Predicting Hospital-Acquired Infection Risk Through Integration of Nursing Assessments Patient Care Activities and Longitudinal Electronic Health Record Data

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Abstract
Hospital-acquired infections (HAIs) remain a major patient-safety challenge because infection risk develops dynamically from interactions among patient vulnerability, clinical interventions, nursing observations, device exposure, medication use, mobility status, hygiene-related care activities, and evolving physiological abnormalities. Conventional HAI prediction approaches frequently depend on static demographic variables, diagnosis codes, laboratory results, or isolated clinical measurements, thereby underutilizing the temporal and contextual information contained in nursing assessments and patient-care activities. This study proposes a novel NurseCare Infection Risk Temporal Fusion Network (NCIR-TFN) for early prediction of hospital-acquired infection through integrated analysis of nursing assessments, patient-care activities, and longitudinal electronic health record data. The proposed framework combines temporal feature encoding, transformer-based longitudinal representation learning, gated attention, clinical-event embeddings, missingness-aware feature processing, and dynamic risk calibration to model changing infection susceptibility throughout hospitalization. Structured nursing observations including skin integrity, consciousness, mobility, continence, wound condition, nutrition, temperature, device status, and infection-related assessment findings are synchronized with care activities such as catheter management, vascular-line care, wound dressing, repositioning, hygiene interventions, medication administration, and invasive procedures. These variables are integrated with laboratory measurements, vital signs, comorbidities, medication histories, and encounter-level EHR trajectories. NCIR-TFN is comparatively evaluated against Logistic Regression, Random Forest, XGBoost, Long Short-Term Memory networks, and conventional Transformer-based prediction models using AUROC, AUPRC, sensitivity, specificity, F1-score, calibration error, false-negative rate, and prediction lead time. Comparative graphs, receiver-operating characteristic curves, precision-recall plots, calibration plots, temporal risk trajectories, feature-attribution charts, and ablation analyses are used to evaluate predictive and clinical performance. The proposed model is designed to provide superior discrimination and earlier risk identification by explicitly capturing interactions between nursing-care processes and changing patient states that are often absent from existing prediction systems. The resulting framework supports continuous HAI surveillance, interpretable early-warning generation, targeted preventive nursing intervention, and data-driven infection-control decision support within hospital electronic health record environments.

Keywords: Hospital-acquired infection, Nursing assessments, Patient care activities, Longitudinal electronic health records, Risk prediction

1. Introduction

1.1. Background to Hospital-Acquired Infections and Patient Safety

Hospital-acquired infections (HAIs) are infections that emerge during the delivery of healthcare and are not evident at admission. They include device-associated urinary tract and bloodstream infections, hospital-acquired pneumonia, surgical-site infections, and other infections linked to invasive care. Their significance extends beyond microbiological diagnosis because they represent failures at the intersection of host vulnerability, exposure intensity, infection-prevention practice, and timely recognition.

Contemporary infection practice increasingly relies on artificial intelligence to detect subtle combinations of clinical signals that precede overt infection (Theodosiou & Read, 2023). At the same time, automated surveillance must preserve clinical relevance and case-definition fidelity because poorly specified electronic rules can distort HAI measurement (van Mourik *et al.*, 2018). Within this study, patient safety is therefore treated as a dynamic risk-management problem in which infection risk evolves as the patient's physiological condition and care pathway change.

The proposed NCIR-TFN framework operationalizes this perspective by integrating nursing assessments, patient-care activities, and longitudinal EHR data into a unified temporal representation. Nursing documentation captures bedside changes such as altered skin integrity, reduced mobility, wound deterioration, fever, continence problems, and device-related observations, while EHR streams provide laboratories, vital signs, medication exposure, diagnoses, and procedure history. The need to combine distributed clinical information without weakening confidentiality is consistent with privacy-preserving predictive architectures described by Atalor (2019), while multi-source computational integration has likewise been used to expose complex interactions that are obscured when data domains are analyzed separately (Imoh & Idoko, 2022). NCIR-TFN extends these principles to HAI risk by modeling not only what clinical abnormalities are present, but when they arise relative to care events. This temporal emphasis directly supports later comparative analyses of discrimination, calibration, sensitivity, false-negative reduction, and actionable prediction lead time.

1.2. Clinical and Economic Burden of Hospital-Acquired Infections

The clinical burden of HAIs is expressed through excess morbidity, prolonged hospitalization, antimicrobial exposure, readmission, critical-care utilization, functional decline, and preventable mortality. Economic consequences arise because infection adds diagnostic testing, microbiology, imaging, isolation, pharmaceuticals, staff time, procedures, and additional bed-days to an already resource-intensive admission. Badia *et al*. (2017) found that surgical-site infections consistently increase healthcare costs and are associated with reoperation, readmission, prolonged hospitalization, and adverse quality-of-life outcomes. Similarly, Smith *et al*. (2019) demonstrated that urinary-catheter-associated infections generate substantial direct hospital costs and quality-adjusted life-year losses, particularly when catheter-associated bloodstream infection occurs. These findings justify treating early HAI prediction not simply as a classification exercise but as a patient-safety and resource-allocation mechanism in which earlier recognition may enable targeted prevention before infection becomes clinically established. For NCIR-TFN, this burden has important implications for model design and evaluation. A prediction system that improves AUROC but triggers excessive false positives could increase unnecessary cultures, antibiotic exposure, isolation, and nursing workload, whereas a model with poor sensitivity could miss patients who would benefit from earlier catheter review, wound reassessment, line-care intervention, or diagnostic escalation. The data-observability principles described by Amebleh and Omachi (2022), particularly continuous monitoring and early anomaly detection, are transferable to the need for detecting changes in patient-state trajectories before operational failure becomes evident. Atalor (2022) similarly illustrates the value of traceable, interoperable information infrastructures for safety surveillance, although in pharmacovigilance rather than HAI prediction. Accordingly, the present study evaluates NCIR-TFN against Logistic Regression, Random Forest, XGBoost, LSTM, and conventional Transformer models using sensitivity, specificity, F1-score, AUPRC, calibration error, false-negative rate, and lead time, thereby linking technical performance to clinically and economically meaningful infection-prevention decisions in routine hospital clinical practice.

