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Predictive Analytics Model for Estimating Same-Day Hospital Discharge Readiness Using Morning Laboratory Results, Active Medication Orders, Vital Sign Stability, Mobility Documentation, and Pending Consultation Status

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Abstract

Hospital discharge delays are costly, disrupt inpatient capacity, and expose patients to avoidable iatrogenic harm. Early identification of patients likely to be ready for discharge could improve patient flow and reduce operational bottlenecks. Current discharge decisions often rely on subjective judgment, fragmented documentation, and sequential review by multiple clinical teams. No single tool routinely integrates the morning snapshot of clinical readiness. This article proposes a predictive model that estimates the probability of same-day discharge readiness by 9 am. The model uses morning laboratory results, active medication orders, vital sign stability, mobility documentation, and pending consultation status. The proposed approach is a supervised classification model using gradient-boosted trees trained on historical inpatient encounters. Features would be assembled from electronic health record data available before morning rounds. Conceptually, the model would generate a calibrated discharge readiness list for clinical review. This list could help care teams focus on borderline patients and support bed-management forecasting. The model could accelerate discharge throughput while maintaining safety by surfacing hidden readiness signals. It is intended to complement, not replace, clinical judgment.

Keywords Machine learning, Predictive analytics, Hospital operations, Electronic health records, Patient flow, Discharge readiness

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Introduction

Delayed hospital discharge is a persistent operational problem because it constrains bed availability, contributes to emergency department boarding, and may force deferral of elective admissions or surgical activity. Predictive analytics has increasingly been proposed as a way to anticipate discharge timing, bed demand, and inpatient flow before bottlenecks become visible to operational leaders [1-4]. Models that estimate discharge volume or patient-level discharge likelihood could therefore support earlier coordination between hospital medicine, nursing, case management, and bed-management teams [5, 6]. In this context, same-day discharge readiness prediction is not merely a statistical task but a hospital operations intervention aimed at improving throughput without encouraging unsafe discharge decisions [7, 8].

Traditional discharge readiness assessment depends heavily on clinician gestalt, local practice norms, and sequential sign-off from multiple services. Surgical and medical discharge decisions often require synthesis of physiological stability, procedure completion, medication feasibility, mobility, and consultant recommendations, yet these signals are distributed across different parts of the electronic health record [5, 9, 10]. Even when structured discharge criteria exist, their practical application is affected by inconsistent documentation, variable timing of rounds, and uncertainty about whether a patient's remaining needs truly require inpatient care [11, 12]. These limitations create an opportunity for predictive models that organize existing information into a clinically reviewable readiness estimate [13, 14].

The electronic health record contains real-time signals that are directly relevant to discharge readiness, including laboratory trajectories, active medication orders, vital sign trends, mobility documentation, procedure status, and consultation activity. Machine learning studies of length of stay, discharge disposition, and hospital flow have shown that routinely collected EHR data can support clinically meaningful prediction tasks when features are aligned with the decision being supported [15–18]. Models using medication records, flowsheets, structured orders, and unstructured notes could help identify patients whose clinical state is stabilizing as well as patients whose discharge is blocked by unresolved care processes [19, 20]. For discharge readiness, the key design issue is not only prediction but also timely morning availability and operational interpretability [21, 22].

This article proposes a predictive analytics model that estimates same-day hospital discharge readiness from the morning clinical snapshot. The model would combine morning laboratory results, active medication orders, vital sign stability, mobility documentation, and pending consultation status into a readiness probability for use during morning rounds and bed-management huddles. Its purpose would be to complement clinical judgment by creating a systematic, transparent, and updateable prioritisation list rather than automating discharge decisions. Such a tool would be expected to support proactive planning, focus attention on modifiable barriers, and improve alignment between patient-level care decisions and hospital-wide capacity management.

Background

Discharge planning and decision-making in hospital medicine

Discharge planning is a multidisciplinary process that requires coordination among physicians, nurses, therapists, consultants, case managers, patients, and families. Predictive models for discharge timing and disposition suggest that discharge decisions are shaped by both clinical recovery and operational processes, including service availability, documentation completion, and anticipated downstream care needs [5, 15, 23]. Structured discharge criteria can improve consistency, but they may remain incomplete when readiness signals are scattered across EHR modules or embedded in narrative documentation [13, 17]. A same-day readiness model should therefore be designed around practical discharge workflow rather than around prediction accuracy alone [1, 22].

