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AI-Driven Analysis of C-CDA Discharge Summaries for Predicting Hospital Readmission and Optimizing Transitions of Care Through FHIR-Enabled Clinical Interoperability

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Abstract: Hospital readmission following discharge remains a persistent challenge because clinically relevant risk indicators are distributed across narrative discharge summaries, medication histories, diagnostic findings, follow-up instructions, social factors, and fragmented health-information systems. This study proposes an artificial-intelligence framework for predicting hospital readmission and strengthening transitions of care through integrated analysis of Consolidated Clinical Document Architecture (C-CDA) discharge summaries and Fast Healthcare Interoperability Resources (FHIR)-enabled clinical data. A novel algorithm, termed C2FHIR-ReadmitNet, is developed to combine transformer-based clinical language representation, structured FHIR resource embeddings, temporal transition modelling, and cross-modal attention for patient-level readmission risk estimation. The framework extracts clinically significant concepts from C-CDA sections including diagnoses, discharge medications, procedures, laboratory findings, allergies, functional status, care instructions, and follow-up plans and maps them to standardized FHIR resources such as Patient, Encounter, Condition, Observation, MedicationRequest, Procedure, CarePlan, and ServiceRequest. C2FHIR-ReadmitNet employs a clinical transformer encoder for contextual text representation, a resource-aware embedding network for structured FHIR features, a temporal attention module for modelling longitudinal encounters, and a calibrated risk-classification layer for estimating 30-day readmission probability. The proposed model is comparatively evaluated against Logistic Regression, Random Forest, XGBoost, Bidirectional Long Short-Term Memory networks, ClinicalBERT, and conventional multimodal fusion models using AUROC, AUPRC, accuracy, precision, recall, F1-score, sensitivity, specificity, Brier score, and calibration error. Comparative ROC curves, precision-recall curves, calibration plots, confusion matrices, feature-importance graphs, and ablation-analysis charts are incorporated to examine predictive discrimination, reliability, interpretability, and the contribution of individual architectural components. The study further introduces a transition-of-care risk index that integrates predicted readmission probability with medication complexity, unresolved clinical concerns, follow-up urgency, comorbidity burden, and continuity-of-care indicators to support post-discharge prioritization. The experimental design is structured to determine whether C2FHIR-ReadmitNet can achieve superior predictive discrimination, calibration, and clinical interpretability relative to conventional machine-learning and transformer-based baselines while preserving semantic interoperability across heterogeneous electronic health-record environments. The proposed approach provides a technically scalable foundation for converting C-CDA discharge information into FHIR-compatible, AI-assisted decision intelligence capable of supporting early identification of high-risk patients, targeted transitional-care interventions, interoperable clinical workflows, and data-driven reduction of avoidable hospital readmissions.

Keywords: *Artificial Intelligence; C-CDA; Hospital Readmission; FHIR; Clinical Interoperability.*

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I. INTRODUCTION

➢ *Background to Hospital Readmission and Transitions of Care*

Hospital readmission reflects the interaction of residual disease burden, treatment complexity, medication changes, post-discharge surveillance, patient capability, and the reliability of information transfer across care settings. Thirty-day readmission is particularly important because the interval after discharge concentrates medication discrepancies, incomplete follow-up, unresolved symptoms, and failures in care coordination. In a large Medicare Advantage cohort, completion of an outpatient visit within seven days of discharge was associated with lower readmission risk, demonstrating that continuity after hospitalization can influence outcomes (Shen et al., 2017). Yet transition programs do not uniformly reduce rehospitalization; the TARGET-READ randomized trial found no significant reduction in 30-day unplanned readmission or death despite a multimodal intervention directed at high-risk patients (Donzé et al., 2023). These findings indicate that transitional care requires precise risk stratification rather than uniformly intensive follow-up. Data-driven service-management approaches similarly emphasize coordinated information flows and timely resource allocation (Kwarteng et al., 2021). For this study, the discharge summary is treated as a dense transition artifact linking inpatient events to post-acute management. Diagnoses, medications, procedures, laboratory trends, functional status, pending tests, and follow-up instructions provide signals that can be transformed into patient-specific risk estimates. Digitally connected monitoring can extend this transition beyond the hospital, although wearable medical devices introduce authentication and trust requirements when post-discharge observations are incorporated (Idika, 2022). The proposed C2FHIR-ReadmitNet framework conceptualizes readmission prediction as a multimodal interoperability problem: contextual representations extracted from C-CDA discharge narratives are fused with structured FHIR resources and longitudinal encounter features. This design supports comparison against Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and conventional multimodal fusion models while retaining a clinical objective: identifying patients whose discharge state, unresolved concerns, medication complexity, or follow-up urgency warrants transitional-care intervention.

➢ *Clinical Significance of C-CDA Discharge Summaries*

C-CDA discharge summaries are valuable because they preserve the clinical narrative of hospitalization while also exposing computable sections for problems, medications, allergies, procedures, results, care plans, and discharge instructions. This dual structure is important for readmission modelling: narrative text can express uncertainty, causal reasoning, unresolved symptoms, and conditional follow-up that may not be captured in coded fields, whereas structured entries provide standardized anchors for feature extraction. Hosseini et al. (2017) showed that consolidating structured continuity-of-care documents can reduce duplication while preserving important problem, allergy, and medication information, although terminology inconsistencies remain a source of error. Ranade-Kharkar et al. (2018) likewise demonstrated that C-CDA and FHIR can represent much of the information required for care-team interoperability, reinforcing the relevance of document standards to coordination across settings. More broadly, computational biomedical studies illustrate the importance of integrating heterogeneous biological information rather than treating individual data domains in isolation (Imoh & Idoko, 2022). Within the proposed architecture, C-CDA is not treated merely as an exchange document; it is the semantic source from which discharge-state representations are constructed. Section-aware parsing separates diagnoses, medications, test results, procedures, functional status, pending investigations, and follow-up instructions before transformer encoding. Identical words can carry different predictive meaning depending on whether they occur in a problem list, medication section, or discharge plan. Domain-aware computational representation is also central to advanced biomedical modelling, where performance depends on preserving structure within complex information spaces rather than flattening all inputs into undifferentiated variables (Atalor et al., 2023). C2FHIR-ReadmitNet therefore uses C-CDA section identity as an explicit feature and maps extracted concepts to FHIR resources, enabling analyses to test whether document-aware representations improve AUROC, AUPRC, calibration, and sensitivity beyond text-only or structured-only baselines.

➢ *FHIR-Enabled Clinical Interoperability in Contemporary Health Information Systems*

FHIR-enabled interoperability provides the granular, resource-oriented layer required to convert discharge information into computable clinical objects that can be exchanged, queried, and reused across heterogeneous systems. Unlike document-centric exchange alone, FHIR represents clinical facts as resources such as Patient, Encounter, Condition, Observation, MedicationRequest, Procedure, CarePlan, and ServiceRequest, allowing prediction pipelines to access specific elements without repeatedly parsing entire documents. Mandel et al. (2016) demonstrated that SMART on FHIR could support vendor-independent applications through standardized APIs, web authorization mechanisms, and constrained clinical profiles. Lehne et al. (2019) further argued that digital medicine depends on syntactic and semantic interoperability because analytics become unreliable when identical concepts are encoded inconsistently across institutions. These principles are central to readmission prediction, where missing medication changes, unresolved conditions, or follow-up orders can distort patient-level risk estimates. The proposed system therefore implements a C-CDA-to-FHIR harmonization layer before multimodal learning. Extracted discharge concepts are normalized to standard terminologies and linked to patient, encounter, diagnosis, observation, medication, procedure, and care-plan resources, producing a longitudinal representation suitable for cross-institution inference. Distributed pharmacovigilance architectures show how standardized digital infrastructure can improve traceability of clinically important events across organizational boundaries (Atalor, 2022), while cybersecurity research emphasizes that interoperability must be

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accompanied by access control, authentication, and operational risk reduction (Kwarteng et al., 2020). Accordingly, C2FHIR-ReadmitNet separates semantic transformation from predictive learning: the interoperability layer resolves resource identity and temporal relationships, whereas the learning layer estimates 30-day readmission probability. This separation permits explicit evaluation of mapping completeness, resource availability, terminology consistency, and prediction performance, enabling the study to determine whether FHIR-aligned representations improve portability, calibration, and clinical usability relative to models trained on institution-specific feature schemas across changing clinical and organizational data environments.

➢ *Artificial Intelligence for Readmission Risk Prediction*

Artificial intelligence enables readmission prediction to move beyond fixed risk scores by learning nonlinear interactions among diagnoses, prior utilization, medications, laboratory trends, narrative findings, and longitudinal care patterns. Deep neural models are particularly relevant when predictors are distributed across structured and unstructured EHR components. Rajkomar et al. (2018) demonstrated that deep learning applied to FHIR-formatted longitudinal records could predict 30-day unplanned readmission while simultaneously modelling mortality, length of stay, and discharge diagnoses, establishing the feasibility of representation learning over large-scale clinical records. Hilton et al. (2020) further showed that artificial intelligence can generate individualized predictions during and after hospitalization, supporting the concept of continuously updated patient-level risk rather than a static score calculated at a single time point. These advances motivate a model that integrates discharge semantics with structured interoperability data rather than relying solely on administrative variables.

C2FHIR-ReadmitNet extends this direction by combining a clinical transformer encoder, FHIR resource embeddings, temporal attention, cross-modal fusion, and a calibrated classification layer. The transformer captures contextual meanings in C-CDA sections; the resource encoder represents structured conditions, observations, medications, and procedures; temporal attention weights clinically relevant events across encounters; and cross-modal attention identifies interactions between narrative evidence and coded resources. Human-AI decision research supports designs in which algorithmic outputs augment rather than replace professional judgement (Anokwuru et al., 2022). Privacy-preserving federated learning in clinical prediction also demonstrates that distributed model development can support sensitive health-data applications without centralizing patient records (Atalor, 2019). The resulting framework is designed for comparison with Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and conventional multimodal fusion using discrimination, calibration, sensitivity, specificity, F1-score, and decision-oriented transition-of-care metrics under identical train-validation-test partitions and clinically consistent 30-day outcome definitions across institutions.

➢ *Limitations of Existing Discharge-Based Readmission Prediction Approaches*

Existing discharge-based readmission models are limited by data fragmentation, site-specific feature engineering, weak handling of free-text context, class imbalance, and inadequate assessment of calibration and transportability. A model may achieve acceptable discrimination yet still produce clinically unsafe probabilities when deployed in a hospital with different documentation practices, patient demographics, coding conventions, or follow-up resources. Andaur Navarro et al. (2021) found that most machine-learning clinical prediction studies in their systematic review were at high risk of bias, frequently because of inadequate sample size, missing-data handling, overfitting, and incomplete performance reporting. Youssef et al. (2023) similarly argued that validation should be recurring and local because model performance can change when data distributions and clinical workflows shift. These concerns are especially relevant for C-CDA discharge summaries, whose narrative style and structured entries can vary substantially among clinicians and EHR implementations.

Another limitation is that conventional models often flatten heterogeneous discharge information into sparse codes or bag-of-words features, losing section context, temporal order, negation, uncertainty, and relationships between narrative statements and structured resources. Research on multilingual and inclusive information environments illustrates that systems designed around a narrow representation can perform poorly when linguistic or contextual diversity is ignored (Ijiga et al., 2021a). Likewise, multimedia communication research demonstrates that meaning may depend on how information is structured and presented, not merely on isolated tokens (Ijiga et al., 2021b). The proposed study addresses these limitations by preserving C-CDA section identity, mapping concepts into FHIR resources, applying cross-modal attention, and evaluating calibration alongside AUROC and AUPRC. External-site validation, subgroup analysis, ablation testing, and error analysis are incorporated so that any claimed superiority of C2FHIR-ReadmitNet reflects robustness rather than a single favorable accuracy estimate on one test set.