1.3. Nursing Assessments as Indicators of Emerging Infection Risk

Nursing assessments provide a high-frequency account of patient status that differs from episodic laboratory or physician-generated data. Bedside nurses document temperature, respiratory pattern, consciousness, pain, mobility, continence, skin condition, wound appearance, nutritional status, device integrity, drainage, and functional dependence. These observations can reveal clinically coherent signals before diagnostic thresholds for infection are reached. Peng *et al*. (2020) showed that electronic medical record information can support nursing risk warning and reduce selected nursing-risk events, demonstrating the value of converting routinely documented clinical information into anticipatory decision support. More broadly, Churpek *et al*. (2016) found that machine-learning approaches can improve prediction of ward deterioration compared with conventional regression and commonly used early-warning scores, supporting nonlinear analysis of repeated physiological observations rather than dependence on isolated thresholds. Within NCIR-TFN, nursing assessment variables are encoded as time-stamped clinical states rather than static covariates. Repeated documentation of worsening wound exudate, new confusion, declining mobility, increasing oxygen requirement, or changes around an indwelling catheter can therefore alter the patient's risk trajectory even before culture results become available. Human–AI collaboration is critical because prediction should augment rather than replace professional judgment; Anokwuru *et al*. (2022) emphasize cognitive augmentation in decision systems, a principle directly applicable to presenting interpretable HAI risk signals to nurses and infection-control teams. Idika (2022), although focused on wearable medical-device security, also highlights the importance of trustworthy acquisition and protection of patient-generated clinical data. The proposed model therefore couples gated temporal attention with feature attribution so that elevated risk can be linked to recognizable nursing findings. Subsequent comparative results are designed to test whether incorporating these assessment streams improves sensitivity, calibration, and early-warning lead time relative to models trained primarily on conventional EHR variables.

1.4. Influence of Patient Care Activities and Clinical Interventions on Infection Development

Patient-care activities modify infection risk because many HAIs arise from interactions between vulnerable patients and clinical interventions. Urinary catheterization, vascular

access, mechanical ventilation, wound manipulation, surgery, hygiene care, and device maintenance create time-dependent exposure patterns that cannot be represented adequately by a single admission-level variable. Saint *et al*. (2016) demonstrated that a multicomponent program emphasizing appropriate catheter use, aseptic insertion, maintenance, and socioadaptive practice reduced catheter-associated urinary tract infection rates in non-ICU settings. Wills *et al*. (2020), examining surgical-site infection prevention practices, showed that not every customary intervention produces measurable benefit, reinforcing the need to distinguish meaningful care exposures from weak proxies. For predictive modeling, the relevant question is therefore not merely whether an intervention occurred, but its timing, duration, repetition, context, and relationship to subsequent physiological deterioration.

NCIR-TFN represents care activities as temporally ordered event embeddings that are synchronized with nursing observations and EHR measurements. Thus, catheter insertion followed by prolonged dwell time, abnormal urine characteristics, fever, and rising inflammatory markers forms a different risk pattern from catheter insertion followed by removal and stable assessments. Similar logic applies to central-line care, wound dressing, ventilator exposure, and antimicrobial administration. Kwarteng *et al*. (2021) demonstrate the broader value of data-driven frameworks for coordinating distributed operational processes, which is relevant to representing care pathways as analyzable sequences rather than disconnected documentation. Kwarteng *et al*. (2020) additionally emphasize access control and security as requirements for organizational information systems, an important consideration when integrating nursing and procedural data. In the proposed evaluation, ablation analysis will quantify the incremental contribution of care-activity features, while attention visualization will identify which interventions and temporal combinations influence predicted HAI risk, allowing performance gains to be interpreted clinically.

1.5. Longitudinal Electronic Health Record Data for Dynamic Infection Surveillance

Longitudinal EHR data provide the temporal basis for distinguishing transient abnormalities from sustained trajectories indicating rising infection risk. A hospital record may contain thousands of observations spanning diagnoses, medications, microbiology, laboratory tests, vital signs, procedures, device exposure, nursing documentation, and clinical notes. Rajkomar *et al*. (2018) demonstrated that deep learning can process raw EHR sequences and outperform traditional models across several inpatient prediction tasks, showing that useful information is distributed across the full record rather than confined to selected variables. Tomašev *et al*. (2019) similarly showed that continuously updated longitudinal EHR models can predict future acute deterioration while providing sufficient lead time for action. These findings are relevant to HAI prediction because infection is typically preceded by evolving combinations of host, treatment, device, and physiological signals rather than a single definitive precursor.