Morning laboratory results as stability indicators

Morning laboratory results can provide early evidence of physiological stability, deterioration, or unresolved treatment needs. For example, stabilizing renal function, haemoglobin, inflammatory markers, and electrolytes may support clinical confidence that a patient no longer requires inpatient monitoring, whereas new abnormalities may indicate the need for reassessment [11, 16, 18]. Predictive models using EHR data often derive value from laboratory trends because they capture both illness severity and response to treatment over time [20, 24]. In a discharge-readiness model, laboratory features should be interpreted as contextual signals rather than rigid discharge rules, since not every clinically ready patient requires daily laboratory testing [7, 19].

Active medication orders as a proxy for ongoing care needs

Active medication orders can indicate whether a patient still depends on inpatient therapies that are difficult to continue safely after discharge. Intravenous antimicrobials, parenteral nutrition, sedatives, anticoagulation titration, and controlled infusions may represent ongoing acuity or unresolved transition planning, while conversion to oral or home-compatible therapy may support discharge preparation [9, 10, 24]. EHR-based predictive systems can use medication route, class, frequency, and recent administration patterns as structured markers of care intensity [12, 20]. These features should be engineered cautiously because some active orders reflect routine continuation rather than barriers to discharge, and their meaning depends on the clinical context [8, 25].

Vital sign stability, mobility, and functional readiness

Vital sign stability remains a core element of discharge safety because abnormal temperature, heart rate, blood pressure, respiratory rate, or oxygen saturation may signal persistent risk after leaving hospital. Evidence linking discharge vital-sign instability with adverse post-discharge outcomes supports the inclusion of recent observation trends in readiness estimation [11]. Functional mobility is similarly important, especially for patients recovering from surgery, neurological illness, or deconditioning, because discharge may be unsafe without adequate ambulation, transfer ability, or therapy clearance [15, 23, 26]. A readiness model should therefore combine physiological stability with functional readiness rather than treating discharge as a purely diagnostic or laboratory-based decision [27, 28].

Pending consultations and their effect on discharge timing

Pending consultations, incomplete recommendations, outstanding imaging, and delayed procedures can prevent discharge even when the primary medical problem is improving. Predictive models of surgical discharge, discharge disposition, and length of stay demonstrate that discharge timing is often shaped by unresolved process dependencies as much as by clinical severity [5, 9, 29]. Consultation status can be represented through active consult orders without completed notes, recent specialist recommendations awaiting action, or unresolved orders linked to discharge-critical decisions [13, 17]. Incorporating these barriers would allow the model to identify modifiable workflow constraints rather than merely classifying patients as clinically stable or unstable [1, 4].

Model Development Overview

High-level predictive pipeline

The proposed predictive pipeline would extract overnight EHR data, assemble a patient-level feature vector before morning rounds, and generate a same-day discharge readiness score at approximately 9 am. This timing aligns the model with operational decisions about rounding priorities, consultant escalation, pharmacy preparation, transport planning, and bed availability forecasting [1, 2, 4]. The output would be displayed in a morning huddle or bed-management dashboard, allowing care teams to review patients ranked by estimated readiness rather than relying only on manual recall [3, 22]. Because the model is intended for workflow support, its design should prioritise timeliness, interpretability, and clinical actionability over technical complexity [8, 30].

Figure 1 presents the proposed linear predictive analytics framework for transforming morning laboratory, medication, vital-sign, mobility, and consultation data into an explainable same-day discharge-readiness estimate for clinician-led review.