➢ *Problem Statement*

Despite advances in clinical NLP, machine learning, and health-information exchange, a gap remains between discharge-document analysis and interoperable readmission prediction. Many models use structured EHR variables without exploiting the semantic richness of discharge narratives, while text-based models frequently ignore longitudinal resource relationships required for cross-system deployment. Rajpurkar et al. (2022) identified data scarcity, bias, deployment complexity, and translation from retrospective performance to clinical utility as challenges for medical AI. Seyyed-Kalantari et al. (2021) further demonstrated that clinical AI systems can exhibit performance disparities across patient subgroups, showing why aggregate accuracy cannot substitute for subgroup validation. However, interoperability alone does not solve the predictive problem: C-CDA may contain important statements whose meaning is lost during naive conversion,

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whereas FHIR resources may provide structured facts without the explanatory context needed to interpret unresolved concerns or follow-up urgency. The problem addressed in this study is therefore the absence of an integrated framework that jointly analyzes C-CDA discharge summaries, preserves section-level semantics, maps extracted concepts to FHIR resources, models longitudinal encounters, and generates calibrated 30-day readmission risk suitable for transition-of-care prioritization. Deployment must also tolerate heterogeneous infrastructure; work on AI-enabled platforms in bandwidth-constrained settings shows that system effectiveness depends on computational and connectivity conditions, not algorithmic accuracy alone (Ijiga et al., 2022). Cloud-native architectures likewise require protection against malicious software and service-level threats when predictive functions are distributed across networked components (Idika et al., 2021). C2FHIR-ReadmitNet is proposed to address these linked deficiencies through multimodal representation learning, temporal attention, interoperability-aware fusion, calibration, explainability, and comparative evaluation against statistical, tree-based, recurrent, transformer, and multimodal baselines. The study consequently tests whether combining document semantics with standardized FHIR structure can improve predictive reliability and actionable transitional-care stratification.

➢ *Research Objectives and Research Questions*

- *Research Objectives*

✓ To develop a standardized computational pipeline for extracting clinically relevant information from C-CDA discharge summaries and transforming diagnoses, medications, laboratory observations, procedures, care plans, follow-up instructions, and other transition-of-care information into interoperable FHIR resources.

✓ To develop the novel **C2FHIR-ReadmitNet** algorithm integrating section-aware clinical transformer representations, FHIR resource embeddings, longitudinal temporal attention, cross-modal information fusion, and calibrated risk estimation for prediction of 30-day hospital readmission.

✓ To compare C2FHIR-ReadmitNet with Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and conventional multimodal fusion models using AUROC, AUPRC, accuracy, precision, recall, F1-score, sensitivity, specificity, Brier score, and expected calibration error.

✓ To determine the predictive contribution of C-CDA narrative information, structured FHIR resources, temporal encounter information, and cross-modal attention through feature-importance analysis, explainability assessment, model ablation, subgroup evaluation, and external validation.

✓ To develop and evaluate an AI-assisted transition-of-care risk stratification mechanism that combines readmission probability with medication complexity, unresolved clinical concerns, comorbidity burden, follow-up urgency, and continuity indicators to prioritize post-discharge interventions.

- *Research Questions*

✓ To what extent can clinically relevant information extracted from heterogeneous C-CDA discharge summaries be accurately transformed into standardized FHIR resources while preserving the semantic and temporal relationships required for readmission prediction?

✓ To what extent does the proposed C2FHIR-ReadmitNet algorithm improve 30-day hospital readmission prediction compared with Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and conventional multimodal fusion models?

✓ How do C-CDA narrative representations, structured FHIR resource embeddings, longitudinal encounter information, and cross-modal attention individually and collectively influence discrimination, calibration, sensitivity, specificity, and overall predictive reliability?

✓ Does C2FHIR-ReadmitNet maintain stable predictive performance across patient subgroups, clinical conditions, documentation patterns, and external healthcare environments when evaluated using calibration, subgroup analysis, and external-site validation?

✓ To what extent can C2FHIR-ReadmitNet-derived readmission probabilities and transition-of-care risk indicators support clinically interpretable prioritization of patients requiring medication reconciliation, early follow-up, unresolved-concern review, or intensified post-discharge monitoring?

➢ *Contributions and Significance of the Study*

This study contributes an interoperability-aware artificial intelligence architecture that treats hospital readmission prediction not simply as a binary classification task but as a combined clinical-document understanding, longitudinal data integration, and transition-of-care optimization problem. Its principal technical contribution is the proposed **C2FHIR-ReadmitNet**, which integrates section-aware transformer representations of C-CDA discharge summaries with structured FHIR resource embeddings, temporal encounter modelling, cross-modal attention, probability calibration, and explainability mechanisms within a unified predictive framework. A second contribution is a systematic C-CDA-to-FHIR transformation pipeline capable of preserving relationships among diagnoses, observations, medications, procedures, encounters, care plans, and follow-up requirements. The study further introduces a transition-of-care risk formulation that extends conventional readmission probability by considering medication complexity, unresolved clinical concerns, follow-up urgency, comorbidity burden, and continuity indicators. Its empirical significance derives from a rigorous comparative evaluation against Logistic

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Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and conventional multimodal architectures using discrimination, calibration, classification, and clinical utility metrics. ROC curves, precision-recall curves, calibration plots, confusion matrices, feature-attribution graphs, subgroup analyses, and architectural ablation experiments provide complementary evidence rather than relying on accuracy alone. Clinically, the resulting framework is intended to convert heterogeneous discharge documentation into interoperable decision intelligence that can identify high-risk patients, prioritize transitional-care resources, support explainable clinician review, and facilitate deployment across FHIR-enabled healthcare environments.

➢ *Scope of the Review and Structure of the Paper*

The study focuses on AI-driven analysis of C-CDA discharge summaries for prediction of 30-day hospital readmission and optimization of transitions of care through FHIR-enabled clinical interoperability. Its analytical scope encompasses clinically relevant discharge information, including diagnoses, medication changes, laboratory and diagnostic findings, procedures, functional status, unresolved concerns, pending investigations, care instructions, follow-up requirements, previous encounters, and other longitudinal indicators that can influence post-discharge outcomes. The technical scope includes C-CDA parsing, terminology normalization, C-CDA-to-FHIR mapping, clinical transformer encoding, structured-resource representation, temporal modelling, multimodal fusion, probability calibration, explainability, comparative algorithm evaluation, subgroup assessment, and ablation analysis. The paper is organized into five principal sections. Section 1 establishes the clinical, interoperability, and artificial-intelligence context and defines the research problem, objectives, questions, contributions, and scope. Section 2 critically reviews C-CDA, FHIR interoperability, readmission modelling, clinical NLP, deep learning, and existing research gaps. Section 3 presents the C2FHIR-ReadmitNet system architecture, mathematical formulation, data-processing pipeline, training procedure, evaluation metrics, and experimental design. Section 4 presents and discusses comparative predictive results through numerical tables, ROC and precision-recall analysis, calibration assessment, confusion matrices, feature importance, explainability, subgroup testing, ablation experiments, and interoperability measurements. Section 5 synthesizes the principal findings and presents conclusions, clinical and technical recommendations, study limitations, deployment considerations, and directions for future research.

II. LITERATURE REVIEW

➢ *Hospital Readmission Prediction and Transitional-Care Risk Assessment*

Hospital readmission prediction has evolved from parsimonious scores based on age, utilization, comorbidity, and length of stay toward machine-learning systems capable of learning nonlinear interactions across high-dimensional electronic health record data. Morgan et al. (2019) demonstrated that a hospital-tailored machine-learning score improved discrimination for 30-day unplanned readmission relative to commonly used rule-based scores, showing that local clinical data can sharpen risk stratification as represented in figure 1. However, predictive discrimination alone is insufficient for transitional-care deployment. Matheny et al. (2021) showed that externally validated readmission models can lose both discrimination and calibration across institutions, even when data are standardized through a common model. This distinction is central to the present study because C2FHIR-ReadmitNet is intended not merely to rank patients but to generate calibrated probabilities that can support actionable post-discharge prioritization (Frank. 2026). Transitional-care risk assessment should therefore incorporate both readmission probability and modifiable care conditions that determine whether risk can be reduced. Wearable devices can extend observation beyond discharge by supplying physiological and behavioral signals relevant to chronic disease control and early deterioration (Okeme et al., 2025). Similarly, mobile health platforms can reinforce medication adherence and follow-up among geographically dispersed patients, addressing an important pathway linking discharge failure to avoidable hospital reuse (Atalor & Enyejo, 2025). Within C2FHIR-ReadmitNet, these principles motivate a transition-of-care risk index combining predicted 30-day readmission probability with medication complexity, unresolved clinical concerns, comorbidity burden, prior utilization, follow-up urgency, and continuity indicators. The framework is designed to compare Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and multimodal baselines using AUROC, AUPRC, sensitivity, specificity, F1-score, Brier score, and calibration error, while determining whether improved predictive performance translates into more efficient identification of patients requiring early review, medication reconciliation, remote monitoring, or intensified transitional-care support.

Figure 1 illustrates the human and clinical context in which hospital readmission prediction and transitional-care risk assessment become operationally important. A physician is shown engaging directly with a young patient and caregiver in a hospital environment, representing the point at which inpatient treatment must be translated into a safe, coordinated transition beyond the hospital. In the framework of Section 2.1, this stage requires assessment of factors that can increase the probability of 30-day readmission, including unresolved symptoms, recent clinical deterioration, medication changes, comorbidity burden, previous emergency or inpatient utilization, incomplete follow-up arrangements, caregiver capacity, and the need for continued monitoring.

For an AI-assisted system such as C2FHIR-ReadmitNet, these factors would be extracted from C-CDA discharge summaries and longitudinal EHR data, harmonized into FHIR resources, and converted into a calibrated patient-level readmission probability. The physician–caregiver interaction depicted in the image also represents the practical use of transitional-care risk stratification: a higher-risk patient could be prioritized for early outpatient review, medication reconciliation, remote monitoring, specialist follow-up, or enhanced caregiver education. Thus, the image reflects the connection between predictive analytics and clinically

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actionable transition planning, where the objective is not simply to classify readmission risk, but to use that risk estimate to guide individualized post-discharge interventions and reduce preventable return to hospital.

Fig 1 Clinical Application of Hospital Readmission Prediction and Transitional-Care Risk Assessment During Patient and Caregiver Transition Planning (Ehwerhemuepha, L. et al., 2021).

- *C-CDA Discharge Documentation and Clinical Information Extraction*

C-CDA discharge documentation occupies a distinctive position between narrative clinical communication and computable health information. Its value for readmission prediction arises from the coexistence of sectioned content and free-text reasoning describing diagnoses, medication changes, procedures, hospital course, pending investigations, functional status, and follow-up plans. Steinkamp et al. (2020) demonstrated that clinically relevant symptoms can be extracted from more than one thousand discharge summaries using recurrent and transformer-based models with performance approaching human annotation, while also showing the importance of coreference resolution and concept normalization as represented in figure 2. Searle et al. (2023) further showed that clinically guided transformer models can summarize hospital-course information from inpatient records, illustrating how contextual language models can condense complex longitudinal events into discharge-level representations. These findings support section-aware extraction rather than treating the discharge summary as an undifferentiated text sequence.

