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Deep Learning Model for Predicting High-Risk Transitions of Care Using Discharge Summaries, Medication Reconciliation Records, Follow-Up Appointment Status, Home Support Indicators, and Social Risk Variables

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Abstract

High-risk transitions of care remain a major source of preventable readmissions, emergency department use, medication harm, and post-discharge deterioration. Existing risk tools often simplify the transition period into structured clinical variables and may not fully represent clinical complexity, social vulnerability, medication safety, or home support. Discharge planning commonly depends on generic risk scores, clinician judgment, and incomplete structured fields. These approaches may overlook risk signals embedded in discharge summaries, medication reconciliation records, follow-up plans, case management documentation, and social risk screening. This manuscript proposes a conceptual deep learning model for predicting high-risk transitions of care. The model is designed to fuse discharge summary narratives, medication reconciliation data, follow-up appointment status, home support indicators, and social risk variables into a unified transition risk score. The proposed architecture combines a clinical language encoder for discharge summaries with a structured-data network for medication, follow-up, home support, and social risk features. These representations are integrated through a multimodal fusion layer that would generate a patient-level risk estimate at the point of discharge. Conceptually, the model could identify patients at elevated risk of readmission, emergency department use, or adverse post-discharge outcomes who might be missed by traditional scores. It would also be expected to highlight clinically interpretable risk drivers that could support targeted transitional care planning. A multimodal deep learning model could strengthen precision transitional care by integrating clinical, logistical, medication-related, and social dimensions of risk. Such a model could help discharge teams prioritize intensified interventions for patients most vulnerable to unsafe care transitions.

Keywords Deep learning, Medication reconciliation, Social determinants of health, Care transitions, Discharge summaries, Readmission prediction

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Introduction

Transitions from hospital to home remain vulnerable periods in which clinical instability, medication changes, incomplete follow-up plans, and fragmented accountability can converge into preventable harm. Readmission prediction models have increasingly used electronic health record data to anticipate post-discharge utilization, yet many approaches still rely on

structured variables that only partially represent the complexity of the discharge process [1-3]. Machine learning studies have shown that readmission risk can be estimated from longitudinal clinical data, but conceptual limitations remain when the discharge narrative, medication reconciliation record, and social environment are not modeled together [4-6]. A care-transition model should therefore treat discharge not as a single administrative event, but as a complex safety-critical handoff across clinical, medication, scheduling, home, and social systems [7, 8].

The electronic health record contains multiple underused data streams that are directly relevant to transition safety. Discharge summaries encode diagnoses, clinical trajectory, pending tests, follow-up instructions, patient education, and concerns that may not appear in structured fields, while medication reconciliation records reveal therapeutic changes and discrepancies that can shape post-discharge risk [9-11]. Appointment scheduling data, home health orders, case management notes, caregiver availability, and social determinants of health documentation further define whether a patient has a feasible recovery plan after leaving the hospital [12-14]. These heterogeneous signals suggest that transition risk cannot be fully inferred from diagnosis codes or prior utilization alone [15, 16].

Deep learning offers a model-oriented framework for combining unstructured and structured discharge-time information. Clinical language models can encode discharge summaries and other narrative notes, while structured neural networks can represent medication discrepancies, appointment status, home support indicators, and social risk variables [11, 17, 18]. Prior work on deep learning with electronic health records, multimodal readmission prediction, and text-enhanced modeling suggests that latent representations from clinical narratives can complement tabular features when predicting adverse outcomes [19-21]. However, the design of such systems must remain conceptual, interpretable, and clinically grounded before experimental evaluation is performed [22, 23].

This article proposes a multimodal deep learning model for predicting high-risk transitions of care using discharge summaries, medication reconciliation records, follow-up appointment status, home support indicators, and social risk variables. The central thesis is that a transition risk score would be most clinically useful when it integrates discharge-time clinical meaning, medication safety, logistical follow-up feasibility, home support, and social vulnerability into a single interpretable prediction. Rather than replacing clinical judgment, the model would support discharge planners, pharmacists, nurses, case managers, and social workers by identifying risk drivers that can be acted on before or shortly after discharge. This approach aligns with broader efforts to use informatics, care coordination, and risk-stratified transitional care to reduce preventable post-discharge harm.