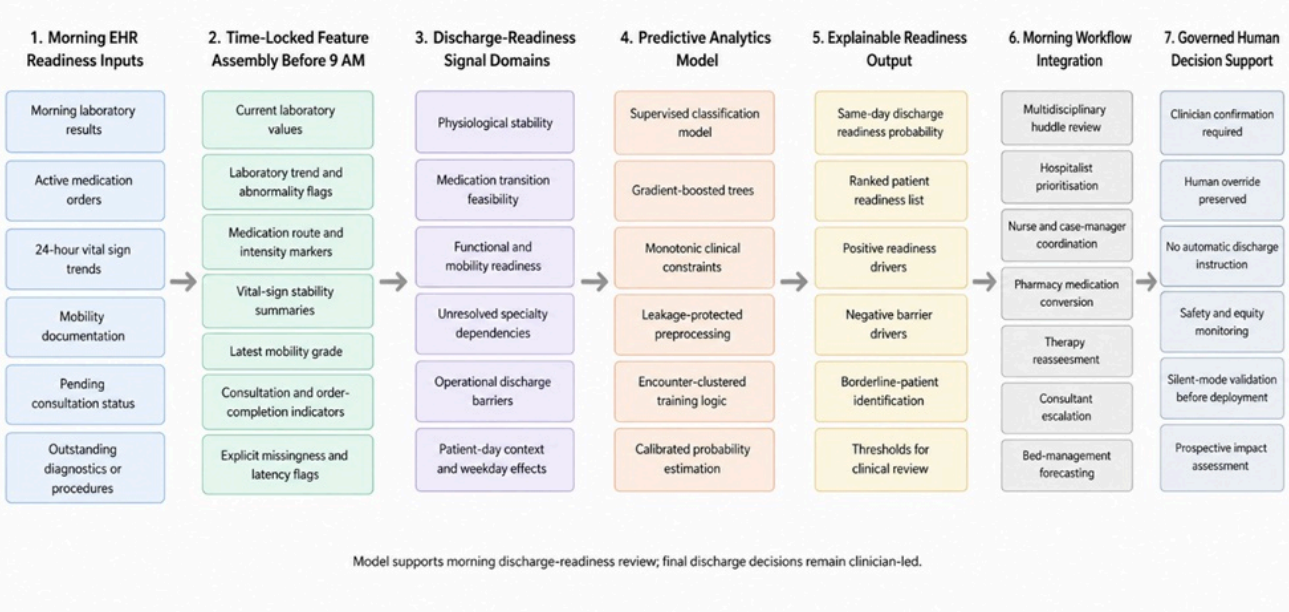


Figure 1. Linear predictive analytics framework for estimating same-day hospital discharge readiness from morning clinical and operational EHR signals.

Core input features

Core inputs would include selected morning laboratory values, recent laboratory trends, active medication orders by route and class, vital sign trends over the prior 24 hours, the most recent mobility score, and a count or flag for pending consultations. These domains are consistent with prior EHR-based prediction work showing that structured clinical data, medication patterns, observations, and documentation-derived features can support prediction of length of stay, discharge disposition, and care trajectory [16, 20, 27, 24]. Mobility and functional status features would be particularly important for surgical, neurological, and frail medical patients, where physiological stability alone may not indicate discharge safety [15, 23, 26]. Pending consultation and outstanding order features would capture operational barriers that are not always reflected in laboratory or vital-sign data [13, 17].

Design principles

The model should be actionable, interpretable, and conservative enough to avoid encouraging premature discharge. A low false-positive orientation would be appropriate because incorrectly flagging a patient as ready could create pressure to discharge despite unresolved clinical needs, whereas a missed opportunity can still be detected through usual clinical review [7, 8, 11]. The readiness score should be updateable as new laboratory results, medication changes, mobility documentation, or consultant notes become available during the morning [1, 12]. This design would position the tool as a dynamic prioritisation aid rather than a static prediction detached from clinical workflow [22, 25].

Data Sources and Feature Engineering

Extracting laboratory, medication, and vital sign features

Laboratory features would be abstracted from the laboratory information system and transformed into current values, recent trends, abnormality indicators, and change from patient-specific baseline where available. Medication features would be drawn from active orders and administration records, distinguishing route, therapeutic class, titration requirement, and recent continuation or discontinuation patterns [12, 20, 24]. Vital sign features would be derived from flowsheets using summary measures over the prior 24 hours, including instability flags and sustained normalization

patterns rather than isolated single readings [11]. These features should preserve clinical meaning while avoiding future data leakage from events occurring after the morning prediction time [7, 19].

