-day discharge likelihood, next-day discharge, predicted discharge date, discharge disposition	Internal validation common; temporal validation variable; some prospective or workflow-oriented validation; limited external validation	Support daily rounds, identify discharge barriers, anticipate bed availability, coordinate case management and discharge tasks	Model growth evidenced with clinical workflow relevance placement model

Follow-up completion and transition adherence prediction	Post-discharge transition clinics, outpatient scheduling systems, care coordination teams, primary care follow-up pathways	Scheduling records, referral data, appointment history, prior no-shows, discharge destination, patient engagement signals, portal activity, social risk factors, care transition notes	Machine learning classifiers, adherence prediction models, logistic regression comparators, risk stratification tools	Follow-up appointment attendance, missed visit risk, transition-of-care adherence, completion of post-discharge plan	Sparse evidence; mostly retrospective or implementation-oriented observational validation; limited external validation	Prioritize outreach, schedule support, care navigation, reminder workflows, transportation or social support referral	Low practical but limited model literature
Post-discharge readmission risk prediction	General hospital medicine, heart failure, pneumonia, chronic obstructive pulmonary disease, intensive care, postoperative care, cardiovascular procedures, older adult care	Electronic medical records, diagnoses, comorbidities, laboratory values, medication lists, prior utilization, length of stay, discharge disposition, procedures, physical activity data, historical patient records	Logistic regression comparators, artificial neural networks, random forests, gradient boosting, deep learning, interpretable scoring tools, federated learning	30-day readmission, early readmission, emergency department revisit, mortality, unplanned adverse events after discharge	Retrospective internal validation common; external validation and prospective validation less frequent; calibration and subgroup testing inconsistently reported	Risk stratification, transitional care referral, discharge planning support, post-discharge monitoring prioritization	Model high for developed mature workflow
Social, functional, and engagement-enhanced discharge risk modeling	Transitional care programs, population health teams, case management, chronic disease management, older adult care	Social determinants, functional status, physical activity, prior utilization, patient engagement, appointment behavior, care access indicators, EHR-derived risk variables	Explainable machine learning, interpretable scoring systems, gradient boosting, federated learning, hybrid clinical-social risk models	Readmission risk, missed follow-up, transition vulnerability, prolonged length of stay, post-discharge deterioration	Variable; often retrospective; fairness and subgroup performance underreported	Identify patients needing added transition support, social work referral, navigation, or monitoring	Emerging concept important limited inconclusive data and governance

End-to-end transfer-discharge trajectory modeling	Whole-hospital patient flow systems, discharge planning programs, integrated care transition platforms	Linked ADT feeds, EHR data, bed management data, discharge documentation, scheduling systems, follow-up records, post-discharge outcomes	Not yet mature; proposed future direction combining longitudinal prediction, time-to-event modeling, interpretable AI, and multi-phase workflow analytics	Sequential risk from placement delay to discharge readiness, follow-up completion, readmission, ED revisit, mortality, and adverse events	Not established; prospective multi-site validation needed	Coordinate bed management, discharge readiness, follow-up planning, and post-discharge risk intervention as one connected workflow	Very high priority for research implementation
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Post-discharge risk prediction dominates

The literature was dominated by post-discharge risk prediction, especially readmission models, reflecting the policy and operational importance of avoidable hospital utilization. This concentration has produced a large variety of models across diseases and settings, including heart failure, pneumonia, chronic obstructive pulmonary disease, intensive care, postoperative care, and cardiovascular procedures [6, 8, 9, 11, 26, 27]. However, the growing number of readmission models also raises concerns about diminishing novelty when studies differ mainly by algorithm or cohort rather than by implementation design. The review suggests that future contributions should move beyond retrospective readmission prediction toward actionable transition interventions.

Discharge readiness models are gaining precision

Discharge readiness models are increasingly moving beyond simple length-of-stay estimation toward dynamic prediction of discharge timing and readiness. Models based on electronic health record data, access logs, and inpatient clinical features showed how discharge likelihood can be estimated during hospitalization rather than only at admission [2, 13–15]. These approaches may support daily multidisciplinary rounds, bed planning, and earlier identification of barriers to discharge. Nevertheless, readiness prediction must be interpreted carefully because predicted discharge likelihood is not equivalent to clinical appropriateness for discharge.