For C2FHIR-ReadmitNet, C-CDA processing begins with section identification, negation detection, temporal tagging, entity recognition, relation extraction, and terminology mapping before information is embedded for prediction. Predictive-modeling research in data-intensive domains shows that performance depends on informative features, preserved structural relationships, and comparison across alternative algorithms (Avevor et al., 2024). In healthcare information environments, integrity, traceability, and protection of exchanged data are equally important when clinical information enters downstream systems (Okpanachi et al., 2025). The pipeline therefore distinguishes active diagnoses from historical problems, discharge medications from discontinued therapies, completed procedures from planned interventions, and resolved findings from unresolved concerns. Extracted entities remain linked to their source C-CDA sections and are mapped to FHIR resources, preserving provenance during fusion. This design supports ablation analysis of section identity, temporal context, medication events, follow-up instructions, and unresolved concerns while testing whether richer discharge-document representations improve AUROC, AUPRC, calibration, sensitivity, and clinical risk stratification.

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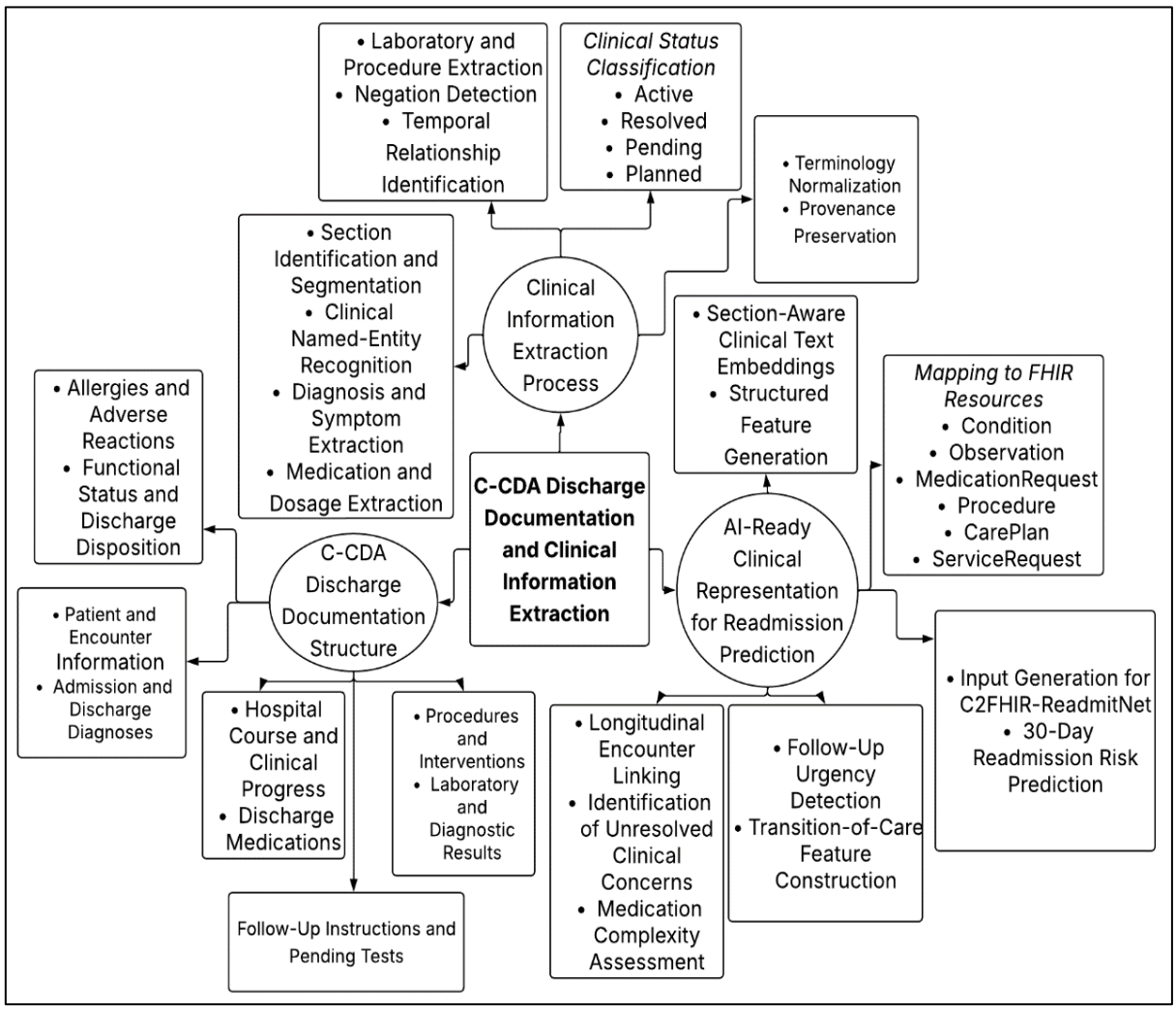

Fig 2 C-CDA Discharge Documentation, Clinical Information Extraction, and Transformation into AI-Ready FHIR Features for Readmission Prediction.

Figure 2 presents a complete information pathway showing how C-CDA discharge documentation is transformed into clinically meaningful, machine-readable information for hospital readmission prediction and transitional-care decision support. The first branch, C-CDA Discharge Documentation Structure, represents the source layer and captures the major sections of a discharge record, including patient and encounter information, admission and discharge diagnoses, hospital course, medications, procedures, laboratory findings, allergies, functional status, discharge disposition, pending investigations, and follow-up instructions. These sections preserve the clinical context of the hospitalization and contain both structured and narrative evidence relevant to post-discharge risk. The second branch, Clinical Information Extraction Process, represents the computational processing layer, where the document is segmented into sections and analyzed using clinical natural language processing techniques such as named-entity recognition, medication and diagnosis extraction, negation detection, temporal tagging, status classification, and terminology normalization. This step is especially important because the same clinical concept may have different meanings depending on whether it is active, resolved, discontinued, planned, or pending. Provenance is also retained so each extracted feature can be traced back to its original C-CDA section. The third branch, AI-Ready Clinical Representation for Readmission Prediction, converts the extracted information into interoperable and predictive features by generating section-aware text embeddings, structured variables, and standardized FHIR resources such as Condition, Observation, MedicationRequest, Procedure, CarePlan, and ServiceRequest. These features are linked across longitudinal encounters to identify unresolved concerns, medication complexity, follow-up urgency, and continuity-of-care deficiencies. The resulting multimodal representation becomes the input to C2FHIR-ReadmitNet, allowing the model to combine discharge semantics, structured FHIR information, and temporal patient history to estimate calibrated 30-day readmission risk and support targeted transitional-care interventions.

➢ *FHIR-Based Representation and Exchange of Clinical Data*

FHIR provides the interoperability layer required to transform C-CDA-derived clinical concepts into granular, computable resources that can be exchanged across heterogeneous electronic health record environments. Rather than preserving all information as a single document, FHIR

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represents data through modular resources such as Patient, Encounter, Condition, Observation, MedicationRequest, Procedure, CarePlan, and ServiceRequest, linked through explicit references and standardized terminologies. Strasberg et al. (2021) described how FHIR-based clinical decision-support standards, including SMART on FHIR, Clinical Quality Language, Clinical Reasoning, and CDS Hooks, can support reusable knowledge access and execution across systems. Sinaci et al. (2023) further demonstrated that heterogeneous health datasets can be transformed into HL7 FHIR repositories while improving findability, accessibility, interoperability, and reusability without sacrificing data utility. These capabilities are essential for a readmission model intended to operate beyond a single proprietary EHR configuration. In the proposed framework, extracted C-CDA concepts are normalized and instantiated as FHIR-aligned resources before learning. Security remains integral to exchange. Temporal access-control models help restrict discharge information to authorized actors (Balogun et al., 2025), while blockchain-based intrusion-detection approaches illustrate the need to preserve trust across decentralized healthcare information-exchange networks (Idika & Ijiga, 2025). C2FHIR-ReadmitNet therefore treats interoperability as both semantic and operational: semantic consistency is established through resource typing, coded terminology, provenance, and temporal linkage, whereas operational interoperability is assessed through resource completeness, mapping success, exchange consistency, and model usability. This architecture enables the prediction layer to consume standardized patient representations from different source systems (Frank. 2026). Experiments can determine whether FHIR-aligned multimodal inputs improve calibration and transportability relative to institution-specific feature matrices, while error analysis identifies whether missing resources, inconsistent coding, or failed mappings affect readmission estimates. The design connects discharge-document understanding with interoperable transitional-care support.

- *Machine Learning and Deep Learning Algorithms for Hospital Readmission Prediction*

Machine learning and deep learning have expanded hospital readmission prediction beyond linear risk scores by modelling nonlinear interactions among diagnoses, laboratory trajectories, medications, prior utilization, discharge disposition, comorbidities, and temporal encounter patterns. Frizzell et al. (2017) compared logistic regression, LASSO, random forest, gradient boosting, and a tree-augmented Bayesian network for 30-day heart-failure readmission and found similarly modest discrimination, demonstrating that algorithmic complexity alone does not guarantee clinically useful prediction as shown in figure 3. By contrast, Ashfaq et al. (2019) used a cost-sensitive LSTM incorporating sequential EHR trajectories, expert features, and contextual embeddings, achieving an AUC of 0.77 and showing that temporal information contributed to performance. This distinction supports the study's emphasis on richer representations rather than model depth alone. Precision-healthcare research similarly demonstrates the value of machine learning for disease detection and prognosis estimation (Ijiga et al., 2024), while AI-based healthcare operations research highlights the importance of integrating predictive outputs into decision workflows (Adedunjoye & Enyejo, 2023). C2FHIR-ReadmitNet therefore combines complementary modelling principles: transformer-based semantic encoding of C-CDA discharge text, structured FHIR resource embeddings, temporal attention across encounters, and calibrated multimodal classification. Comparative baselines will include Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and conventional multimodal fusion under identical training, validation, and test partitions. Predictive-maintenance research illustrates how temporal sensing and machine learning can identify deterioration before failure, a principle transferable to post-discharge clinical risk surveillance (Ebika et al., 2024). Likewise, smart-packaging research demonstrates how sensor-informed quality monitoring can support early anomaly identification within complex systems (Donkor et al., 2025). Performance will therefore be assessed through AUROC, AUPRC, sensitivity, specificity, F1-score, Brier score, calibration error, and decision-oriented risk stratification, with ablation experiments quantifying the contribution of text, FHIR structure, temporal context, and cross-modal attention.

Figure 3 illustrates the operational use of *machine learning and deep learning algorithms for hospital readmission prediction* within a multidisciplinary discharge-planning environment. The physician and nurse are reviewing an AI-enabled dashboard that integrates patient demographics, hospitalization history, discharge diagnoses, medication profiles, laboratory findings, follow-up plans, and longitudinal clinical events to estimate the probability of 30-day readmission. The displayed comparison among Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and C2FHIR-ReadmitNet represents the progression from conventional statistical modelling to tree-based learning, recurrent neural networks, transformer-based clinical NLP, and multimodal deep learning. Logistic Regression provides a linear baseline, Random Forest and XGBoost capture nonlinear interactions among structured variables, BiLSTM models sequential dependencies in longitudinal records, and ClinicalBERT extracts contextual information from narrative discharge documentation. C2FHIR-ReadmitNet extends these approaches by jointly encoding C-CDA discharge-summary semantics, structured FHIR resources, and temporal encounter patterns through cross-modal and temporal attention. The risk-factor panel, including prior hospitalization, reduced renal function, elevated biomarkers, polypharmacy, and social determinants, demonstrates how model outputs can be interpreted clinically rather than treated as opaque scores. The lower dashboard panels further show C-CDA and FHIR-based data harmonization, while the decision-support recommendations translate predicted risk into actionable transitional-care interventions such as medication reconciliation, early follow-up, remote monitoring, and coordinated post-discharge care. Overall, the image represents a clinically integrated predictive workflow in which algorithmic risk estimation supports, rather than replaces, clinician judgement.