Mobility documentation and functional status extraction

Mobility documentation would be extracted from physical therapy notes, nursing mobility assessments, structured activity orders, and flowsheet entries describing ambulation, transfers, assistance level, and device use. Because mobility may be recorded inconsistently, feature engineering should combine structured fields with simple natural language concepts such as “ambulates independently,” “requires assistance,” or “not yet assessed” [15, 17, 26]. Surgical and neurological discharge-disposition studies suggest that functional status and post-acute care needs are central to safe discharge planning, making mobility a readiness domain rather than an optional contextual variable [23, 28, 29]. The resulting structured mobility grade would be expected to help differentiate patients who are physiologically stable from those who still need therapy clearance or discharge support [27].

Pending consultation and outstanding orders

Pending consultation status would be represented by active consult requests without completed recommendations, unresolved specialty notes, or documented recommendations requiring action before discharge. Outstanding diagnostic or procedural orders, such as imaging, procedures, or discharge-critical tests, would be treated as negative readiness indicators when they remain incomplete at the morning prediction time [9, 10, 13]. These features capture discharge barriers that often arise from coordination delays rather than direct physiological instability [4, 5]. By surfacing these drivers, the model could support targeted action, such as expediting a specialty recommendation or clarifying whether an outstanding order is truly required before discharge [1, 22].

Table 1 defines how each morning EHR data domain can be translated into clinically interpretable discharge-readiness constructs, feature representations, safety concerns, and actionable workflow responses.

Table 1. Conceptual Mapping of Morning EHR Signals to Discharge-Readiness Constructs

Morning data domain	Readiness construct captured	Example feature representations	Expected directional interpretation	Main safety concern	Actionable clinical response
Morning laboratory results	Physiological stability or unresolved instability	Current abnormality flags; trend from prior value; change from baseline; missing/delayed result indicator	Stabilizing or normalized values may support readiness; new abnormalities reduce readiness	Overinterpreting labs when testing was unnecessary or delayed	Review abnormal results before rounds; clarify whether additional monitoring is required
Active medication orders	Ongoing inpatient treatment dependence	IV route; titration requirement; high-risk medication class; recent discontinuation; oral conversion status	IV or titrated therapies generally reduce readiness; oral-compatible regimens support readiness	Treating routine medications as discharge barriers	Prioritize medication reconciliation, oral conversion, or home-infusion planning
Vital sign stability	Short-term clinical safety	24-hour instability flags; sustained normalization; oxygen	Stable observations support readiness; recurrent instability reduces readiness	Ignoring isolated artifacts or undocumented clinical context	Confirm bedside stability and determine whether

		requirement; fever recurrence			monitoring is still needed
Mobility documentation	Functional discharge feasibility	Latest mobility score; assistance level; ambulation status; therapy clearance; "not assessed" flag	Independent or cleared mobility supports readiness; limited or undocumented mobility reduces readiness	Penalizing patients because documentation is delayed	Trigger therapy reassessment or nursing mobility confirmation
Pending consultation status	Unresolved specialty dependency	Active consult without recommendation; recommendation awaiting action; unresolved specialty note	Pending discharge-critical consultation reduces readiness	Confusing nonessential consultations with true discharge blockers	Escalate consultant sign-off or clarify whether discharge can proceed
Outstanding orders or procedures	Operational completion barrier	Pending imaging; incomplete procedure; discharge-critical test not resulted	Incomplete discharge-critical workup reduces readiness	Encoding local practice delays as clinical unreadiness	Expedite test completion or cancel nonessential pending orders
Missingness and latency	Data reliability and workflow readiness	Missing lab flag; stale vital signs; absent mobility note; delayed consult documentation	Missingness may reduce confidence rather than directly imply unreadiness	Misclassifying documentation gaps as patient risk	Refresh prediction and prompt targeted documentation review

Predictive Analytics Architecture

Model choice: gradient-boosted trees with monotonic constraints

Gradient-boosted trees would be a suitable modelling approach because they can accommodate nonlinear interactions among laboratory values, medication status, vital signs, mobility, and consultation features while remaining more interpretable than many deep learning architectures. Monotonic constraints could be applied where clinical logic is clear, such as ensuring that additional pending consultations or unresolved discharge-critical orders should not increase estimated readiness [6, 18, 31]. This approach would align with the broader need for clinically plausible, auditable machine learning systems in hospital operations [8, 25]. Although alternative models could be considered, the priority should be a transparent architecture that can be explained to clinicians and safely embedded into workflow [12, 22].