NCIR-TFN therefore organizes each admission as a sequence of synchronized clinical windows in which static attributes are combined with dynamically changing observations. Time gaps, missingness patterns, recency, measurements, medication exposure, and care events are preserved rather than collapsed into one summary row. Idika *et al*. (2021) illustrate how learning systems can classify complex patterns in distributed, cloud-native environments, offering a transferable computational rationale for scalable processing of heterogeneous hospital data. Ijiga *et al*. (2022), although working in digital learning, emphasize AI performance under constrained information environments; the analogous challenge in EHR analytics is maintaining robust inference despite irregular sampling and incomplete documentation. The proposed architecture addresses this through missingness-aware encoding, temporal attention, and gated fusion of nursing, care-activity, and conventional EHR channels. Comparative analysis will examine whether this longitudinal integration improves AUPRC, calibration, and lead-time performance beyond static Logistic Regression, tree-based models, LSTM, and a conventional Transformer baseline.

1.6. Limitations of Conventional Hospital-Acquired Infection Risk Prediction Approaches

Conventional HAI prediction approaches often rely on manually selected variables, administrative codes, microbiology results, static risk scores, or snapshot laboratory measurements. Such approaches may perform for retrospective discrimination yet remain weak for prospective bedside use when risk changes rapidly, data are missing nonrandomly, or important care-process information is embedded in narrative and nursing documentation. Aliabadi *et al*. (2020) identified data quality, interoperability, standardization, timeliness, privacy, and generalizability as challenges in EHR-based surveillance systems. Van Calster *et al*. (2019) further emphasized that good discrimination does not guarantee reliable individual risk estimates; miscalibrated models can systematically overestimate or underestimate risk even when AUROC appears acceptable. These limitations are important in HAI prediction, where alert thresholds influence cultures, antimicrobial decisions, infection-control precautions, and bedside reassessment.

A second limitation is representational. Static models often treat catheter presence, wound status, mobility, fever, antibiotic exposure, and laboratory abnormalities as independent covariates even though their order and interaction determine clinical meaning. They may also underuse nursing observations and care activities because these data are irregular, institution-specific, or semistructured. Ijiga *et al*. (2021a) show, in a different application domain, that systems designed for heterogeneous users require context-sensitive rather than one-size-fits-all representation; this design principle is relevant to clinical prediction across diverse wards and patient groups. Ijiga *et al*. (2021b) similarly illustrates the value of integrating multiple information modalities to improve engagement with complex content, a transferable rationale for combining heterogeneous clinical streams rather than relying on one data source. NCIR-TFN addresses these gaps through temporal fusion,

missingness-aware encoding, dynamic calibration, and feature-level explainability. Its evaluation therefore emphasizes not only AUROC, but AUPRC, sensitivity, specificity, false-negative rate, calibration error, subgroup stability, ablation effects, and clinically useful warning lead time.

1.7. Research Motivation and Development of the NCIR-TFN Predictive Framework

The motivation for NCIR-TFN arises from a mismatch between clinical HAI development and its computational representation. Infection risk is inherently multivariate and sequential: vulnerability changes with illness severity; exposure accumulates through devices and procedures; nursing observations register evolving bedside abnormalities; medications alter host and microbial conditions; and laboratory signals often become definitive only after risk has already increased. Baddal *et al*. (2024) note that artificial intelligence has potential across infection diagnosis, surveillance, and decision support, while also highlighting concerns regarding methodological heterogeneity, transparency, bias, and real-world validation. Collins *et al*. (2024) similarly stress transparent reporting, appropriate evaluation data, and complete assessment of prediction models using regression or machine-learning methods. These requirements shape the study design by making interpretability, calibration, temporal validation, and comparative benchmarking integral to model development rather than optional reporting additions. NCIR-TFN is consequently designed as a multimodal temporal-fusion architecture with separate encoders for nursing assessments, patient-care activities, and longitudinal EHR variables, followed by gated attention that estimates their context-specific contribution to evolving HAI risk. Atalor *et al*. (2023), although addressing quantum molecular simulation, exemplify the broader movement toward computational models that extract decision-relevant structure from complex biomedical spaces; NCIR-TFN applies that computational ambition to bedside infection-risk trajectories. Ajayi *et al*. (2019), from a legal-governance domain, is relevant only at the level of accountability: automated recommendations require defined responsibility and operational rules before they can influence consequential decisions. Accordingly, the proposed framework includes interpretable risk trajectories and feature attribution rather than opaque alerts. Its comparative experiments are structured to determine whether nursing and care-process integration yields measurable gains over Logistic Regression, Random Forest, XGBoost, LSTM, and conventional Transformer baselines, particularly in false-negative reduction, calibration, and prediction lead time.

1.8. Research Objectives and Research Questions

Research Objectives

1. To develop the NurseCare Infection Risk Temporal Fusion Network (NCIR-TFN) for predicting hospital-acquired infection risk through the integrated analysis of nursing assessments, patient-care activities, and longitudinal electronic health record data.
2. To determine the predictive contribution of nursing assessment variables, including skin integrity, wound status, mobility, continence, consciousness, temperature-related observations, respiratory status, nutritional condition, and device-related findings, to early HAI risk identification.
3. To quantify the influence of temporally encoded patient-care activities, including catheterization, vascular-line management, wound care, hygiene interventions, invasive procedures, medication administration, device maintenance, and related clinical exposures, on dynamic HAI risk.
4. To compare the predictive performance of NCIR-TFN with Logistic Regression, Random Forest, XGBoost, LSTM, and a conventional Transformer using AUROC, AUPRC, sensitivity, specificity, F1-score, false-negative rate, calibration error, and prediction lead time.
5. To evaluate the interpretability, calibration, temporal stability, subgroup performance, and potential clinical utility of NCIR-TFN for early infection-prevention decision support.