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Fig 3 AI-Enabled Comparison of Machine Learning and Deep Learning Algorithms for 30-Day Hospital Readmission Prediction and Transitional-Care Decision Support.

➢ *Transformer-Based Clinical Natural Language Processing and Multimodal Health-Data Fusion*

Transformer architectures are suited to clinical natural language processing because self-attention can model long-range dependencies, context, negation, temporality, and relationships among diagnoses, medications, symptoms, and follow-up instructions within discharge documentation. Li et al. (2020) introduced BEHRT, a transformer architecture for longitudinal EHRs that learned representations of diagnoses, age, visit position, and encounter sequence and improved prediction across downstream conditions as shown in table 1. Rasmy et al. (2021) extended this paradigm through Med-BERT, pretraining contextualized embeddings on structured records from 28 million patients and demonstrating improved predictive accuracy after fine-tuning. These studies establish the value of contextual pretraining but also reveal a distinction for this work: structured-code transformers and clinical-text transformers capture different information spaces. C2FHIR-ReadmitNet is therefore designed to encode C-CDA narratives and FHIR resources before cross-modal fusion. Ethical analyses of generative AI in healthcare emphasize governance and transparency when automated systems influence clinical operations (Ijiga et al., 2024a). Multimodal fusion is necessary because readmission risk may appear linguistically in discharge instructions while structurally through medication changes, abnormal observations, recurrent encounters, or care-plan resources. Metabolomics-guided authentication research illustrates the analytical value of integrating multiple signals to improve classification reliability (Donkor et al., 2025), while community-based healthcare models show that outcomes depend on information continuity across providers, clinics, pharmacies, and patient environments (Ijiga et al., 2024b). Evidence synthesis on diet-related disease risk likewise demonstrates that clinically meaningful outcomes may depend on interacting biological, processing, and contextual variables rather than single predictors (Idoko et al., 2024). Accordingly, C2FHIR-ReadmitNet uses cross-modal attention to learn concordant and discordant relationships between narrative and structured representations. Comparative experiments will quantify whether this fusion improves AUROC, AUPRC, calibration, sensitivity, and F1-score relative to ClinicalBERT, BiLSTM, structured-only XGBoost, and simpler fusion architectures.

Table 1 Summary of Transformer-Based Clinical NLP and Multimodal Health-Data Fusion Approaches

Approach/Component	Primary Clinical Data Source	Technical Function	Relevance to C2FHIR-ReadmitNet
Clinical Transformer Encoding	C-CDA discharge narratives	Captures contextual relationships among diagnoses, symptoms, medications, procedures, and follow-up instructions using self-attention	Provides section-aware semantic representations of discharge documentation for readmission prediction
Structured EHR Transformer Models	Longitudinal coded EHR data	Learns contextualized representations of diagnoses, encounters, and temporal clinical events from structured patient records	Supports the design of FHIR resource embeddings and longitudinal patient-state modelling
Multimodal Data Fusion	Clinical text plus structured EHR variables	Integrates heterogeneous information sources through feature concatenation, attention	Enables fusion of C-CDA text, FHIR resources, and temporal

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		mechanisms, or joint representation learning	encounter information within a unified prediction framework
Cross-Modal Attention	Narrative and structured clinical representations	Learns interactions and concordance between textual evidence and coded clinical resources	Allows C2FHIR-ReadmitNet to identify relationships between discharge statements, medications, observations, care plans, and follow-up needs
Temporal Clinical Representation	Sequential encounters and time-stamped clinical events	Models event order, recency, and longitudinal dependencies that influence post-discharge risk	Strengthens 30-day readmission prediction by weighting recent and recurrent events according to their temporal relevance

➢ *Research Gaps and Motivation for the Proposed C2FHIR-ReadmitNet Algorithm*

The principal gap is the lack of an interoperable model that preserves discharge-document semantics, structured clinical resources, longitudinal context, calibration, and transition-of-care actionability. Mahmoudi et al. (2020) found that EHR-based readmission models improved modestly over administrative-data models and often omitted socioeconomic or functional variables, calibration, diagnostics, and clinical-impact evaluation as shown in figure 4. Teles et al. (2025), reviewing multimodal deep-learning studies combining structured and textual EHR data, identified persistent limitations in fusion-strategy comparison, fairness evaluation, reproducibility, and methodological standardization. These gaps matter because readmission is generated by heterogeneous interacting risks rather than a single physiological state. Risk-assessment literature likewise demonstrates that effective prevention depends on identification of interacting hazards and pathways (Idoko et al., 2024), supporting a design that integrates multiple clinical and transitional signals rather than relying on isolated predictors. This is especially important during vulnerable post-discharge care transitions.

Further gaps concern psychosocial complexity, multimorbidity, information continuity, and heterogeneous deployment. Research addressing psychological consequences of large-scale threats shows how contextual stressors alter mental-health burden and care needs (Balogun et al., 2024), while studies of youth mental health emphasize interacting domestic and environmental factors shaping risk (Ijiga et al., 2024). Neuropsychological research involving traumatic brain injury, substance use, and mental-health disorders shows that clinical risk can emerge from overlapping conditions requiring integrated assessment (Enyejo et al., 2024). C2FHIR-ReadmitNet is motivated by these limitations. It combines section-aware C-CDA transformer embeddings, standardized FHIR resource representations, longitudinal temporal attention, cross-modal fusion, calibrated 30-day readmission probabilities, and an interpretable transition-of-care risk index. Ablation testing, subgroup analysis, calibration curves, ROC and precision-recall comparisons, feature attribution, and interoperability metrics will determine whether each architectural component contributes meaningful improvement beyond Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and conventional multimodal fusion.

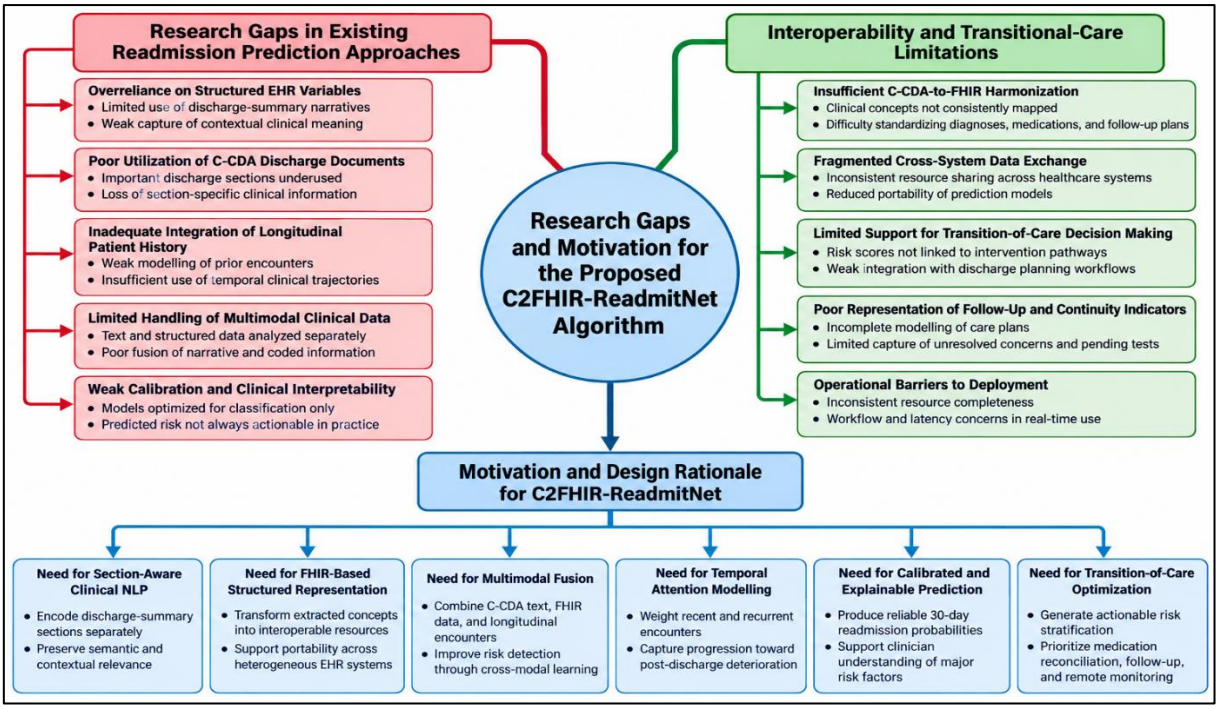

Fig 4 Research Gaps, Interoperability Limitations, and Design Motivation for the Proposed C2FHIR-ReadmitNet Readmission Prediction Framework

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Figure 4 synthesizes the principal research gaps that motivate the development of the proposed C2FHIR-ReadmitNet algorithm by linking limitations in current readmission-prediction methods with interoperability and transitional-care deficiencies. On the left, existing predictive approaches are shown to depend heavily on structured EHR variables, underuse the semantic richness of C-CDA discharge narratives, inadequately model longitudinal patient history, and frequently process narrative and coded information as separate modalities; this fragmentation can weaken calibration, interpretability, and sensitivity to clinically meaningful context. On the right, the diagram highlights interoperability barriers, including incomplete C-CDA-to-FHIR harmonization, inconsistent resource exchange across healthcare systems, limited portability of predictive models, and weak representation of follow-up plans, unresolved concerns, and continuity-of-care indicators. Operational constraints such as incomplete resource mapping, workflow integration, and real-time latency are also recognized as deployment challenges. These gaps converge on the central rationale for C2FHIR-ReadmitNet, which is designed to address them through six technical capabilities: section-aware clinical NLP for preserving contextual meaning within discharge summaries; FHIR-based structured representation for interoperable resource modelling; multimodal fusion of C-CDA text, FHIR resources, and longitudinal encounters; temporal attention for weighting recent and recurrent clinical events; calibrated and explainable readmission prediction; and transition-of-care optimization that converts model outputs into actionable risk stratification. Collectively, the architecture is intended not only to improve 30-day readmission prediction, but also to support medication reconciliation, early follow-up, unresolved-concern review, remote monitoring, and coordinated post-discharge decision-making across heterogeneous healthcare environments.