Input feature vector and preprocessing

The input feature vector would include numeric, categorical, temporal, and missingness indicators, with preprocessing designed to preserve the clinical meaning of absent data. For example, a missing morning laboratory result may indicate either a delayed draw or that the test was not clinically needed, and the model should distinguish missingness from abnormality rather than treating all missing values as noise [19, 20]. Similar logic applies to mobility documentation, because absence of a therapy note may reflect low need, delayed assessment, or documentation gaps [15, 17]. Preprocessing should therefore encode missingness explicitly, normalize values relative to appropriate baselines, and prevent leakage from post-prediction events [7, 32].

Output: same-day discharge readiness probability

The model output would be a continuous same-day discharge readiness probability ranging from 0 to 1, interpreted as a prioritisation signal for clinical review rather than an automatic discharge instruction. A tunable threshold could be used to flag patients as likely ready for discharge, but threshold choice should depend on local tolerance for missed opportunities versus unsafe prioritisation [1, 8, 11]. The dashboard should present the score with top contributing factors so that clinicians can understand whether low readiness is driven by unstable vital signs, active intravenous therapy, limited mobility, or pending specialty input [12, 22]. This output structure would support practical action during morning rounds while preserving final authority for the treating team [25, 30].

Addressing Temporal Dynamics and Confounding

Defining the time window for prediction

The model should be run at a fixed morning time, such as 9 am, to forecast whether discharge readiness could be achieved by 5 pm the same day. This fixed prediction window is essential because discharge models can otherwise appear more accurate by unintentionally using information that became available only after clinical decisions had already occurred [13, 19]. Features should therefore be restricted to laboratory results, medication orders, vital signs, mobility documentation, and consultation status available before the prediction timestamp [7, 20]. A strict temporal design would make the model more credible for real-time operations and more aligned with morning clinical workflow [1, 14].

Repeated measures and clustering

A patient may be eligible for same-day discharge prediction on several consecutive inpatient days, creating repeated observations within a single encounter. Day-level modelling can reflect the evolving discharge decision, but evaluation should account for clustering by patient encounter to avoid overestimating reliability [19, 33]. This issue is especially important when clinical improvement is gradual, because adjacent hospital days may contain highly correlated laboratory, medication, vital-sign, and mobility features [16, 34]. The model should therefore be assessed as a longitudinal decision-support tool rather than as a set of independent one-time predictions [18, 31].

Incorporating temporal trends and weekday effects

Same-day discharge readiness is influenced not only by patient physiology but also by operational context, including weekday staffing, hospital census, procedural availability, and seasonal occupancy pressure. Forecasting studies of discharge volume and inpatient bed demand show that system-level patterns can affect whether clinically improving patients actually leave the hospital on a given day [2-4]. Contextual variables such as admission day, hospital day, weekday, census pressure, and service line could help the model distinguish clinical unreadiness from operational delay [1, 6]. These features should be interpreted cautiously because they may encode local practice patterns that require temporal and external validation before deployment elsewhere [7, 33].

Model Interpretability and Clinical Trust

Explaining discharge readiness scores to clinicians

Clinicians are more likely to trust a discharge readiness score when the model identifies the specific factors driving its estimate. SHAP-style explanations could show, for example, that active intravenous antibiotics, an unresolved cardiology consultation, unstable oxygen saturation, or limited mobility reduced the readiness estimate [11, 12, 27]. Such explanations convert prediction into action by helping teams identify modifiable barriers, including consultant escalation, medication conversion, or therapy reassessment [5, 9]. Interpretability is also important because clinical AI tools can fail when they are technically valid but poorly aligned with bedside reasoning and safety expectations [8, 25].