Placement delay is the missing link

Placement delay prediction was the least developed area despite being central to patient flow. Operational analytics studies showed that inpatient flow and discharge patterns can be modeled, but few studies directly predicted delayed placement after an admission decision or transfer request [3]. This gap is important because discharge readiness and post-discharge risk models cannot fully address hospital crowding if they do not connect to bed assignment, transfer prioritization, and unit-level capacity constraints. Future research should explicitly model placement delay as a patient-level and system-level outcome using bed management and admission-discharge-transfer data.

Follow-up completion is underserved

Follow-up completion prediction remains underserved even though missed follow-up can undermine discharge plans and contribute to avoidable readmission. Studies of transition clinic adherence and post-discharge appointment status show that follow-up is measurable and potentially predictable, but the evidence base remains small [18, 19]. This limitation may reflect fragmentation between inpatient records, outpatient scheduling platforms, and community care data. Because

follow-up completion is an actionable outcome, predictive models in this area could directly support outreach, scheduling assistance, transportation coordination, and targeted care navigation.

Data fragmentation limits multi-phase models

The evidence suggests that no mature model currently predicts the full trajectory from placement delay to discharge readiness, follow-up completion, and post-discharge risk. Instead, studies usually focus on one phase, one outcome, and one data environment, such as inpatient discharge prediction or readmission risk after discharge [1, 5, 14]. This fragmentation limits the ability of hospitals to coordinate predictive insights across emergency departments, inpatient units, bed management teams, discharge planners, and outpatient follow-up clinics. End-to-end modeling would require interoperable data pipelines that link real-time operational data with clinical and post-discharge information.

The implementation gap across all domains

Across the evidence base, model development was more common than prospective deployment or impact evaluation. Even studies with strong technical designs often did not show whether predictions changed discharge decisions, reduced length of stay, improved follow-up, or prevented adverse events [7, 17, 23]. This gap is especially important in care transitions, where prediction without action may add cognitive burden rather than improve outcomes. Implementation studies should therefore evaluate not only model accuracy but also workflow fit, alert fatigue, clinician trust, equity, and measurable patient or operational benefit.

Figure 2 synthesizes the review findings into an evidence-to-implementation map linking application domains, data sources, model families, target outcomes, validation maturity, implementation barriers, governance concerns, and future research priorities.



Figure 2. Evidence-to-Implementation Synthesis Map of Machine Learning for Patient Transfer and Discharge Planning

Social and functional features are increasingly recognized

Social determinants, functional status, and patient engagement indicators were increasingly recognized as relevant to discharge risk and transitional care outcomes. Studies involving follow-up completion, readmission, physical activity, and broader electronic patient records suggest that social, behavioral, and functional data can provide important context beyond diagnoses and laboratory results [18, 19, 21, 31]. However, these features remain inconsistently captured and may be missing, biased, or documented unevenly across populations. Incorporating them responsibly requires careful attention to measurement quality, fairness, interpretability, and the risk of reinforcing structural inequities.

Limitations

Review limitations

This review was limited by its English-language restriction, reliance on peer-reviewed publications, and broad scope across multiple related but methodologically heterogeneous domains. Because studies differed in populations, predictors, outcomes, model families, and validation designs, meta-analysis was not appropriate, and synthesis relied on structured narrative comparison [1, 5, 20]. The evidence base may also be affected by publication bias, because unsuccessful deployment attempts and operational models used internally by hospitals may not be published. In addition, the 31 core references cited here represent the most relevant studies from a larger screened evidence base rather than an exhaustive list of every prediction model touching hospital discharge.

Evidence base limitations

The underlying literature was limited by retrospective single-site model development, inconsistent external validation, limited prospective testing, and sparse reporting of real-world implementation. Many studies emphasized discrimination or algorithm comparison but provided less detail on calibration, decision thresholds, workflow integration, fairness, or clinical actionability [8, 9, 25, 26]. Placement delay and follow-up completion were particularly underdeveloped, while post-discharge readmission prediction was much more common but often disconnected from intervention design [18, 19, 23]. These limitations reduce confidence that current models can be adopted safely and effectively without local validation and implementation evaluation.

Comparison with prior reviews

Prior reviews have usually focused on narrower parts of the transfer-discharge continuum, especially discharge prediction, length-of-stay estimation, and readmission risk. A systematic literature review of patient discharge prediction emphasized statistical and machine learning approaches for anticipating discharge timing, while electronic medical record-based readmission reviews concentrated on risk model development and validation rather than end-to-end discharge planning [1, 5]. Disease-specific reviews and studies in heart failure, chronic obstructive pulmonary disease, pneumonia, and postoperative populations further demonstrate that post-discharge risk has often been studied as a stand-alone prediction problem [6, 8, 11, 20]. This narrower focus has advanced model development but has not fully addressed how transfer bottlenecks, readiness assessment, follow-up completion, and post-discharge outcomes interact across the patient journey.