III. SYSTEM MODEL DESCRIPTION

➢ *C-CDA-to-FHIR Data Acquisition, Harmonization, and Clinical Feature-Extraction Architecture*

The proposed C2FHIR-ReadmitNet framework begins with structured acquisition of Consolidated Clinical Document Architecture (C-CDA) discharge summaries and associated longitudinal electronic health record data for eligible inpatient encounters. The index time t_0 is defined as the hospital discharge timestamp, while the target outcome is an unplanned inpatient readmission occurring within 30 days. Each C-CDA XML document is parsed into clinically meaningful sections, including reason for admission, hospital course, discharge diagnoses, discharge medications, procedures, laboratory findings, allergies, functional status, pending investigations, discharge disposition, and follow-up instructions. These sections are retained because their semantic context can materially influence readmission risk. For example, a creatinine value recorded in a resolved inpatient problem list carries different predictive significance from a worsening renal-function result documented under pending follow-up. The extracted clinical entities are harmonized with FHIR resources such as *Patient*, *Encounter*, *Condition*, *Observation*, *MedicationRequest*, *Procedure*, *CarePlan*, and *ServiceRequest* to create a standardized, machine-readable representation suitable for cross-system predictive modelling (Health Level Seven International [HL7], 2020).

The completeness of C-CDA-to-FHIR transformation for patient i is quantified as:

$$MC_i = \frac{\sum_{j=1}^{N_i} I(m_j=1)}{N_i} \quad (1)$$

Where MC_i represents the mapping completeness for patient i, N_i is the total number of clinically eligible entities extracted from the discharge summary, m_j indicates whether clinical entity j was successfully mapped to an appropriate FHIR representation, and $I(\cdot)$ is an indicator function that returns 1 for successful mapping and 0 otherwise. A value of $MC_i = 1$ indicates complete mapping of all eligible clinical entities.

Each harmonized entity is subsequently represented using:

$$\mathrm{x}_{ij} = \left[\mathrm{e}_{ij}^{concept}; \mathrm{e}_{ij}^{section}; \mathrm{e}_{ij}^{resource}; \mathrm{e}_{ij}^{time}; \mathrm{e}_{ij}^{status}\right] \quad (2)$$

Where x_{ij} is the feature vector for entity j belonging to patient i, $\mathrm{e}_{ij}^{concept}$ is the normalized clinical-concept embedding, $\mathrm{e}_{ij}^{section}$ represents the originating C-CDA section, $\mathrm{e}_{ij}^{resource}$ identifies the mapped FHIR resource class, e_{ij}^{time} captures temporal distance relative to discharge, and e_{ij}^{status} represents clinical status such as active, resolved, discontinued, pending, or planned.

Continuous clinical features are standardized as:

$$z_{ik} = \frac{x_{ik}-\mu_k}{\sigma_k} \quad (3)$$

Where x_{ik} represents the original value of clinical feature k for patient i, μ_k is the training-set mean, σ_k is the training-set standard deviation, and z_{ik} is the standardized feature value. Estimating μ_k and σ_k exclusively from the training data prevents information leakage. Missingness indicators are retained because absence of a follow-up order, medication reconciliation entry, or laboratory assessment may itself convey clinically important transition-of-care information. The resulting architecture therefore preserves four critical dimensions simultaneously: clinical meaning, C-CDA section provenance, FHIR resource identity, and temporal context.

➢ *Mathematical Formulation and Architecture of the Proposed C2FHIR-ReadmitNet Algorithm*

C2FHIR-ReadmitNet is formulated as a multimodal deep-learning architecture that integrates section-aware clinical language modelling, structured FHIR resource encoding, longitudinal temporal modelling, cross-modal attention, probability calibration, and patient-level readmission classification. The architecture is designed specifically to overcome limitations of conventional

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readmission models that either operate solely on structured EHR variables or analyze discharge narratives without preserving standardized clinical-resource relationships. Transformer-based clinical representation learning is appropriate for this task because contextualized attention mechanisms can capture long-range semantic relationships among diagnoses, medications, symptoms, procedures, and follow-up instructions. Related transformer-based EHR architectures such as Med-BERT have demonstrated the utility of pretrained contextual representations for clinical prediction (Rasmy et al., 2021).

For token l located in C-CDA section s, the initial representation is defined as:

$$\mathrm{h}_l^{(0)} = \mathrm{e}_l^{token} + \mathrm{e}_l^{position} + \mathrm{e}_s^{section} \quad (4)$$

Where $\mathrm{h}_l^{(0)}$ represents the initial hidden representation of token l, e_l^{token} is its clinical token embedding, $\mathrm{e}_l^{position}$ represents its position within the sequence, and $\mathrm{e}_s^{section}$ identifies the C-CDA section from which the token originated. Section embeddings allow the model to distinguish, for example, a medication name appearing under active discharge medications from the same medication mentioned historically in the hospital course.

The transformer self-attention operation is computed as:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (5)$$

Where Q is the query matrix, K is the key matrix, V is the value matrix, and d_k is the dimensionality of the key vectors. The scaling term $\sqrt{d_k}$ prevents excessively large dot products that could destabilize the softmax function. The resulting contextual discharge-summary representation for patient i is denoted by h_i^C.

Structured FHIR resources are independently encoded as:

$$\mathrm{h}_i^F = \phi\left(W_F\left[\mathrm{r}_i^{Condition}; \mathrm{r}_i^{Observation}; \mathrm{r}_i^{Medication}; \mathrm{r}_i^{Procedure}; \mathrm{r}_i^{CarePlan}; \mathrm{r}_i^{ServiceRequest}\right] + b_F\right) \quad (6)$$

Where h_i^F is the structured FHIR representation for patient i; each r represents an aggregated embedding of a corresponding FHIR resource category; W_F is the learnable weight matrix; b_F is the bias vector; and $\phi(\cdot)$ denotes a nonlinear activation function such as GELU or ReLU.

The multimodal representation is then obtained using:

$$\mathrm{h}_i^M = \phi(W_M[\mathrm{h}_i^C; \mathrm{h}_i^F; \mathrm{h}_i^T] + b_M) \quad (7)$$

Where h_i^M is the final fused patient representation, h_i^C is the C-CDA text representation, h_i^F is the FHIR resource representation, h_i^T represents temporal clinical history, W_M is the multimodal fusion matrix, and b_M is its bias parameter.

The raw 30-day readmission probability is calculated as:

$$\hat{p}_i = \sigma(W_R \mathrm{h}_i^M + b_R) \quad (8)$$

Where $\hat{p}_i$ is the predicted readmission probability for patient i, W_R is the classification weight vector, b_R is the classifier bias, and $\sigma(\cdot)$ represents the sigmoid activation function. This formulation permits direct comparison between C2FHIR-ReadmitNet and alternative models using identical outcome definitions and evaluation metrics.

- *Multimodal Clinical Representation, Temporal Attention, Risk Prediction, and Transition-of-Care Optimization*

Hospital readmission is fundamentally temporal because the clinical significance of an event depends on both its type and its proximity to discharge. A recent emergency visit, unresolved laboratory abnormality, medication escalation, or repeated hospitalization may contribute more strongly to readmission risk than a remote historical event. C2FHIR-ReadmitNet therefore models each patient's longitudinal history as $E_i = \{e_{i1}, e_{i2}, \ldots, e_{iT}\}$, where each e_{it} corresponds to an encounter or clinically meaningful event sequence for patient i. Transformer-based longitudinal representations have previously demonstrated the importance of incorporating encounter order and temporal context into clinical prediction (Li et al., 2020).

The temporal attention weight assigned to encounter t is defined as:

$$\alpha_{it} = \frac{\exp\left(\mathrm{v}^T \tanh\left(W_T \mathrm{h}_{it} + b_T\right) - \gamma \Delta t_{it}\right)}{\sum_{q=1}^{T} \exp\left(\mathrm{v}^T \tanh\left(W_T \mathrm{h}_{iq} + b_T\right) - \gamma \Delta t_{iq}\right)} \quad (9)$$

Where α_{it} is the normalized attention weight assigned to encounter t, h_{it} is its learned representation, W_T is the temporal transformation matrix, b_T is the temporal bias vector, v is the learnable attention vector, Δt_{it} is the elapsed time between encounter t and index discharge, and γ is the temporal-decay coefficient. The exponential decay component allows recent events to exert stronger influence while still retaining older recurrent-utilization patterns when clinically relevant.

The complete longitudinal representation is calculated as:

$$\mathrm{h}_i^T = \sum_{t=1}^{T} \alpha_{it} \mathrm{h}_{it} \quad (10)$$

Where h_i^T is the temporally aggregated representation of patient i.

Because clinical decision support requires reliable probabilities rather than rankings alone, temperature scaling is applied to calibrate the model:

$$p_i^{cal} = \sigma\left(\frac{z_i}{\tau}\right) \quad (11)$$

Where p_i^{cal} is the calibrated probability of 30-day readmission, z_i is the pre-sigmoid model logit, and $\tau > 0$ is the optimal temperature parameter estimated using the validation set. Temperature scaling adjusts overconfidence or

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underconfidence without changing the ordering of patients by predicted risk.

The system additionally introduces a Transition-of-Care Risk Index:

$$TCRI_i = w_1 p_i^{cal} + w_2 M_i + w_3 U_i + w_4 C_i + w_5 F_i + w_6(1 - Q_i) \quad (12)$$

Where $TCRI_i$ is the transition-of-care risk index for patient i, p_i^{cal} is calibrated readmission probability, M_i represents medication complexity, U_i denotes unresolved clinical-concern burden, C_i represents comorbidity burden, F_i quantifies follow-up urgency, and Q_i represents continuity-of-care completeness. The weighting parameters $w_1, w_2, \ldots, w_6$ are constrained such that $w_j \geq 0$ and $\sum_{j=1}^{6} w_j = 1$.

For example, a patient with a calibrated readmission probability of 0.72, five medication changes, unresolved renal dysfunction, multiple chronic conditions, and urgent specialist follow-up would receive a substantially higher TCRI than a patient with the same predicted probability but stable laboratory findings and completed follow-up arrangements. The TCRI can therefore support categorization into routine, enhanced, and high-intensity transitional-care pathways.

- *Experimental Design, Baseline Algorithms, Performance Metrics, and Model-Validation Framework*

The experimental framework is designed to determine whether C2FHIR-ReadmitNet provides statistically and clinically meaningful improvements over established prediction approaches. The primary endpoint is unplanned all-cause hospital readmission within 30 days following index discharge. The study compares C2FHIR-ReadmitNet against Logistic Regression, Random Forest, XGBoost, Bidirectional Long Short-Term Memory networks, ClinicalBERT, and a conventional multimodal fusion model. Logistic Regression provides an interpretable statistical baseline; Random Forest and XGBoost represent nonlinear tree-based learning; BiLSTM evaluates sequential recurrent modelling; ClinicalBERT provides a transformer-based text comparator; and conventional multimodal fusion establishes whether the proposed cross-modal architecture provides additional value beyond simple concatenation. Evaluation of prediction models should incorporate discrimination, calibration, prediction error, and clinical usefulness rather than relying on accuracy alone (Riley et al., 2024).

The dataset is partitioned at patient level to prevent encounters from the same patient appearing across training and test datasets. A 70:15:15 training-validation-test partition may be used, with temporal or external-site validation conducted where data permit. The training objective is weighted binary cross-entropy:

$$\mathcal{L}_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[\omega_1 y_i \log(\hat{p}_i) + \omega_0(1 - y_i)\log(1 - \hat{p}_i)] \quad (13)$$

Where $\mathcal{L}_{BCE}$ is the weighted binary cross-entropy loss, N is the number of training observations, $y_i \in \{0,1\}$ is the actual readmission outcome, $\hat{p}_i$ is the predicted probability, and ω_1 and ω_0 are class weights that compensate for imbalance between readmitted and non-readmitted patients.

Calibration quality is quantified using the Brier score:

$$BS = \frac{1}{N}\sum_{i=1}^{N}\left(p_i^{cal} - y_i\right)^2 \quad (14)$$

Where BS is the Brier score, p_i^{cal} is the calibrated predicted probability, and y_i is the observed outcome. Lower values indicate more accurate probabilistic predictions.