Background

High-risk transitions of care

High-risk transitions of care can be understood as discharge episodes in which the patient's clinical condition, treatment plan, social context, or care coordination needs create elevated vulnerability to readmission, emergency department use, medication harm, or unmet post-discharge needs. Studies of readmission prediction have highlighted that risk is concentrated among patients with complex comorbidity, prior utilization, functional vulnerability, fragmented follow-up, and social disadvantage [1, 3, 6]. Machine learning models have attempted to improve identification of these patients, yet conventional prediction tools may not capture the dynamic and multidisciplinary nature of discharge safety [4, 5]. For a deep learning model, the relevant unit of prediction is therefore not only the patient's disease burden, but the interaction between clinical status, discharge plan, treatment changes, and the recovery environment [7, 8].

Discharge summaries and medication reconciliation

Discharge summaries are central transition documents because they summarize hospital course, diagnoses, procedures, medication changes, follow-up needs, and unresolved clinical issues. Natural language processing studies show that these narratives can provide predictive information beyond structured fields, particularly when clinical text contains risk factors, uncertainty, missing follow-up instructions, or documentation gaps relevant to readmission [9-11]. Medication

reconciliation records add a distinct safety dimension by comparing admission and discharge medication lists, identifying omissions, duplications, high-risk medications, or regimen complexity that may contribute to post-discharge adverse drug events [24, 25]. A transition-risk model should therefore encode both narrative discharge meaning and medication-change structure rather than treating medication reconciliation as a secondary administrative artifact [18, 26].

The role of follow-up appointments and home support

Follow-up appointment status is a critical transition variable because scheduled, timely, and attended post-discharge care can create an opportunity to detect clinical deterioration, clarify medications, and reinforce the discharge plan. Evidence linking follow-up appointment status to readmission risk supports the need to distinguish whether follow-up is scheduled, whether it occurs soon enough for the patient's condition, and whether the appointment is ultimately missed [12]. Home support indicators also influence risk because living alone, limited caregiver availability, lack of home health support, and poor care coordination can reduce the patient's ability to execute complex discharge instructions [13, 27]. A model that includes follow-up timing and support indicators could better represent the practical feasibility of recovery after discharge [20, 28].

Social risk variables in transition outcomes

Social risk variables increasingly appear in electronic health records through structured screening tools, social work notes, case management documentation, and ICD-10 Z-codes. Housing instability, food insecurity, transportation barriers, income constraints, social isolation, and related social determinants of health can influence whether patients obtain medications, attend appointments, access nutrition, and maintain a safe recovery environment [14-16]. Studies of Z-code use and social risk adjustment show both the promise and incompleteness of structured social risk capture, which creates challenges for predictive modeling and fairness [29, 30]. A transition model should therefore incorporate social risk variables with caution, recognizing that missing social data may reflect screening practices rather than absence of need [31, 32].

Multimodal deep learning for clinical risk prediction

Multimodal deep learning is well suited to transition-risk modeling because it can encode free-text discharge summaries and structured clinical or social variables within the same architecture. Prior work has demonstrated the conceptual value of combining structured and unstructured electronic health record data for clinical prediction, including readmission and adverse outcome modeling [17, 18, 21]. Clinical transformer models such as ClinicalBERT illustrate how discharge summaries and other clinical notes can be transformed into latent representations that preserve contextual meaning for downstream prediction [11, 22]. A multimodal transition model would build on this logic by fusing clinical narrative, medication reconciliation, appointment status, home support, and social risk into a discharge-time representation [19, 20, 33].

Model Development Overview

High-level predictive pipeline

At discharge, the proposed model would ingest the signed discharge summary, admission and discharge medication lists, scheduled follow-up appointment details, case management notes describing home support, and available social risk screening data to generate a transition risk score. This pipeline reflects the idea that readmission and post-discharge harm are not only clinical outcomes, but also consequences of how well the discharge plan fits the patient's home and social context [2, 13, 15]. The model would be triggered near the point of discharge, when documentation and medication reconciliation are sufficiently mature to support risk estimation [9, 25]. Its output would be designed for discharge planning rather than retrospective reporting, supporting earlier identification of patients who could benefit from intensified transitional care [12, 28].