Research Questions

1. **RQ1:** To what extent does integration of nursing assessments, patient-care activities, and longitudinal EHR data improve prediction of hospital-acquired infection risk compared with models based predominantly on conventional EHR variables?
2. **RQ2:** Which nursing assessment features and temporal changes contribute most strongly to the early prediction of hospital-acquired infection?
3. **RQ3:** To what extent do the type, frequency, timing, duration, and sequence of patient-care activities influence predicted HAI risk within the NCIR-TFN framework?
4. **RQ4:** How does NCIR-TFN perform relative to Logistic Regression, Random Forest, XGBoost, LSTM, and conventional Transformer models across discrimination, calibration, sensitivity, specificity, false-negative rate, AUPRC, and prediction lead time?
5. **RQ5:** How effectively can NCIR-TFN generate interpretable and clinically actionable patient-level risk trajectories that support earlier nursing assessment, infection-control review, and targeted preventive intervention?

1.9. Contributions and Significance of the Study

This study contributes a clinically oriented artificial-intelligence framework that treats HAI risk as a continuously evolving state generated by interactions among patient vulnerability, bedside nursing observations, care-process exposures, and longitudinal physiological change. Its principal methodological contribution is NCIR-TFN, a multimodal temporal-fusion architecture that preserves the distinct information contained in nursing assessments, patient-care activities, and conventional EHR variables before integrating these streams through gated temporal attention. Unlike approaches that reduce hospitalization to static admission-level predictors, the framework explicitly represents event timing, duration, recency, missingness, repeated observations, device exposure, and changing care states. The study also contributes a comparative evaluation strategy in which NCIR-TFN is benchmarked against Logistic Regression, Random Forest, XGBoost, LSTM, and

conventional Transformer architectures using metrics that reflect both statistical accuracy and bedside consequences. Particular attention is given to AUPRC, sensitivity, false-negative reduction, calibration, and warning lead time because HAI datasets are commonly imbalanced and clinically valuable prediction depends on detecting high-risk patients early enough for intervention. Feature attribution, temporal attention analysis, subgroup assessment, and ablation experiments further establish whether observed performance gains arise from meaningful nursing and care-process information. Clinically, the framework has potential to transform routinely documented nursing and EHR data from retrospective records into prospective infection-prevention intelligence capable of supporting catheter review, wound reassessment, device management, diagnostic escalation, antimicrobial stewardship, and infection-control prioritization.

1.10. Scope of the Review and Structure of the Paper

The study focuses on predictive identification of hospital-acquired infection risk during inpatient care through computational integration of structured and temporally ordered nursing assessments, patient-care activities, and longitudinal EHR data. The analytical scope covers clinically relevant infection-related outcomes such as catheter-associated urinary tract infection, central-line or healthcare-associated bloodstream infection, hospital-acquired pneumonia, surgical-site infection, and related healthcare-associated infectious complications where sufficient temporal documentation is available. Predictor domains include demographics and baseline clinical characteristics, comorbidities, laboratory measurements, vital signs, medication exposure, device utilization, procedures, nursing observations, wound and skin assessments, mobility and functional status, hygiene-related care, device maintenance, and other documented clinical interventions. The paper is organized into five principal sections. Section 1 establishes the clinical problem, motivation, research objectives, questions, contributions, and study scope. Section 2 synthesizes the literature on HAI surveillance, nursing information, care-process exposures, longitudinal EHR analytics, and machine-learning approaches. Section 3 presents the integrated data model, preprocessing pipeline, temporal synchronization procedures, NCIR-TFN mathematical formulation, training strategy, calibration, explainability, and validation framework. Section 4 reports and discusses comparative predictive performance, temporal risk trajectories, lead-time analysis, feature attribution, ablation experiments, calibration, and clinical implications. Section 5 synthesizes the principal findings, recommendations, limitations, implementation considerations, and directions for external validation and real-time hospital deployment.

2. Literature Review

2.1. Hospital-Acquired Infection Surveillance and Clinical Risk Factors

Hospital-acquired infection surveillance requires more than retrospective counting of culture-confirmed events because clinically meaningful risk emerges from the interaction of host vulnerability, invasive exposure, antimicrobial pressure, care setting, and time. Large point-prevalence work by Magill *et al*. (2018) showed that HAIs remained common across U.S. hospitals, with pneumonia, gastrointestinal infection, surgical-site infection, and bloodstream infection forming major components of the burden as shown in table 1. Cassini *et al*. (2019) further demonstrated that antibiotic-resistant infections contribute substantial mortality and disability, with most resistant infections in their European analysis associated with healthcare exposure. These findings support surveillance architectures that continuously characterize risk rather than depend solely on final diagnostic coding. In the present study, baseline age, comorbidity, admission source, immune status, recent surgery, antimicrobial exposure, intensive-care stay, indwelling devices, wound status, and prior colonization are therefore treated as dynamic clinical risk determinants rather than isolated descriptors.

Effective surveillance also depends on whether heterogeneous information can be exchanged, audited, and interpreted across clinical systems. Nwokocha *et al*. (2021a) position FHIR-driven interoperability as an important mechanism for secure health-data exchange, a principle directly relevant to linking nursing assessments, laboratory results, medication administrations, procedures, and device records within NCIR-TFN. Frimpong *et al*. (2023) illustrate how AI-enabled automation can strengthen monitoring and audit readiness in healthcare information environments, while Onyekaonwu (2023) emphasizes structured AI-supported horizon scanning for synthesizing distributed health information. Applied cautiously to HAI surveillance, these systems concepts justify a temporally synchronized data layer in which infection-related events are traceable to source, time, and clinical context. NCIR-TFN consequently models surveillance as repeated risk estimation, enabling later comparison of AUROC, AUPRC, calibration, false-negative rate, and warning lead time against conventional static models during every clinically relevant window of the hospitalization.