This review differs from prior reviews by integrating four related transitional phases rather than treating discharge prediction or readmission prediction in isolation. The evidence shows that discharge readiness models, patient flow analytics, follow-up adherence models, and post-discharge risk models occupy adjacent but weakly connected parts of the same operational pathway [2, 3, 17, 18]. Studies of discharge prediction and inpatient flow suggest that earlier prediction may help bed planning, while follow-up and readmission studies show that post-discharge coordination remains an important downstream determinant of outcomes [16, 19, 23]. By synthesizing these areas together, the review highlights that the practical challenge is not only predicting one outcome accurately but aligning predictions across hospital operations and transitional care.

The main novel contribution of this review is the identification of a missing end-to-end predictive chain linking placement delay, discharge readiness, follow-up completion, and post-discharge risk. Current models tend to be siloed by setting, data source, and outcome, with inpatient models rarely extending into outpatient follow-up and post-discharge risk models rarely feeding back into discharge planning workflows [14, 21, 25, 31]. Even advanced approaches such as interpretable readmission tools, federated readmission prediction, and workflow-integrated discharge date models remain focused on discrete decision points rather than the full transfer-discharge trajectory [11, 17, 23]. This gap suggests the need for research designs that evaluate patient flow and transitional care as a connected system rather than as isolated prediction tasks.

Recommendations

For researchers

Researchers should prioritize multi-phase prediction studies that connect placement delay, discharge readiness, follow-up completion, and post-discharge risk within the same analytic framework. Future models should be evaluated prospectively, compared with existing clinical workflows, and linked to patient-centered and operational outcomes rather than reported only as retrospective prediction exercises [7, 17, 23]. Studies should also move beyond algorithm comparison by specifying intended users, decision thresholds, intervention pathways, and safeguards for unsafe discharge or inequitable prioritization [4, 22, 24]. This shift would help determine whether machine learning improves care transitions rather than simply predicting adverse outcomes after they occur.

For journal editors

Journal editors should require stronger reporting standards for machine learning studies in transfer and discharge planning. Manuscripts should clearly report temporal validation, external validation where feasible, calibration, missing data handling, model updating plans, decision thresholds, and implementation context [5, 7, 20]. Editors should also encourage authors to describe whether predictors are available in real time, whether outputs are interpretable to clinical and operational users, and whether the model has been tested in the workflow it is intended to support [2, 14, 17]. These requirements would improve reproducibility and reduce the number of studies that present technically plausible but operationally under-specified prediction tools.

For hospital administrators

Hospital administrators should invest in integrated data infrastructure that links electronic health records, admission-discharge-transfer feeds, bed management systems, discharge documentation, scheduling systems, and post-discharge outcomes. The current evidence shows that discharge readiness, inpatient flow, follow-up completion, and readmission risk models often draw on different data streams, limiting their use as coordinated decision-support tools [3, 18, 19, 31]. Administrators should also ensure that predictive outputs are embedded into multidisciplinary rounds, bed huddles, discharge planning meetings, and transition clinics rather than delivered as isolated alerts [2, 17]. Such integration is necessary if machine learning is to support real-time flow management and safer care transitions.

For vendors

Vendors developing predictive tools for discharge planning should design interoperable systems that can operate across inpatient, operational, and outpatient care environments. Tools should support transparent risk explanations, configurable thresholds, role-specific displays, audit trails, and integration with bed management, scheduling, referral, and care coordination workflows [14, 18, 23]. Vendor systems should avoid framing predictions as autonomous discharge decisions and instead present them as structured support for clinicians, case managers, bed managers, and transition teams [2, 4, 12]. Products should also include monitoring for calibration drift, subgroup performance, and unintended consequences after deployment.

Research gaps

End-to-end transfer-discharge risk trajectory models

No identified study provided a mature end-to-end model that predicted the entire continuum from placement delay to discharge readiness, follow-up completion, and post-discharge adverse events. Existing studies were usually anchored to one outcome, such as next-day discharge, discharge disposition, appointment adherence, or readmission risk [4, 11, 14, 25]. This leaves hospitals without predictive systems that can anticipate how upstream placement problems may influence discharge readiness or how discharge readiness interacts with follow-up completion and subsequent risk [3, 19]. Future research should develop trajectory-based models that represent the patient journey as a sequence of linked operational and clinical risks.