Core input modalities

The unstructured input modality would consist primarily of discharge summary text, including hospital course, assessment, discharge instructions, pending issues, medication explanations, and follow-up plans. Structured inputs would include medication discrepancy flags, high-risk medication classes, follow-up appointment status and timing, home support indicators such as living alone or caregiver availability, home health orders, and social risk variables such as housing, transportation, and food insecurity [14, 24, 29]. These modalities would be modeled as complementary rather than redundant, because discharge summaries may describe clinical concerns while structured fields capture scheduling, medications, and social screening in computable form [10, 18]. This design follows evidence that both text and structured data can contribute to readmission modeling and that social context can meaningfully alter risk interpretation [17, 20, 32].

Design principles

The model would be designed to be holistic, multimodal, interpretable, real-time, and sensitive to the ethical use of social data. Holism means that the model represents clinical status, medication safety, follow-up feasibility, home support, and social vulnerability as interacting dimensions of transition risk rather than isolated predictors [13, 15, 27]. Interpretability is essential because discharge planners must understand whether the score is driven by medication discrepancies, missing follow-up, lack of caregiver support, social needs, or unresolved clinical issues [10, 14, 25]. Sensitivity to social data is equally important because social risk variables may be incompletely documented, unevenly screened, or associated with structural inequities that should guide supportive intervention rather than punitive risk labeling [29–31].

Data Sources and Feature Engineering

Discharge Summary NLP and feature extraction

Discharge summary preprocessing would segment narrative text into clinically meaningful sections such as hospital course, discharge diagnosis, medications, follow-up instructions, pending studies, and patient education. A clinical transformer model could encode the full narrative while also allowing extraction of latent representations for risk-relevant content such as unresolved symptoms, complex follow-up instructions, medication changes, and ambiguous discharge planning language [11, 22]. Prior NLP-based readmission studies suggest that unstructured clinical text can improve recognition of risk factors that may be missing or poorly represented in structured fields [9, 10]. In the proposed model, the text branch would therefore transform narrative discharge documentation into a dense representation that can be fused with medication, appointment, home support, and social variables [18, 21].

Medication reconciliation features

Medication reconciliation features would compare admission and discharge medication lists to identify new medications, discontinued therapies, dose changes, duplications, omissions, high-risk medication classes, and regimen complexity. These features are clinically important because adverse drug events after discharge can arise from medication discrepancies, unclear instructions, patient misunderstanding, or insufficient monitoring after medication changes [24, 25]. In a structured-data branch, medication-related variables could be represented as binary discrepancy flags, categorical medication classes, counts of medication changes, or embeddings of medication concepts, without asserting any experimental performance [26]. The goal would be to let the model learn how medication safety signals interact with clinical narrative, follow-up timing, and home support in shaping transition risk [3, 20].

Follow-up, home support, and social risk encoding

Follow-up appointment variables would encode whether follow-up is scheduled, the type of appointment, timing relative to discharge, and whether later status updates indicate missed or completed care. Home support variables would include structured indicators for living alone, caregiver availability, home health orders, durable medical equipment needs, and case management documentation of support limitations [12, 13, 27]. Social risk variables would be encoded from

structured screening results, ICD-10 Z-codes, or documented needs related to housing, transportation, food access, income strain, and social isolation [14, 16, 29]. These variables should include missingness indicators so the model can distinguish documented absence of need from lack of screening or incomplete documentation [30-32].

Table 1 presents the proposed transition-risk signal architecture, showing how each clinical, medication, logistical, home-support, and social domain contributes distinct information to post-discharge safety prediction.