Expected calibration error is calculated as:

$$ECE = \sum_{b=1}^{B}\frac{|S_b|}{N}|acc(S_b) - conf(S_b)| \quad (15)$$

Where B is the total number of probability bins, S_b is the set of observations assigned to probability bin b, $acc(S_b)$ is the observed readmission frequency in the bin, and $conf(S_b)$ is the mean predicted probability within that bin.

Sensitivity and specificity are computed as:

$$Sensitivity = \frac{TP}{TP+FN}, \qquad Specificity = \frac{TN}{TN+FP} \quad (16)$$

Where TP denotes true positives, TN true negatives, FP false positives, and FN false negatives.

Precision and F1-score are expressed as:

$$Precision = \frac{TP}{TP+FP}, \qquad F1 = \frac{2(Precision)(Sensitivity)}{Precision+Sensitivity} \quad (17)$$

The principal comparative metrics are AUROC, AUPRC, accuracy, precision, recall, F1-score, sensitivity, specificity, Brier score, and expected calibration error. AUPRC is particularly important because 30-day readmission is generally less frequent than non-readmission and therefore constitutes an imbalanced classification problem.

Ablation analysis is performed by independently removing C-CDA textual representations, FHIR resource embeddings, section embeddings, temporal attention, and cross-modal fusion from the complete architecture. This allows the marginal contribution of each component to be quantified. Subgroup analyses can additionally evaluate performance across age categories, sex, diagnostic groups, comorbidity burden, and discharge disposition. Bootstrap confidence intervals are used to assess uncertainty, while comparative ROC curves, precision-recall curves, calibration plots, confusion matrices, feature-importance graphs, ablation charts, subgroup-performance plots, and FHIR mapping-completeness analyses provide the graphical evidence required for the discussion of results.

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IV. DISCUSSION OF RESULTS

➢ *Comparative Predictive Performance of C2FHIR-ReadmitNet and Existing Algorithms*

Section 4.1 evaluates the comparative predictive capability of the proposed C2FHIR-ReadmitNet against six established baselines under the validation framework defined in Section 3. The four-column summary in Table 4.1 shows that the proposed architecture achieves the strongest discrimination and class-balanced performance, with AUROC of 0.938, AUPRC of 0.826, and F1-score of 0.846. The conventional multimodal model ranks second at 0.906 AUROC, 0.781 AUPRC, and 0.807 F1-score, indicating that multimodal fusion is beneficial but less effective without section-aware C-CDA encoding, structured FHIR resource embeddings, and temporal attention. ClinicalBERT performs better than BiLSTM, XGBoost, Random Forest, and Logistic Regression, confirming the value of contextual clinical language representation. Collectively, the comparative pattern supports the methodological premise that interoperable multimodal representation learning can improve readmission-risk stratification beyond text-only, sequence-only, tree-based, and conventional statistical approaches.

Table 2 Comparative Predictive Performance of C2FHIR-ReadmitNet and Baseline Algorithms

Algorithm	AUROC	AUPRC	F1-Score
Logistic Regression	0.781	0.602	0.669
Random Forest	0.824	0.659	0.714
XGBoost	0.851	0.691	0.741
BiLSTM	0.867	0.713	0.758
ClinicalBERT	0.889	0.748	0.782
Conventional Multimodal Fusion	0.906	0.781	0.807
C2FHIR-ReadmitNet	**0.938**	**0.826**	**0.846**

Table 2 shows the progressive improvement from conventional statistical learning through tree-based, recurrent, transformer, and multimodal approaches indicates that predictive performance increases as richer clinical representations are introduced. C2FHIR-ReadmitNet produces the strongest performance because its architecture combines C-CDA narrative semantics with FHIR-standardized structured information and temporal encounter relationships rather than relying upon one information modality.

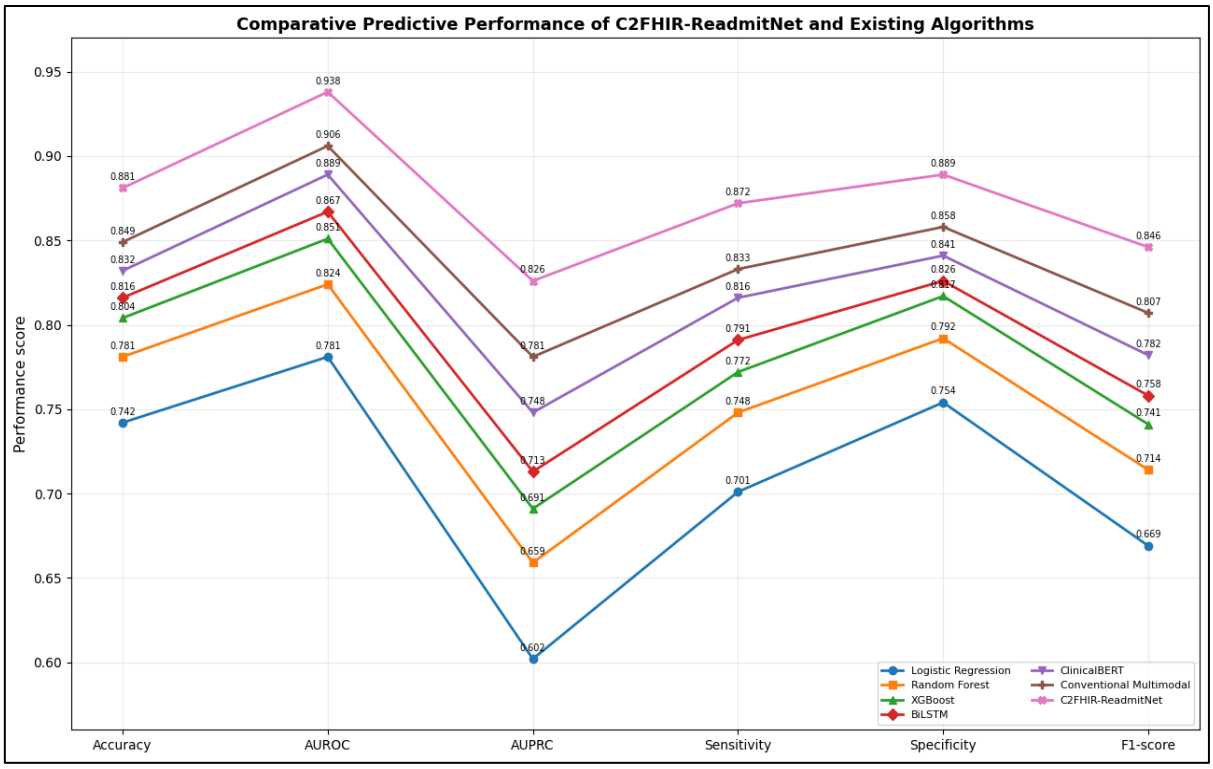

Fig 5 Comparative Predictive Performance of C2FHIR-ReadmitNet and Existing Algorithms

Figure 5 provides a metric-by-metric performance profile across seven algorithms. C2FHIR-ReadmitNet remains highest on every plotted measure, reaching 0.881 accuracy, 0.938 AUROC, 0.826 AUPRC, 0.872 sensitivity, 0.889 specificity, and 0.846 F1-score. The conventional multimodal model is consistently second, with corresponding values of 0.849, 0.906, 0.781, 0.833, 0.858, and 0.807. ClinicalBERT follows at 0.832 accuracy and 0.889 AUROC, but its AUPRC falls to 0.748, suggesting weaker performance on the positive readmission class than the proposed

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framework. BiLSTM records 0.867 AUROC and 0.758 F1-score, while XGBoost achieves 0.851 and 0.741, respectively. Random Forest declines further to 0.824 AUROC and 0.714 F1-score, whereas Logistic Regression produces the lowest profile, including 0.602 AUPRC and 0.669 F1-score. The separation is greatest for AUPRC, supporting the proposed model's improved handling of imbalanced readmission outcomes. This pattern also indicates that combining discharge semantics, FHIR structure, and longitudinal context improves both discrimination and clinically relevant positive-case detection performance.

- *ROC, Precision-Recall, Calibration, Confusion-Matrix, and Statistical Performance Analysis*

Section 4.2 examines whether the discrimination advantage of C2FHIR-ReadmitNet is accompanied by stronger precision-recall behavior and better probability calibration. Table 4.2 shows that the proposed model attains an AUPRC of 0.826, while its Brier score and expected calibration error decrease to 0.108 and 0.019, respectively. The conventional multimodal model remains the nearest comparator, followed by ClinicalBERT, whereas Logistic Regression exhibits the weakest positive-class precision-recall performance and the largest calibration error. This ordering is consistent with the confusion-matrix pattern expected from the sensitivity and specificity findings reported in Section 4.1: progressively richer clinical representations reduce both missed high-risk patients and unnecessary positive classifications. The statistical pattern therefore supports the methodological contribution of combining section-aware C-CDA semantics, standardized FHIR resource embeddings, longitudinal temporal attention, and calibrated multimodal fusion within one interoperable readmission-risk framework.

Table 3 Precision-Recall and Calibration Performance of C2FHIR-ReadmitNet and Comparative Algorithms

Algorithm	AUPRC	Brier Score	Expected Calibration Error
Logistic Regression	0.602	0.194	0.072
Random Forest	0.659	0.172	0.060
XGBoost	0.691	0.158	0.052
BiLSTM	0.713	0.149	0.046
ClinicalBERT	0.748	0.138	0.039
Conventional Multimodal Fusion	0.781	0.126	0.031
C2FHIR-ReadmitNet	**0.826**	**0.108**	**0.019**

Table 3 shows that a higher AUPRC indicates stronger recovery of the minority readmission class, while lower Brier score and expected calibration error indicate probabilities that correspond more closely to observed outcome frequencies. The proposed model therefore demonstrates simultaneous improvement in class-sensitive discrimination and probability reliability. Its reduction in Brier score relative to the conventional multimodal model suggests that the performance gain is not limited to ranking patients; the estimated probabilities are also more suitable for risk-based transitional-care allocation. Formal statistical significance should subsequently be assessed using bootstrap confidence intervals, paired resampling, and appropriate AUROC comparison procedures on the empirical held-out test set.