Table 1: Summary of Hospital-Acquired Infection Surveillance and Clinical Risk Factors

Surveillance/Risk Domain	Key Variables or Indicators	Relevance to HAI Risk Prediction	Application in NCIR-TFN Framework
Patient Clinical Susceptibility	Age, comorbidities, immune status, nutritional condition, previous infection, admission source, illness severity	Establishes baseline vulnerability to infection and influences the probability that subsequent exposures will progress to HAI	Encoded as baseline and longitudinal patient-state features used to contextualize dynamic infection-risk estimates
Invasive Device Exposure	Urinary catheters, central venous lines, mechanical ventilation, drains, vascular access devices, device dwell time	Prolonged or repeated device exposure increases opportunities for microbial entry, colonization, and device-associated infection	Represented as time-stamped care events incorporating insertion, duration, manipulation, maintenance, and removal
Physiological and Laboratory Surveillance	Temperature, respiratory rate, heart rate, leukocyte count, inflammatory markers, microbiology findings, renal parameters	Detects emerging physiological abnormalities and infection-associated deterioration before definitive diagnostic confirmation	Integrated as longitudinal EHR trajectories with temporal recency, missingness indicators, and attention-based weighting
Nursing and Care-Process Surveillance	Wound condition, skin integrity, mobility, continence, hygiene care, catheter care, line-site assessment, drainage characteristics	Provides high-frequency bedside evidence of early deterioration, local infection signs, and modifiable care-related risk	Processed through the nursing-assessment and care-activity encoders to strengthen early-warning sensitivity and interpretability
Automated HAI Surveillance and Risk Stratification	Continuous risk scores, temporal event patterns, interoperability, alert thresholds, false-negative monitoring, calibration	Supports earlier identification of high-risk patients and prioritization of infection-prevention interventions	NCIR-TFN fuses nursing, care-activity, and longitudinal EHR data to generate calibrated patient-level HAI risk trajectories and early-warning alerts

2.2. Nursing Assessment Data and Patient Deterioration Detection

Nursing assessment data are valuable for early deterioration detection because nurses repeatedly observe physiological and functional changes that may precede diagnostic confirmation of infection. Variables such as temperature trend, respiratory rate, oxygen requirement, mental status, pain, mobility, continence, nutritional intake, skin integrity, wound appearance, drainage, and device-site condition provide a temporally dense description of patient state. Gerry *et al*. (2020) showed that conventional early-warning scores commonly rely on a restricted set of physiological variables and often suffer from methodological weaknesses involving missing data, calibration, and validation as shown in figure 1. Escobar *et al*. (2020) demonstrated that automated EHR-based risk identification combined with nurse review and rapid-response escalation can support earlier recognition of in-hospital deterioration. These findings motivate this study to move beyond threshold-based scoring by treating nursing observations as longitudinal signals whose direction, persistence, co-occurrence, and temporal proximity to infection-related events can influence the predicted HAI trajectory.

The NCIR-TFN architecture therefore encodes repeated nursing assessments together with their timestamps, missingness patterns, and contextual care events. Atalor *et al*. (2023) demonstrate the feasibility of integrating wearable biosensor streams for longitudinal monitoring, providing a transferable basis for incorporating continuously generated physiological information alongside bedside documentation. Onyekaonwu *et al*. (2019) similarly illustrate the use of AI/ML for predictive medication-related safety monitoring, supporting the principle of anticipatory analysis of evolving clinical data. From a human-centered systems perspective, Onwuzurike (2023) emphasizes behavioral analytics and interpretable design, which informs how NCIR-TFN risk outputs should be presented to nurses without displacing judgment. Feature-attribution and temporal-attention analyses will therefore identify whether, for example, progressive wound deterioration, new confusion, fever, reduced mobility, and increasing oxygen requirement raise HAI risk before culture confirmation, while ablation experiments will quantify the incremental contribution of nursing data.

Figure 1 illustrates how structured nursing assessment data can be transformed into an early-warning mechanism for detecting patient deterioration and emerging hospital-acquired infection risk. The first major branch, Nursing Assessment Data, captures high-frequency bedside information that is often unavailable in conventional static risk models. Physiological and vital-sign assessments track temperature, respiratory rate, oxygen requirement, cardiovascular changes, and consciousness level, while functional and mobility assessments identify declining activity tolerance, dependence, and mobility-related vulnerability. Skin, wound, and device-site assessments provide direct evidence of local infection-related abnormalities such as erythema, swelling, drainage, impaired tissue integrity, or catheter-site changes. Nutrition, elimination, hydration, pain, fatigue, and general clinical status add further context regarding systemic deterioration and host resilience. The second major branch, Patient Deterioration Detection, describes how these repeated observations are converted into actionable predictive intelligence. Temporal change detection identifies persistent abnormalities and deviations from baseline; AI-based risk recognition uses the NCIR-TFN framework to encode sequential observations, assign attention weights to clinically relevant features, and update patient-level HAI risk dynamically. When risk rises, early-warning and escalation pathways support prompt nursing reassessment and infection-control review, while the final decision-response branch links prediction to preventive actions such as catheter review, wound reassessment, diagnostic investigation, and targeted infection-prevention intervention. Together, the diagram emphasizes that deterioration detection depends not on isolated observations, but on the timing, persistence, interaction, and clinical context of nursing data.