Transparency for care coordination

A multidisciplinary rounds report should display the readiness score beside the leading positive and negative drivers, allowing hospitalists, nurses, therapists, pharmacists, and case managers to act on the same information. This format would support care coordination by linking model output to concrete tasks, such as confirming mobility clearance, reconciling medication route, or resolving outstanding investigations [15, 17, 22]. Transparency is particularly important in discharge workflows because the final decision depends on coordinated judgment rather than a single clinician's isolated action [1, 30]. The tool should therefore be framed as shared situational awareness rather than as an algorithmic directive [7, 8].

Clinical Deployment and Discharge Workflow Integration

Integration into morning huddles and bed-management dashboards

The readiness list would be automatically generated before morning huddles and pushed to the hospitalist team, charge nurses, case managers, and bed-board managers. Patients with high estimated readiness could be reviewed early for medication conversion, discharge documentation, transport planning, and consultant sign-off, while borderline patients could be targeted for rapid barrier resolution [1, 2, 4]. This operational use case aligns with prior work showing that discharge prediction tools may support multidisciplinary rounds and reduce avoidable delays when embedded into actual care processes [3, 5]. The model would be expected to provide the greatest value when it prompts earlier action rather than merely predicting what would have happened anyway [22].

Tiered response and human override

A tiered workflow would allow different responses to different readiness levels without treating the score as an automatic discharge order. Low-score patients could trigger case-management review or identification of persistent barriers, whereas high-score patients could be prioritised for consultant sign-off and discharge preparation while remaining subject to clinician review [12, 25]. Human override is essential because patient preference, social support, caregiver availability, and clinical nuance may not be fully captured in EHR-derived features [7, 32]. This safeguard also helps prevent automation bias and supports responsible implementation of predictive models in clinical care [8, 30].

Evaluation Strategy

Predictive performance metrics

Evaluation should include discrimination, precision-recall performance, calibration, and threshold-specific specificity at high sensitivity, but these metrics should be reported only after formal validation rather than assumed in model description. Calibration is especially important because a readiness probability must be interpretable for clinical prioritisation and operational planning [6, 12, 14]. Evaluation should also examine whether the model behaves consistently across service lines, mobility strata, medication-dependence patterns, and consultation burden [15, 27, 24]. Because premature discharge is a safety concern, threshold selection should be tied to clinical review requirements rather than purely statistical optimization [8, 11].

Temporal and external validation

Temporal validation should test the model on later admissions than those used for development, preserving the real-world chronology of hospital practice and reducing optimism from random splitting. External validation should then examine whether the model transfers to a hospital with different patient demographics, staffing models, discharge policies, and documentation practices [7, 19, 33]. Such validation is necessary because clinical machine learning models can degrade when local workflows, EHR configurations, or patient populations differ from the development setting [20, 25]. A discharge

readiness model should therefore be treated as an adaptable operational tool requiring local assessment before clinical use [13, 22].

Prospective impact assessment

Before active deployment, the model should undergo silent-mode prospective evaluation in which predictions are generated but not shown to clinicians. This phase would compare estimated readiness with actual same-day discharge decisions, unresolved barriers, and clinician review without changing care processes [1, 2, 21]. If silent-mode results support clinical plausibility, a subsequent before-after or pragmatic trial could evaluate whether model-assisted rounds improve morning discharge planning, bed-capacity forecasting, and workflow coordination without compromising safety [3-5]. Impact assessment should also monitor unintended consequences, including inequitable prioritisation, overreliance on the score, and delayed attention to patients not flagged by the model [8, 32].

Table 2 provides a governance-oriented evaluation framework linking technical validation, workflow safety, equity monitoring, silent-mode testing, and clinician oversight for responsible deployment of same-day discharge-readiness prediction.