Table 1. Transition-Risk Signal Architecture Across Clinical, Medication, Logistical, Home, and Social Domains

Risk Domain	Primary Data Source	What the Model Should Learn	Why It Matters for Transition Safety	Example Actionable Interpretation
Clinical instability	Discharge summary narrative	Unresolved symptoms, pending tests, uncertain trajectory, complex instructions	Identifies patients whose discharge plan may not match clinical complexity	“Risk appears driven by unresolved clinical issues and complex follow-up needs.”
Medication safety	Medication reconciliation record	New medications, discontinued drugs, dose changes, duplications, high-risk classes	Captures preventable medication harm after discharge	“Risk appears medication-driven; pharmacist review is indicated.”
Follow-up feasibility	Appointment scheduling data	Absence of follow-up, delayed appointment timing, specialty-care gaps	Determines whether deterioration can be detected early	“Risk is increased because follow-up is delayed beyond the recommended window.”
Home support	Case management notes and structured support fields	Living alone, limited caregiver availability, home health needs, equipment needs	Measures whether the discharge plan can realistically be carried out at home	“Risk reflects limited home support and need for care coordination.”
Social vulnerability	Social risk screening, Z-codes, social work documentation	Transportation barriers, housing instability, food insecurity, financial strain	Identifies modifiable barriers to recovery and access	“Risk is amplified by transportation and resource-access barriers.”
Documentation uncertainty	Missingness patterns across social/support fields	Lack of screening, incomplete documentation, uncertain availability of support	Prevents missing data from being misread as absence of risk	“Risk estimate should be interpreted cautiously because support data are incomplete.”

Multimodal Deep Learning Architecture

Text encoding branch for discharge summaries

The text encoding branch would use a clinical transformer to convert discharge summary text into contextual embeddings that represent the patient's hospital course, discharge plan, medication instructions, and unresolved issues. A ClinicalBERT-like approach could be fine-tuned conceptually for transition-risk prediction, either by producing a single document-level representation or by classifying specific discharge-summary sections before fusion [11]. This branch would be especially useful for capturing narrative details such as uncertainty, complex instructions, social concerns mentioned in prose, or gaps in follow-up documentation that are not fully represented in structured fields [9, 10, 22]. Its

output would remain one component of a broader multimodal architecture rather than a stand-alone readmission predictor [18, 21].

Structured data branch and feature fusion

The structured branch would encode medication reconciliation features, follow-up appointment status, home support indicators, and social risk variables through a feed-forward neural network designed for tabular clinical data. Feature fusion could occur through concatenation, late fusion, gated multimodal integration, or cross-attention between the discharge-summary representation and structured feature embeddings [17, 18, 20]. This architecture would allow the model to represent interactions such as high-risk medication changes combined with limited caregiver support, missed follow-up risk combined with transportation barriers, or unresolved clinical issues combined with inadequate home services [12, 14, 24]. Prior multimodal readmission modeling supports the conceptual value of combining heterogeneous data types, while implementation should be evaluated prospectively before clinical reliance [19, 21, 33].

Output layer: transition risk score

The output layer would generate a transition risk score representing the likelihood of a high-risk post-discharge trajectory, such as readmission, emergency department use, or clinically meaningful deterioration within a defined follow-up window. A sigmoid output could be used for a single composite outcome, while a multi-task architecture could conceptually estimate related outcomes such as medication-related harm, missed follow-up, or need for urgent care without reporting experimental results [1, 3, 34]. The score would be paired with interpretable risk drivers so discharge teams can identify whether the main concern relates to clinical instability, medication discrepancies, appointment gaps, home support limitations, or social barriers [4, 6, 23]. In this model-oriented design, prediction is valuable only if it supports actionable transitional care decisions before preventable harm occurs [25, 28].

Figure 1 illustrates the proposed multimodal deep learning pathway through which discharge narratives, medication reconciliation data, follow-up status, home support indicators, and social risk variables are transformed into an interpretable transition-risk estimate and routed toward tailored transitional care interventions.