Prospective, randomised evaluations

Prospective and randomized evaluations remain a major gap across the field. Some studies included prospective validation or workflow integration, but the broader literature still relies heavily on retrospective model development and internal validation [7, 17, 23]. There is little evidence that machine learning-informed discharge planning reduces placement delay, improves follow-up completion, prevents readmission, or improves patient experience when compared with usual care. Pragmatic trials, stepped-wedge designs, and silent-to-active deployment studies are needed to determine whether predictive models produce measurable benefit in real operational settings.

Equity and fairness

Equity and fairness remain insufficiently studied in machine learning models for transfer and discharge planning. Many models include demographic, utilization, social, or functional variables, but few studies explicitly evaluate whether predictions perform equitably across race, socioeconomic status, language, disability, rurality, insurance status, or access to follow-up care [19, 21, 23, 31]. This is important because discharge planning algorithms could inadvertently deprioritize patients with fragmented records or amplify existing disparities in access to post-discharge services. Future studies should report subgroup performance, assess bias in predictor availability, and evaluate whether model-guided interventions reduce or worsen inequities.

Table 2 summarizes the main implementation gaps, governance risks, future research priorities, and operational implications for machine learning-supported transfer and discharge planning.

Table 2. Implementation Gaps, Governance Risks, and Future Research Agenda for Machine Learning-Supported Transfer and Discharge Planning

Recurring limitation or gap	Practical consequence for care transitions	Safety or governance concern	Recommended future research direction	Implementation implication
Retrospective single-site model development dominates the evidence base	Models may perform well in development datasets but fail when local workflow, patient mix, staffing patterns, or discharge processes differ	Limited generalizability, calibration drift, and unsafe transfer of models across institutions	Conduct temporal, external, and multi-site validation before clinical deployment	Hospitals should require local validation and recalibration before adopting discharge planning algorithms
Placement delay prediction is underdeveloped	Upstream bottlenecks in bed assignment and transfer coordination remain weakly supported by predictive analytics	Operational decisions may remain reactive, increasing boarding, crowding, and delayed inpatient placement	Develop models using ADT feeds, bed management logs, occupancy, staffing, isolation needs, service availability, and transfer queues	Embed predictions into bed huddles, capacity management dashboards, and transfer coordination workflows
Follow-up completion prediction is sparse	Patients at risk of missed post-discharge follow-up may not receive timely outreach or navigation support	Models may overlook social barriers, digital access gaps, transportation problems, or caregiver limitations	Link inpatient discharge records with outpatient scheduling, referral, portal, call-center, and social support data	Use predictions to trigger care navigation, reminder calls, transport support, and targeted transition clinic scheduling

Discharge readiness models may predict timing rather than appropriateness	A patient predicted to leave soon may not actually be clinically, functionally, or socially ready for safe discharge	Risk of premature discharge if model outputs are misinterpreted as clinical clearance	Distinguish discharge likelihood from discharge appropriateness, and include clinical, functional, social, and pending-task indicators	Display predictions as decision support for multidisciplinary review, not as autonomous discharge recommendations
Post-discharge readmission models are numerous but often disconnected from interventions	Risk scores may identify high-risk patients without specifying what action should follow	Prediction without action can increase alert burden without improving outcomes	Pair risk models with defined intervention pathways, thresholds, and accountable clinical roles	Link risk outputs to transition planning, medication reconciliation, follow-up scheduling, home support, and monitoring
External validation and prospective silent testing are uncommon	Model performance and usability are uncertain under real-time operational conditions	Undetected performance degradation may occur after deployment	Use silent trials, stepped-wedge studies, pragmatic trials, and post-deployment monitoring	Move from offline validation to staged implementation with safety monitoring before active clinical use
Social determinants and functional status are inconsistently captured	Models may miss important drivers of discharge barriers, missed follow-up, and readmission	Biased or incomplete documentation may worsen inequity or misclassify vulnerable patients	Standardize capture of social risk, mobility, caregiver support, access barriers, and patient engagement indicators	Pair social-risk prediction with supportive services rather than punitive prioritization
Interpretability and accountability are inconsistently reported	Clinicians, case managers, and administrators may not understand or trust predictions	Poor explainability can obscure unsafe recommendations or make accountability unclear	Require interpretable outputs, reason codes, audit trails, and model cards for discharge planning tools	Predictions should show actionable drivers such as pending consults, unstable vitals, missed follow-up risk, or social barriers
No mature end-to-end transfer-discharge trajectory model was identified	Hospitals lack a connected predictive view from placement delay through discharge readiness and post-discharge outcomes	Siloed models may optimize one stage while shifting risk to another stage	Develop longitudinal models linking placement delay, readiness, follow-up completion, and post-discharge risk	Build integrated platforms that support bed management, discharge planning, care coordination, and post-discharge monitoring together
Limited evidence of measured operational or patient outcome improvement	It remains unclear whether models reduce delays, improve follow-up, prevent readmission, or improve patient experience	Adoption may be driven by technical enthusiasm rather than demonstrated benefit	Evaluate impact on length of stay, boarding time, safe discharge, follow-up completion, readmission, mortality, equity, and workload	Procurement and publication standards should require implementation outcomes, not only prediction metrics