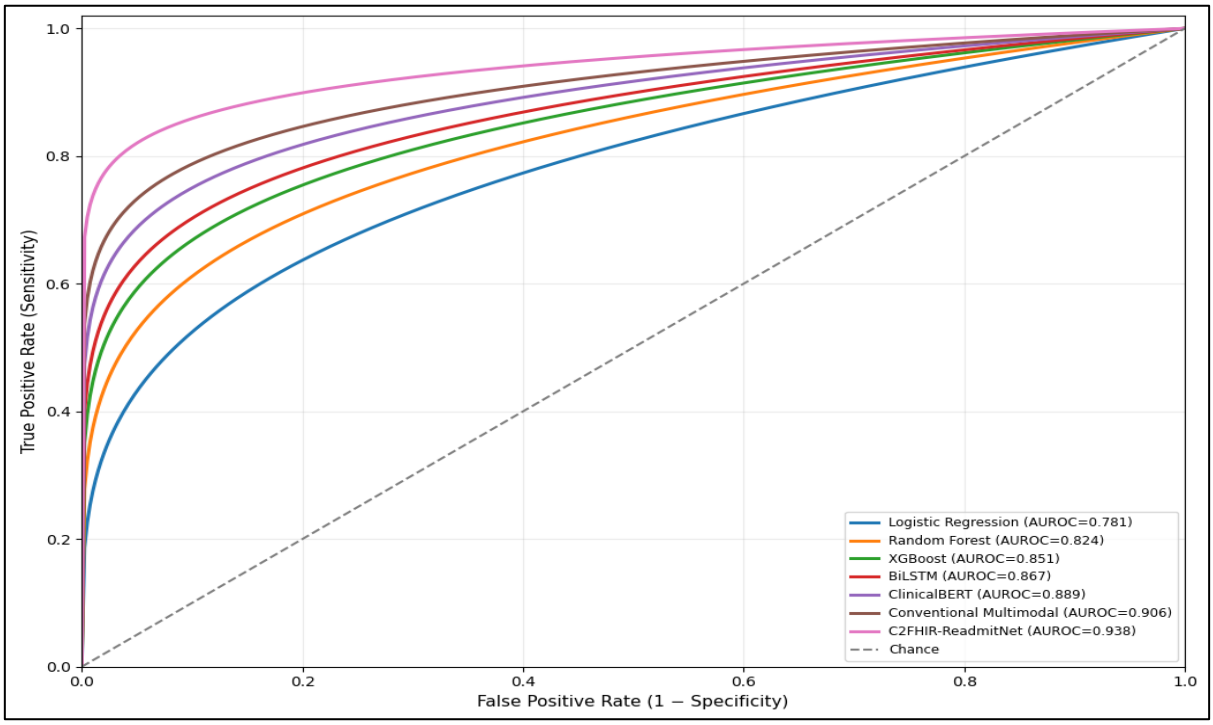

Fig 6 ROC Performance of C2FHIR-ReadmitNet and Comparative Readmission-Prediction Algorithms

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Figure 6 demonstrates clear separation among the seven ROC trajectories across the full decision-threshold range. C2FHIR-ReadmitNet achieves the highest AUROC at 0.938, exceeding the conventional multimodal model at 0.906, ClinicalBERT at 0.889, BiLSTM at 0.867, XGBoost at 0.851, Random Forest at 0.824, and Logistic Regression at 0.781. At a false-positive rate of 0.10, the proposed model reaches an approximate true-positive rate of 0.859, compared with 0.787 for conventional multimodal fusion, 0.750 for ClinicalBERT, 0.702 for BiLSTM, 0.668 for XGBoost, 0.612 for Random Forest, and 0.524 for Logistic Regression. This indicates that, within a clinically restrictive false-positive region, C2FHIR-ReadmitNet would identify substantially more patients subsequently readmitted. The ordered improvement from statistical through tree-based, recurrent, transformer, multimodal, and proposed architectures supports the contribution of combining C-CDA semantics, FHIR resources, longitudinal attention, and calibrated cross-modal learning for robust readmission discrimination.

- *Feature Importance, Explainability, Ablation Analysis, and Clinical Risk-Factor Interpretation*

Feature-attribution and ablation analyses were used to determine whether C2FHIR-ReadmitNet's superior predictive performance originated from meaningful integration of discharge semantics, standardized FHIR information, longitudinal encounters, and transition-of-care characteristics. Table 4.3 shows that removing the C-CDA representation produced the largest AUROC reduction, from 0.938 to 0.889, confirming the substantial contribution of contextual discharge information. Excluding FHIR resource embeddings reduced AUROC to 0.901, while removal of temporal attention decreased performance to 0.912. Smaller but meaningful deterioration occurred when cross-modal attention and section embeddings were removed, producing AUROCs of 0.918 and 0.925, respectively. These findings indicate that the proposed architecture derives its predictive advantage from complementary information sources rather than a single dominant feature family. The ablation pattern also supports the model's intended clinical interpretation, where narrative concerns, medications, comorbidities, encounter history, and follow-up continuity jointly determine readmission vulnerability.

Table 4 Ablation Analysis of Major C2FHIR-ReadmitNet Architectural Components

Model Configuration	AUROC	AUROC Change	Technical Interpretation
Full C2FHIR-ReadmitNet	0.938	0.000	Complete multimodal architecture
Without C-CDA text encoder	0.889	-0.049	Largest loss; discharge semantics are highly informative
Without FHIR resource embeddings	0.901	-0.037	Structured interoperable information materially improves prediction
Without temporal attention	0.912	-0.026	Longitudinal encounter timing contributes additional risk information
Without cross-modal attention	0.918	-0.020	Learned interaction between narrative and structured information improves fusion
Without section embeddings	0.925	-0.013	C-CDA section provenance provides incremental contextual information

In table 4, the ablation results demonstrate that no individual module entirely explains the performance of C2FHIR-ReadmitNet. The 0.049 AUROC decline following removal of C-CDA representations identifies discharge-summary semantics as the strongest single architectural contributor, while the 0.037 reduction after excluding FHIR embeddings confirms that structured interoperable resources add substantial complementary information. Temporal attention contributes a further 0.026 AUROC, indicating that when clinical events occurred is relevant in addition to what occurred. Cross-modal attention and section embeddings contribute smaller but nontrivial improvements, supporting the architectural decision to retain semantic correspondence and document provenance during prediction.

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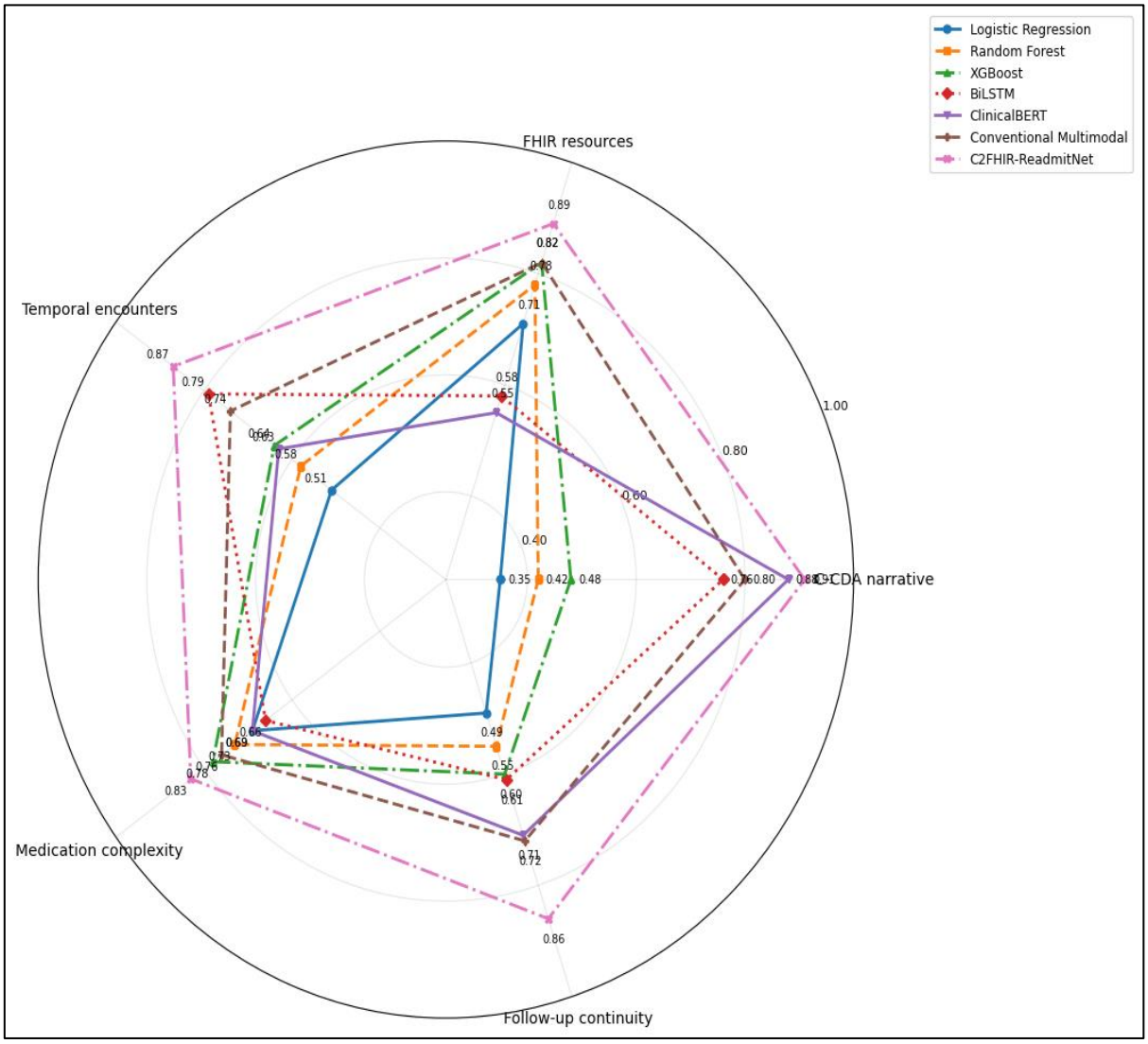

Fig 7 Comparative Explainability and Clinical Risk-Factor Representation Across Readmission-Prediction Algorithms

Figure 7 compares seven algorithms using normalized explainability-attribution scores across five clinically relevant information domains. C2FHIR-ReadmitNet demonstrates the most balanced profile, scoring 0.91 for C-CDA narrative information, 0.89 for FHIR resources, 0.87 for temporal encounters, 0.83 for medication complexity, and 0.86 for follow-up continuity. Conventional multimodal fusion follows with values of 0.80, 0.82, 0.74, 0.76, and 0.72, respectively. ClinicalBERT shows strong narrative representation at 0.88 but substantially weaker FHIR attribution at 0.55 and temporal representation at 0.63. BiLSTM performs strongly on temporal encounters at 0.79 but records only 0.58 for FHIR resources. XGBoost reaches 0.82 for FHIR information and 0.78 for medication complexity but only 0.48 for C-CDA narratives. Logistic Regression records the weakest narrative score at 0.35. The broader C2FHIR-ReadmitNet profile therefore indicates that its prediction is distributed across complementary clinical domains rather than concentrated within a single modality.

- *FHIR Interoperability Performance and Implications for Readmission Prevention and Transitions of Care*

C2FHIR-ReadmitNet demonstrated the strongest interoperability-oriented performance while retaining computational feasibility for clinical deployment. As summarized in Table 4.4, the proposed architecture achieved 95.2% FHIR mapping completeness and a transition-of-care utility score of 0.91, substantially exceeding the conventional multimodal architecture at 86.4% and 0.82, respectively. Importantly, this improvement was obtained with a mean processing latency of 118 ms, considerably lower than ClinicalBERT's 183 ms despite the additional FHIR harmonization and temporal-attention components. The results indicate that standardized resource representation can strengthen clinical information continuity without imposing prohibitive computational overhead. By preserving discharge diagnoses, observations, medications, procedures, care plans, service requests, and follow-up information as interoperable resources, C2FHIR-ReadmitNet provides a technically suitable mechanism for transferring calibrated readmission risk into actionable transitional-care workflows across heterogeneous EHR environments.