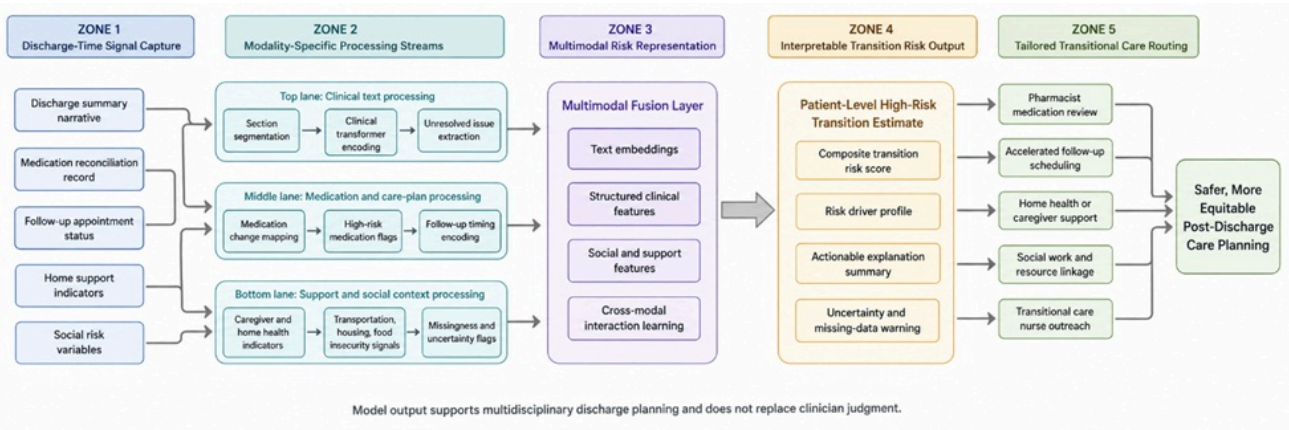


Figure 1. Multimodal Deep Learning Pathway for Predicting and Acting on High-Risk Transitions of Care

Handling Temporal, Missing, and Censored Data

Temporal nature and time-sensitive features

Transition risk is temporally dynamic because a discharge plan that appears safe at the time of discharge may become unsafe if follow-up is delayed, medications are not obtained, home support changes, or symptoms worsen. The model

would therefore treat variables such as follow-up appointment lead time, time since discharge, and missed appointment status as time-sensitive features rather than static discharge attributes [12]. Temporal updating could allow the risk estimate to change when new information enters the electronic health record, such as appointment nonattendance, medication clarification calls, or home health initiation [33, 34]. This design would align the prediction task with the real-world trajectory of post-discharge care rather than limiting risk assessment to a single discharge timestamp [2, 8].

Managing missing social and support data

Missing social and support data should be treated as an important modeling challenge rather than as evidence that a patient has no social needs. Social determinants of health documentation, ICD-10 Z-code use, caregiver availability, and home support indicators are often inconsistently captured across hospitals, clinicians, and patient populations [14, 29]. The model would use missingness indicators, structured uncertainty encoding, and sensitivity analyses so that incomplete social screening does not unfairly reduce estimated risk or obscure unmet need [30, 31]. This approach is essential because social risk variables may reflect both patient vulnerability and institutional documentation practices, requiring careful interpretation in any model used for discharge planning [15, 32].

Handling censored outcomes and competing risks

Post-discharge outcomes may be censored or complicated by competing events such as death, hospice transfer, planned readmission, transfer to another facility, or loss of follow-up outside the health system. A transition-risk model should distinguish preventable adverse transitions from outcomes that are clinically expected or not meaningfully modifiable through discharge intervention [4, 6]. Appropriate conceptual handling could include outcome definitions that separate unplanned readmission, emergency department use, medication-related harm, and other adverse events while accounting for competing clinical trajectories [1, 3]. This would help ensure that the model supports transitional care planning rather than conflating preventable safety failures with unavoidable disease progression [7, 23].

Model Interpretability and Clinical Trust

Explaining transition risk for discharge planners

Interpretability is central to clinical trust because discharge planners need to understand why a patient has been classified as high risk and what can be changed before discharge. The model could provide explanation layers that identify whether the score is driven by discharge-summary language, medication discrepancies, lack of caregiver support, missed or delayed follow-up, transportation barriers, or other documented social needs [9, 10, 14]. SHAP-style feature attribution, section-level text highlighting, and structured feature summaries could help clinicians connect the risk score to practical interventions without treating the model as an opaque authority [11, 22]. Interpretability would be especially important when social risk variables are involved, because explanations should direct supportive care rather than reinforce bias or stigma [31, 32].