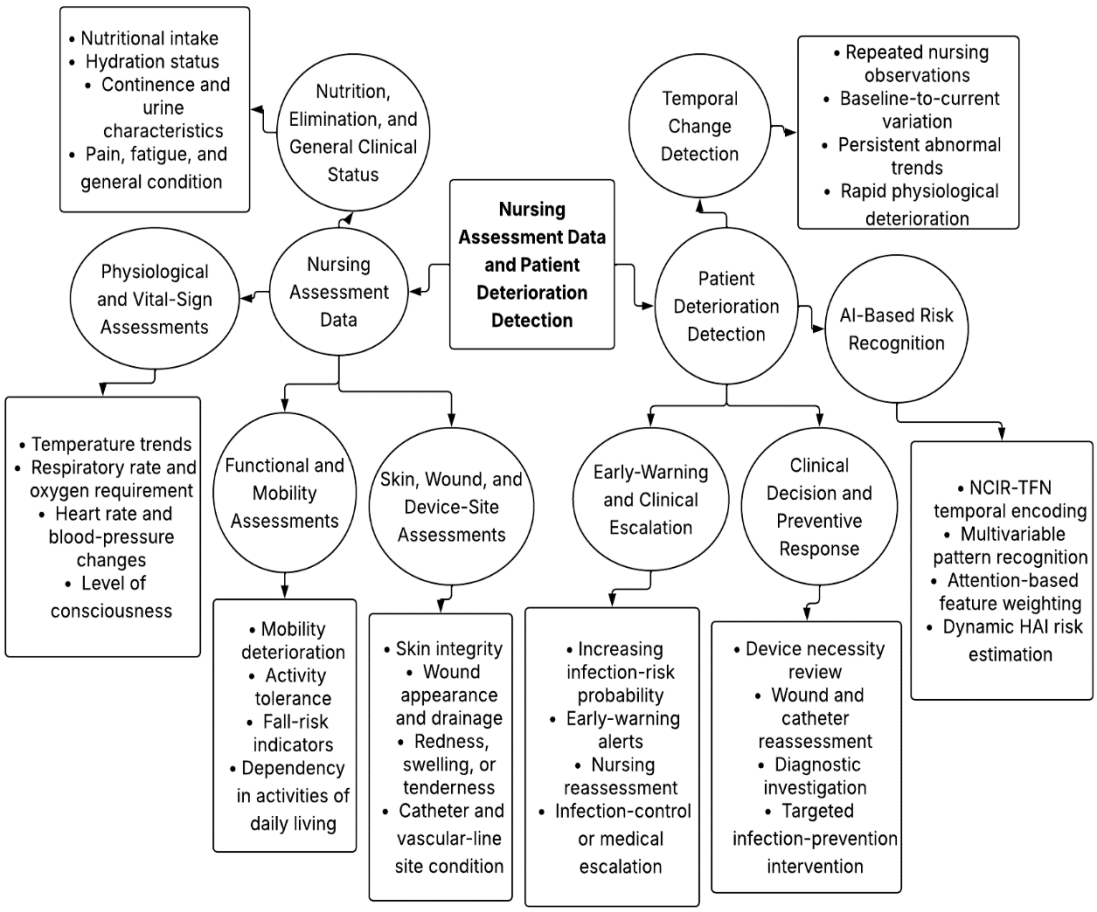

Fig 1: Nursing Assessment Data Pathway for Temporal Patient Deterioration Detection and Early HAI Risk Recognition.

2.3. Patient Care Activities, Device Exposure, and Infection Risk

Patient care activities can modify pathways through which hospital-acquired infections develop. Central venous catheters, urinary catheters, mechanical ventilation, surgery, wound manipulation, vascular access, and invasive procedures increase exposure to microbial entry points, while maintenance quality, device duration, aseptic technique, and timely removal alter risk. Buetti *et al.* (2022) emphasize practices for preventing central line-associated bloodstream infection, including appropriate indication, insertion precautions, maintenance and prompt device removal as shown in figure 2. Meddings *et al.* (2019) describe a tiered approach to catheter-associated urinary tract infection prevention that prioritizes avoiding unnecessary catheterization, improving insertion and maintenance practices, and reducing catheter duration. For predictive modeling, these findings imply that device exposure should not be encoded as a binary variable; cumulative dwell time, manipulations, replacement episodes, care omissions, and temporal coupling with physiological change are clinically more informative.

NCIR-TFN therefore represents care activities as timestamped event sequences aligned with nursing assessments and longitudinal EHR measurements. Nwokocha *et al.* (2021b) describe agile health-information integration and clinical data-platform adoption, supporting the systems requirement for joining care events into an analyzable workflow. Anokwuru and Okoh (2023) examine operational considerations in healthcare-technology design, which is relevant to building predictive tools that fit clinical workflows rather than create documentation burden. Ononiwu *et al.* (2023), although focused on secure remote engineering, provide architectural principles involving modular microservices and controlled deployment that can support scalable processing of event-rich hospital data. Within NCIR-TFN, catheter insertion followed by prolonged dwell time, repeated line access, abnormal device-site observations, fever, and rising inflammatory markers should generate a different risk representation from an uncomplicated short exposure. Ablation and attention analyses will test whether care-activity encoding measurably improves sensitivity, calibration, false-negative reduction, and lead time beyond models using conventional patient variables alone.