Risk of workflow misalignment and alert fatigue	Predictions may appear outside the decision point where they are needed or overwhelm clinical teams	Alerts may be ignored, misused, or delegated without clear responsibility	Study human factors, role-specific displays, threshold design, and actionability in real workflows	Embed outputs into multidisciplinary rounds, discharge task lists, bed meetings, transition clinics, and care management queues
Need for governance standards in AI-augmented discharge planning	Hospitals may deploy models without consistent rules for monitoring, accountability, or bias management	Unmonitored models can drift, reinforce disparities, or influence unsafe discharge decisions	Establish standards for transparency, validation, fairness, monitoring, escalation, and post-deployment review	Health systems should create governance committees for discharge AI, including clinicians, operations leaders, informatics, ethics, and patient safety representatives

Implications

For research practice

The evidence suggests that research practice should shift from single-domain accuracy studies toward holistic patient-journey prediction. Readmission models, discharge readiness tools, flow analytics, and follow-up adherence models each provide partial insight, but none fully captures the sequence of risks that begins with placement and continues after discharge [1, 3, 5, 18]. Future studies should combine operational, clinical, social, functional, and engagement data to support longitudinal risk assessment across the transition pathway [11, 21, 31]. This approach would better reflect how hospital flow and transitional care unfold in practice.

For clinical practice

In clinical practice, machine learning predictions should augment rather than replace multidisciplinary discharge planning. Prediction outputs may help teams identify patients likely to experience delayed placement, uncertain discharge readiness, missed follow-up, or post-discharge deterioration, but final decisions must remain grounded in clinical judgment, patient preferences, caregiver capacity, and service availability [2, 4, 23]. The most useful models will be those that provide interpretable, timely, and actionable information to clinicians, case managers, bed managers, and transition coordinators [17, 18]. Poorly integrated models risk becoming additional alerts rather than meaningful decision-support tools.

For policy

Policy efforts should establish standards for AI-augmented discharge planning, including transparency, validation, bias monitoring, accountability, and post-deployment evaluation. Current evidence shows that machine learning is increasingly used in discharge and readmission prediction, but implementation reporting remains inconsistent and prospective outcome evaluation is limited [2, 5, 7]. Regulators and health systems should require evidence that predictive tools are safe, interpretable, locally validated, and monitored after deployment [22-24]. Policy should also promote interoperable data systems that allow hospitals to connect bed management, discharge planning, follow-up scheduling, and post-discharge outcomes.

Conclusion

Machine learning for patient transfer and discharge planning has grown substantially from 2017 to 2024. The most developed evidence areas are post-discharge risk prediction and discharge readiness prediction, particularly models for

readmission risk, discharge timing, and next-day discharge likelihood. These models show promise for supporting proactive planning, but most remain closer to retrospective prediction than demonstrated care improvement.

Placement delay and follow-up completion prediction remain underexplored despite their practical importance. Placement delay affects emergency department flow, inpatient capacity, and the timing of downstream discharge work. Follow-up completion determines whether discharge plans translate into continuity of care after the patient leaves hospital. These domains represent critical leverage points for improving hospital flow and transitional safety.

The central limitation of the evidence base is the gap between model development and prospective, integrated implementation. Many studies show that machine learning can classify or rank risk, but far fewer show that predictions change decisions, reduce delays, improve follow-up, or prevent adverse outcomes. Future work must therefore evaluate prediction as part of an intervention, not as a stand-alone technical product.

A coordinated research agenda is needed to move from isolated prediction tasks to whole-journey modeling. Such an agenda should connect placement, discharge readiness, follow-up, and post-discharge risk into a unified view of patient flow and transitional care. The next generation of models should be interpretable, equitable, workflow-integrated, prospectively evaluated, and designed to support multidisciplinary decision-making. Only then can machine learning become a practical tool for safer discharge planning and more reliable care transitions.

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