Integration into discharge team workflow

The transition risk score should be integrated into multidisciplinary discharge workflow rather than displayed as an isolated prediction. In practice, the score and its explanation could appear in a discharge dashboard reviewed by hospitalists, nurses, pharmacists, case managers, social workers, and transitional care teams during discharge planning rounds [13, 28]. The explanation should guide concrete adjustments, such as medication review, earlier follow-up, transportation support, caregiver teaching, home health referral, or social work involvement [12, 24]. Such workflow integration would reflect the broader patient-safety principle that predictive analytics should support coordinated action rather than simply label patients as high risk [27, 25].

Clinical Deployment and Transitional Care Integration

Pre-discharge risk scoring and alerting

The model would run when the discharge order is placed or when the discharge summary and medication reconciliation record reach a usable state, generating a risk score before the patient leaves the hospital. If the score exceeds a locally defined threshold, the system could alert transitional care nurses, pharmacists, case managers, or discharge coordinators for review [2, 33]. The alert should include the most relevant risk drivers so that the care team can distinguish between clinical instability, medication complexity, follow-up gaps, home support limitations, and social barriers [4, 20]. Deployment should avoid alert fatigue by linking risk alerts to actionable workflows and by allowing local governance to refine when and how the score is surfaced [6, 23].

Linking risk to tailored transitional care resources

A high-risk score would be clinically meaningful only if it triggers tailored transitional care resources matched to the patient's risk profile. Medication-driven risk could prompt pharmacist-led medication reconciliation and counseling, follow-up risk could trigger appointment acceleration or reminder outreach, home support risk could prompt home health referral, and social risk could prompt social work or community resource linkage [12, 13, 15]. This closed-loop design would connect model output to concrete care coordination steps, making the prediction part of an intervention pathway rather than a passive report [13, 28]. Because social and logistical barriers may be modifiable through targeted support, the model should be framed as a tool for resource allocation and harm prevention rather than as a deterministic forecast [14, 30].

Table 2 translates model-identified transition-risk drivers into targeted transitional care responses, emphasizing that prediction becomes clinically meaningful only when linked to specific multidisciplinary actions.

Table 2. Risk-to-Intervention Translation Framework for Model-Guided Transitional Care

Dominant Risk Driver Identified by Model	Interpretation for Discharge Team	Recommended Transitional Care Response	Responsible Team Member(s)	Intended Safety Function
Medication discrepancy or regimen complexity	Patient may be vulnerable to adverse drug events or misunderstanding	Pharmacist-led medication reconciliation, counseling, high-risk medication review	Pharmacist, hospitalist, nurse	Reduce medication-related harm
Missing or delayed follow-up	Patient may deteriorate before outpatient reassessment	Schedule earlier appointment, coordinate specialty follow-up, add reminders	Discharge coordinator, nurse navigator, clinic staff	Improve continuity and early detection
Limited caregiver or home support	Patient may be unable to execute discharge instructions safely	Home health referral, caregiver teaching, equipment planning	Case manager, nurse, home health liaison	Strengthen home recovery capacity
Transportation, housing, food, or financial barrier	Patient may be unable to access care, medications, or safe recovery conditions	Social work referral, community resource linkage, transportation support	Social worker, case manager	Reduce socially mediated transition risk
Unresolved clinical issue in discharge	Patient may require closer monitoring or clarified care	Clarify discharge instructions, escalate to	Hospitalist, nurse, care team	Prevent unsafe discharge

summary	plan	physician review, document contingency plan		ambiguity
High score with unclear explanation	Prediction may reflect complex or poorly documented risk	Multidisciplinary review before discharge decision	Hospitalist, pharmacist, nurse, case manager, social worker	Preserve clinical oversight and prevent blind reliance on automation

Evaluation Strategy

Predictive performance metrics

Although this article does not report experiments or performance numbers, a future evaluation should assess discrimination, calibration, precision-recall behavior, and clinical usefulness against traditional risk scores. Metrics such as AUROC, calibration plots, decision-curve analysis, and net reclassification improvement would be appropriate only after empirical validation using real discharge episodes and clearly defined outcomes [4, 5]. Evaluation should compare the full multimodal model with versions that use only structured data, only text, or narrower subsets of medication, follow-up, support, and social variables [17, 18]. Such comparisons would help determine whether discharge summaries, medication reconciliation features, and social context add clinically meaningful information beyond conventional readmission predictors [10, 19].