Table 2. Evaluation and Governance Framework for Safe Same-Day Discharge-Readiness Prediction

Evaluation or governance layer	Core question	Recommended assessment approach	Failure mode addressed	Deployment implication
Temporal design	Were only pre-9 AM data used?	Lock all features to the morning prediction timestamp and audit for post-prediction leakage	Inflated accuracy from future information	Required before any reported performance claims
Predictive discrimination	Can the model distinguish likely ready from not-ready patients?	AUROC, precision-recall analysis, service-line subgroup performance	Poor ranking of patients for review	Supports readiness-list usefulness
Calibration	Do predicted probabilities match observed readiness rates?	Calibration plots, calibration slope, observed-to-expected ratios	Misleading probability estimates	Required for bed-management forecasting
Threshold safety	What cutoff balances throughput and safety?	Threshold-specific sensitivity, specificity, false-positive review burden	Premature discharge pressure	Thresholds should trigger review, not discharge
Explainability	Can clinicians understand why a patient was ranked high or low?	Patient-level driver display using top positive and negative contributors	Low trust or unhelpful black-box output	Dashboard must show actionable drivers
Equity and subgroup behavior	Does performance vary across patient groups or services?	Stratified calibration and error analysis by service, age, mobility status, medication burden, and consultation load	Inequitable prioritisation	Requires monitoring before and after deployment
Silent-mode validation	Does the model behave plausibly	Prospective predictions hidden from teams; compare with actual	Workflow disruption from	Mandatory pre-implementation

	before clinicians see it?	readiness and discharge barriers	immature model	phase
Clinical impact	Does model-assisted review improve operations safely?	Before-after study or pragmatic trial measuring discharge timing, safety events, clinician burden, and patient experience	Prediction without operational benefit	Needed before claiming clinical effectiveness
Human governance	Is final authority preserved?	Audit override frequency, documentation of disagreement, and clinician feedback	Automation bias or unsafe reliance	Model remains advisory only
Ongoing monitoring	Does performance degrade over time?	Periodic recalibration, drift checks, data-latency audits, and workflow review	EHR, staffing, or policy changes reducing validity	Continuous local governance required

Limitations

Data completeness and timeliness

The proposed model would depend on timely and accurate EHR documentation, which may not always be available before morning rounds. Morning laboratory results may be delayed, mobility assessments may be charted after the model run, medication orders may not reflect bedside administration reality, and consultation status may lag behind verbal recommendations. These limitations could reduce the usefulness of the readiness score even when the model architecture is conceptually appropriate. Deployment would therefore require close attention to data latency, documentation workflows, and mechanisms for refreshing predictions as new information becomes available.

Operational context and patient preference

Same-day discharge may be delayed for reasons that are partly or entirely outside the clinical data captured by the model. Transportation barriers, family availability, insurance authorization, post-acute placement, home support, patient preference, and caregiver readiness may override physiological stability or favourable medication and mobility signals. These factors mean that the model should estimate discharge readiness rather than guarantee actual discharge. Its output should be interpreted as a prompt for coordinated review, not as a substitute for patient-centred discharge planning.

Conclusion

A predictive analytics model for same-day hospital discharge readiness could help convert fragmented morning clinical data into a structured readiness estimate. By combining laboratory results, active medication orders, vital sign stability, mobility documentation, and pending consultation status, the model would provide an early view of which patients may be approaching discharge readiness. Its purpose would be to support timely clinical review, not to automate discharge decisions.

The main strength of this approach is its synthesis of multiple readiness signals into a single clinically reviewable score. Such a score could help teams identify patients who need early medication conversion, therapy reassessment, consultant input, or discharge coordination. It could also help bed-management teams anticipate capacity earlier in the day.

Important challenges remain before such a model could be safely deployed. Data latency, inconsistent documentation, unmeasured social barriers, and site-specific workflow variation could all affect model usefulness. Rigorous prospective

evaluation would be needed to ensure that the tool improves throughput without encouraging unsafe or inequitable discharge practices.

Future work should test model-assisted discharge rounds in pragmatic clinical studies comparing structured predictive support with standard practice. These studies should examine not only discharge timing but also safety, clinician trust, workflow burden, patient experience, and equity. A well-designed discharge readiness model could become a practical bridge between clinical predictive analytics and hospital operations.

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