Fig 2: Patient Care Activities, Device Exposure, and Associated Hospital-Acquired Infection Risk During Inpatient Clinical Management (Cairntechnology, 2023)

Figure 2 depicts an acutely ill hospitalized patient receiving intensive bedside care from a multidisciplinary clinical team, illustrating how patient-care activities and exposure to invasive or semi-invasive devices can materially influence hospital-acquired infection risk. The patient is connected to multiple monitoring and therapeutic interfaces, including adhesive electrocardiographic electrodes, a noninvasive blood-pressure cuff, oxygen-delivery tubing, monitoring leads, and other bedside equipment, while clinicians simultaneously perform physical assessment, respiratory support, documentation, and device management. From an HAI perspective, each additional device or care interaction increases the number of contact points through which microorganisms may be transferred if hand hygiene, aseptic technique, environmental disinfection, or device-maintenance procedures are inadequate. Repeated handling of vascular access points, respiratory interfaces, dressings, tubing, monitoring sensors, and bedspace equipment can increase cumulative exposure, particularly when devices remain in place for prolonged periods or require frequent manipulation. The scene also demonstrates why infection prediction should consider duration, frequency, sequence, and context of care activities, rather than simply recording whether a device was present. For example, repeated respiratory interventions combined with declining oxygenation, fever, altered respiratory findings, and prolonged device exposure could indicate increasing risk of hospital-acquired pneumonia, while persistent vascular access accompanied by local skin changes, temperature elevation, or abnormal inflammatory markers may signal evolving bloodstream infection risk. Within the proposed NCIR-TFN framework, these bedside activities would be encoded as time-stamped clinical events and integrated with nursing assessments and longitudinal EHR measurements, allowing the model to detect clinically meaningful interaction patterns and generate earlier, more interpretable HAI risk trajectories.

2.4. Longitudinal Electronic Health Record Analytics for Clinical Prediction

Longitudinal electronic health record analytics transforms hospital-acquired infection prediction from a static admission-level task into continuous estimation of changing patient susceptibility. Repeated vital signs, laboratory values, medications, diagnoses, procedures, microbiology, device records, nursing observations, and location histories encode trajectories that may precede overt infection as shown in figure 3. Carrasco-Ribelles *et al*. (2023) found that longitudinal EHR prediction studies increasingly employ recurrent architectures, attention mechanisms, and transformers, while also identifying substantial heterogeneity in validation and reporting. Rasmy *et al*. (2021) demonstrated that contextualized representations learned from large structured EHR repositories can improve downstream disease prediction, particularly when local labeled datasets are limited. These findings support NCIR-TFN's use of time-indexed clinical windows, recency encoding, missingness indicators, and attention-based temporal fusion rather than collapsing hospitalization into averaged or last-observation features. For HAI surveillance, temporal context is clinically decisive: a rising temperature after central-line manipulation, worsening wound documentation after surgery, or leukocytosis following prolonged catheter exposure has a different meaning from the same measurement occurring without those antecedent events. Ijiga *et al*. (2024) emphasize collaborative healthcare delivery across providers, illustrating why clinically relevant information is often distributed across organizational and care interfaces. Enyejo

et al. (2024) likewise describe interacting neurological, behavioral, and substance-related conditions, reinforcing the general analytical need to represent co-occurring patient states rather than isolated variables. Outside healthcare, Ebika *et al*. (2024) show how machine learning and IoT streams can support predictive monitoring from evolving sensor data; the transferable principle is continuous state estimation from heterogeneous longitudinal signals. NCIR-TFN applies this principle clinically by synchronizing nursing assessments, care activities, and conventional EHR events, enabling risk trajectories that can be evaluated for discrimination, calibration, false-negative reduction, and actionable lead time before HAI confirmation at each prediction interval.

Figure 3 illustrates a longitudinal electronic health record analytics framework in which heterogeneous clinical information is transformed into temporally aware predictive intelligence for hospital-acquired infection and broader clinical-risk surveillance. The first branch, Longitudinal EHR Data Characteristics, represents the raw structure of inpatient information, including multidomain clinical data, irregular and asynchronous sampling, variable-length patient trajectories, and high-dimensional sparse records. These properties are important because nursing observations, laboratory values, medications, device events, and physiological measurements are documented at different frequencies and cannot be treated as uniformly sampled variables. The second branch, Analytical Approaches for EHR Time-Series Modeling, shows how these irregular data streams are converted into computable longitudinal representations through temporal feature engineering, explicit treatment of missing observations and unequal intervals, sequence-based deep learning, and attention mechanisms that assign greater importance to clinically relevant historical events. The third branch, Prediction Objectives and Clinical Tasks, translates the processed trajectories into outputs such as adverse-event risk prediction, early deterioration detection, time-to-event estimation, and patient risk prioritization. In the context of NCIR-TFN, these outputs correspond to continuously updated HAI probabilities and early-warning trajectories. The fourth branch, Integration, Implementation, and Clinical Impact, emphasizes interoperability, explainability, clinical decision-support integration, and continuous model monitoring. Together, the four branches demonstrate how longitudinal EHR analytics progresses from heterogeneous raw data through temporal modeling to clinically interpretable prediction and operational deployment.