Temporal and external validation

Temporal validation should use strict chronological separation between development and evaluation periods to assess whether the model remains useful as documentation practices, care pathways, and patient populations change. External validation should evaluate the model in hospitals with different discharge workflows, medication reconciliation practices, social screening programs, patient demographics, and follow-up infrastructure [1, 2]. This is particularly important for social risk variables and ICD-10 Z-codes because coding and screening intensity may differ substantially across sites [29, 32]. A model that appears plausible in one setting should not be deployed elsewhere without local validation, recalibration, and governance review [8, 31].

Prospective impact on readmission and transition measures

Prospective evaluation should focus on whether model-guided transitional care improves patient-centered and safety-oriented outcomes when compared with usual discharge planning. A pragmatic trial could conceptually compare model-informed resource allocation with standard risk-based workflows, measuring readmission, emergency department use, medication-related adverse events, completed follow-up, care coordination actions, and patient-reported transition experience [7, 23]. The evaluation should also examine whether the model changes clinician behavior, increases appropriate transitional care referrals, and reduces inequities in access to discharge support [27, 30]. Such an impact study would be necessary because a well-calibrated prediction model is not automatically an effective patient-safety intervention [6, 28].

Limitations

Documentation and data quality

The proposed model would depend heavily on the quality, timeliness, and completeness of discharge summaries, medication reconciliation records, appointment data, home support documentation, and social risk screening. Discharge

summaries vary in structure and narrative detail, and important risk factors may be omitted, copied forward, or documented after the patient has already left the hospital [9, 11]. Medication reconciliation data may contain discrepancies that reflect either true medication safety problems or incomplete documentation, while social risk variables may be missing because screening was not performed [24, 29]. These data quality limitations mean that any future model should be evaluated not only for prediction but also for robustness to documentation variation [8, 18].

Generalizability and sociotechnical challenges

Generalizability may be limited in settings without mature medication reconciliation workflows, structured follow-up scheduling, home support documentation, or systematic social risk screening. Hospitals that serve different populations or use different documentation templates may produce discharge summaries and structured variables that shift the meaning of model inputs [20, 21]. Sociotechnical challenges would also include alert fatigue, clinician trust, workflow fit, accountability for acting on risk predictions, and ensuring that social risk information leads to support rather than stigmatization [14, 31]. For these reasons, local validation, interdisciplinary governance, implementation science, and patient-centered oversight would be essential before clinical deployment [28, 32].

Conclusion

A multimodal deep learning model for predicting high-risk transitions of care could provide a more complete view of discharge safety than models based only on structured clinical variables. By integrating discharge summaries, medication reconciliation records, follow-up appointment status, home support indicators, and social risk variables, the model could represent the transition from hospital to home as a multidimensional clinical and social handoff.

The key strength of the proposed approach is its ability to fuse narrative and structured data into an interpretable transition risk score. Such a model could help discharge teams identify whether risk is driven by unresolved clinical issues, medication discrepancies, delayed follow-up, limited caregiver support, home service needs, or social barriers.

Important challenges remain, including incomplete documentation, uneven social risk screening, cross-site variation, and the need to ensure that model outputs lead to supportive interventions rather than passive risk labeling. The model would also require careful governance so that predictions are used to improve care coordination, not to ration care or reinforce inequities.

Future work should prioritize multisite pragmatic trials, external validation, and partnerships with safety-net health systems where transition risks are often intensified by social and logistical barriers. If designed and evaluated responsibly, this type of model could support safer, more equitable, and more proactive transitional care for patients at greatest risk of preventable post-discharge harm.

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