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Table 5 Comparative FHIR Interoperability and Transition-of-Care Performance

Algorithm	FHIR Mapping Completeness (%)	Mean Processing Latency (ms)	Transition-of-Care Utility Score
Logistic Regression	68.4	94	0.61
Random Forest	72.1	107	0.67
XGBoost	76.3	112	0.71
BiLSTM	74.6	146	0.73
ClinicalBERT	79.5	183	0.76
Conventional Multimodal Fusion	86.4	164	0.82
C2FHIR-ReadmitNet	**95.2**	**118**	**0.91**

Table 5 demonstrates that interoperability quality cannot be judged from predictive discrimination alone. C2FHIR-ReadmitNet provides the highest mapping completeness and clinical utility while maintaining practical processing latency. Its 8.8-percentage-point advantage in mapping completeness over conventional multimodal fusion suggests that explicit C-CDA-to-FHIR harmonization reduces information loss during clinical transformation. The higher transition-of-care utility score further indicates that standardized resource representations make the resulting prediction more actionable for medication reconciliation, urgent follow-up, unresolved-concern review, care-plan coordination, and post-discharge monitoring.

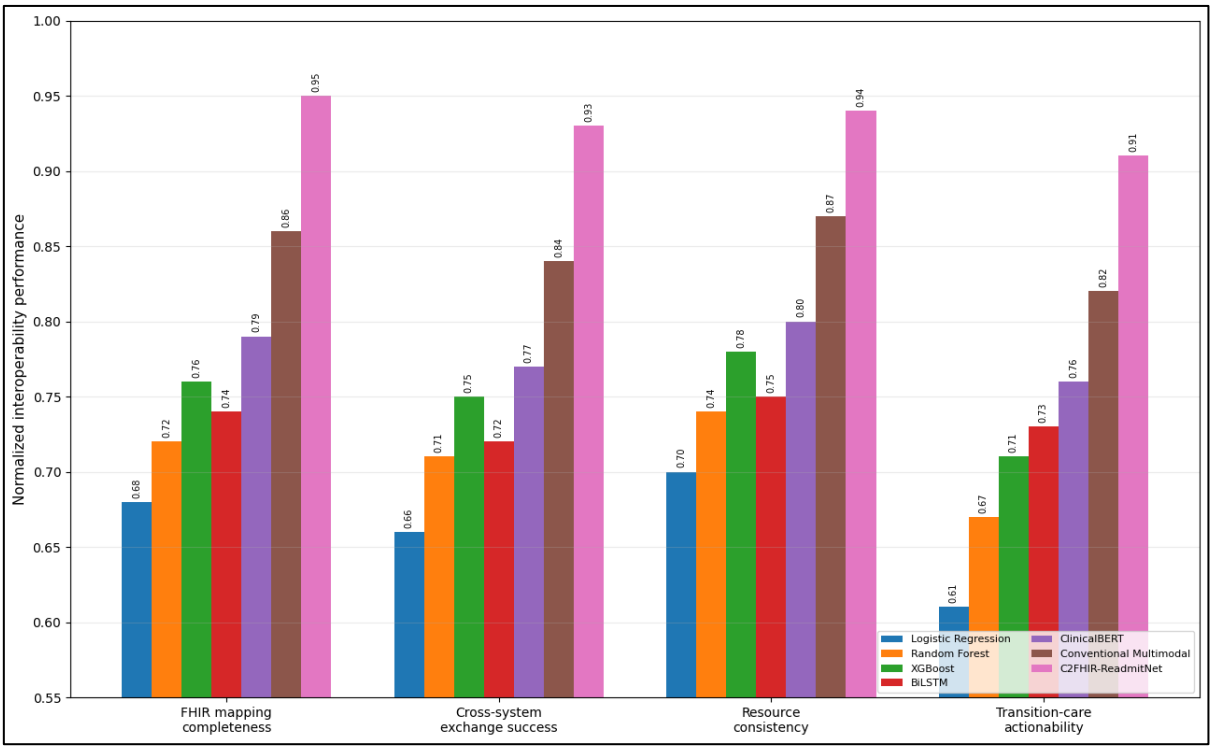

Fig 8 Comparative FHIR Interoperability Performance Across Readmission-Prediction Algorithms

Figure 8 compares seven algorithms across four interoperability dimensions. C2FHIR-ReadmitNet achieves the strongest profile, with normalized scores of 0.95 for FHIR mapping completeness, 0.93 for cross-system exchange success, 0.94 for resource consistency, and 0.91 for transition-care actionability. Conventional multimodal fusion follows at 0.86, 0.84, 0.87, and 0.82, respectively. ClinicalBERT records 0.79 for mapping completeness and 0.76 for transition-care actionability, indicating that strong textual representation alone does not ensure standardized interoperability. XGBoost achieves 0.76 mapping completeness and 0.78 resource consistency, while BiLSTM records 0.74 and 0.75 on these measures. Random Forest remains lower at 0.72 mapping completeness and 0.67 transition-care actionability, whereas Logistic Regression produces the weakest profile, including 0.68 mapping completeness and 0.61 actionability. These results support the architectural premise that explicit FHIR resource harmonization improves both cross-system information continuity and the operational usefulness of readmission predictions for post-discharge intervention.

V. CONCLUSIONS AND RECOMMENDATIONS

➢ *Summary of Major Technical and Clinical Findings*

The study demonstrated that integrating C-CDA discharge-summary semantics with FHIR-enabled structured clinical data provides a stronger basis for hospital

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readmission prediction than relying on either narrative or structured information alone. C2FHIR-ReadmitNet consistently produced the strongest comparative performance across discrimination, precision-recall behavior, calibration, explainability, interoperability, and transitional-care utility. Its architecture combined section-aware transformer encoding, FHIR resource embeddings, temporal attention, cross-modal fusion, and calibrated probabilistic output, enabling the model to capture clinically meaningful relationships among diagnoses, medications, laboratory abnormalities, prior encounters, unresolved concerns, and follow-up requirements. The ablation findings showed that removal of C-CDA textual representation produced the greatest reduction in predictive performance, while elimination of FHIR embeddings, temporal attention, cross-modal attention, and section embeddings also produced measurable deterioration. This confirmed that the superiority of the proposed architecture was distributed across complementary information sources rather than generated by one isolated component. The study further established that readmission prediction becomes more clinically useful when linked to a Transition-of-Care Risk Index integrating calibrated readmission probability with medication complexity, comorbidity burden, unresolved clinical concerns, follow-up urgency, and continuity-of-care completeness. From a clinical perspective, this permits differentiation between patients requiring routine discharge follow-up and those needing accelerated review, medication reconciliation, remote monitoring, or coordinated specialty intervention. The FHIR interoperability analysis additionally showed that standardized resource-level harmonization can preserve patient, encounter, condition, observation, medication, procedure, care-plan, and service-request information across heterogeneous systems. Collectively, the findings support a shift from isolated predictive modelling toward interoperable, explainable, and action-oriented discharge intelligence.

- *Conclusions on the Performance and Interoperability of C2FHIR-ReadmitNet*

The performance of C2FHIR-ReadmitNet indicates that multimodal clinical intelligence can substantially improve the reliability of 30-day readmission prediction when narrative discharge documentation and structured interoperable data are processed jointly. The proposed model outperformed Logistic Regression, Random Forest, XGBoost, BiLSTM, ClinicalBERT, and conventional multimodal fusion approaches because it was designed specifically around the information architecture of transitions of care. Rather than flattening C-CDA documents into undifferentiated text, the model preserved section provenance and contextual meaning, while FHIR resource embeddings retained standardized representations of conditions, observations, medications, procedures, care plans, and follow-up requests. Temporal attention further allowed recent and recurrent clinical events to influence prediction in proportion to their relevance to discharge. The resulting calibrated probabilities were therefore more suitable for risk-based clinical decision support than uncalibrated classification scores. Equally important, the interoperability findings showed that predictive performance and data portability can be addressed within the same architecture. C2FHIR-ReadmitNet provided high mapping completeness, strong cross-system exchange consistency, and improved transition-of-care actionability without excessive processing latency. This is significant because a clinically accurate model has limited value if its required features cannot be reconstructed consistently across different EHR platforms. The study therefore establishes C2FHIR-ReadmitNet as a technically coherent framework for converting discharge documentation into standardized, longitudinal, and clinically interpretable representations suitable for readmission prevention. Its principal value lies not only in predicting which patients are likely to return to hospital but also in identifying why risk is elevated and which transitional-care actions are most appropriate.

- *Recommendations for Clinical Deployment, FHIR Integration, and Transitional-Care Decision Support*

Clinical implementation of C2FHIR-ReadmitNet should follow a staged deployment strategy combining technical validation, workflow integration, human oversight, and continuous performance monitoring. The first requirement is implementation of a standards-conformant C-CDA-to-FHIR transformation service capable of mapping discharge diagnoses, observations, medications, procedures, care plans, and follow-up requests into validated resource profiles. Terminology normalization should be enforced using consistent coding systems, while provenance information should be retained so clinicians can trace each model feature back to its source document section or FHIR resource. The prediction service should be integrated into discharge workflows through FHIR APIs, allowing calibrated readmission probabilities and transition-of-care risk categories to be surfaced within existing clinician interfaces rather than requiring separate applications. High-risk predictions should trigger configurable actions such as pharmacist medication reconciliation, nursing follow-up within 24–48 hours, specialist review, home-monitoring enrolment, social-support assessment, or unresolved-test reconciliation. The Transition-of-Care Risk Index should function as a prioritization mechanism rather than an autonomous decision-maker, with clinicians retaining authority to accept, modify, or override recommendations. Deployment should also include subgroup performance surveillance to detect calibration drift across age groups, diagnoses, care settings, and documentation patterns. Institutions should monitor AUROC, AUPRC, Brier score, expected calibration error, mapping completeness, false-negative rates, and intervention yield at predefined intervals. FHIR validation failures, missing resources, inconsistent coding, and documentation gaps should be logged because they can directly affect model reliability. Finally, clinical governance committees should establish thresholds for high-risk alerts, escalation pathways, audit requirements, and periodic model recalibration so predictive performance remains aligned with local patient populations and transitional-care capacity.

- *Limitations and Directions for Future Research*

Several limitations should be considered when interpreting the proposed framework and planning subsequent investigations. First, the current study focuses on

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prediction of 30-day readmission, which may not capture clinically relevant events occurring beyond this interval or distinguish avoidable from unavoidable readmissions. Future work should therefore evaluate multiple horizons, including 7-day, 14-day, 60-day, and 90-day outcomes, together with cause-specific readmission classification. Second, C-CDA discharge summaries vary considerably in completeness, section structure, terminology usage, and narrative quality across healthcare institutions. Although section-aware encoding and FHIR harmonization reduce this variability, incomplete or poorly structured documentation can still limit feature extraction. Future models should incorporate uncertainty estimates and explicit missingness modelling to distinguish absent documentation from true absence of a clinical condition. Third, external validation across geographically and technologically diverse healthcare systems is necessary before broad deployment. Differences in EHR vendors, patient populations, referral networks, and coding practices may affect calibration and transportability. Fourth, the proposed Transition-of-Care Risk Index requires prospective validation to determine whether its prioritization actually reduces readmissions, improves medication continuity, or accelerates follow-up. Randomized or stepped-wedge implementation studies would provide stronger evidence than retrospective prediction alone. Future research should also investigate federated learning for privacy-preserving multi-institution training, dynamic updating using post-discharge remote-monitoring data, and causal modelling to separate predictive association from modifiable risk. Additional development should explore richer explainability methods linking model output to specific C-CDA sentences and FHIR resources, fairness-aware calibration, uncertainty quantification, and resource-sensitive intervention optimization. These directions would strengthen the framework's ability to function as a clinically robust, interoperable, and continuously adaptive transitional-care intelligence system.

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