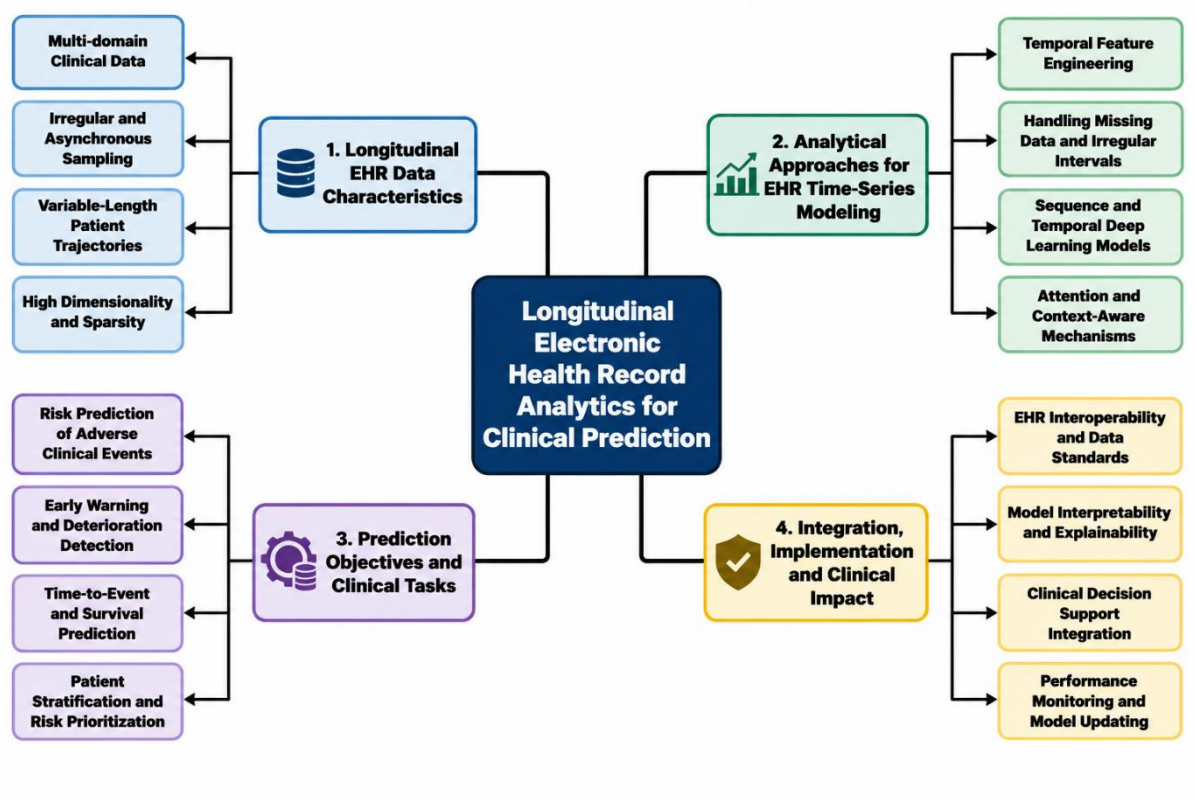

Fig 3: Longitudinal EHR Analytics Framework for Temporal Clinical Risk Prediction and Decision Support.

2.5. Machine Learning and Deep Learning Approaches for Hospital-Acquired Infection Prediction

Machine learning and deep learning approaches offer advantages for HAI prediction because infection risk is nonlinear, time-dependent, and generated by interactions among host factors, invasive devices, medications, care processes, and physiological change. Wiens and Shenoy (2018) described machine learning as valuable in healthcare epidemiology for patient risk stratification, identification of infection-related risk factors, and analysis of complex electronic health data as shown in figure 4. Barchitta *et al*. (2021) further demonstrated that an SVM incorporating characteristics and severity information could identify ICU patients at elevated HAI risk more accurately than SAPS II alone. These findings justify comparing NCIR-TFN with Logistic Regression, Random Forest, XGBoost, LSTM, and a conventional Transformer because each benchmark captures a different level of nonlinearity, temporal dependence, and representational complexity.

The present framework extends conventional prediction by

integrating nursing assessments and care activities with longitudinal EHR variables rather than relying mainly on admission features or isolated laboratory measurements. Ijiga *et al*. (2024) describe machine-learning applications for automated interpretation, disease detection, and prognosis, supporting computational feature learning in precision healthcare. D. O. Idoko *et al*. (2024) emphasize structured risk assessment for infectious-disease mitigation, relevant to prioritizing modifiable exposures such as device duration, hygiene failures, wound deterioration, and unsafe care conditions. P. I. Idoko *et al*. (2024) also illustrate, through systematic evaluation of diabetes-related risk, the importance of distinguishing interacting determinants rather than attributing outcomes to a single exposure. Within NCIR-TFN, gated attention assigns context-sensitive weights to nursing, care-process, and EHR channels, while class weighting and calibration address rare-event prediction. Comparative graphs will therefore examine AUROC, AUPRC, sensitivity, specificity, F1-score, calibration error, false-negative rate, and prediction lead time, allowing superiority to be judged on both statistical discrimination and clinically meaningful early-warning performance in practice. Figure 4 illustrates the practical application of machine learning and deep learning for hospital-acquired infection prediction within an intensive-care environment. At the bedside, the patient is continuously connected to physiological monitoring systems and therapeutic devices, while the clinician reviews an AI-enabled HAI prediction dashboard that synthesizes longitudinal EHR data, nursing assessments, laboratory results, vital-sign trends, medication exposure, and device-related variables. The upper workflow demonstrates the computational pipeline: raw clinical data are first collected, cleaned, normalized, temporally aligned, and transformed into predictive features before being processed by models such as XGBoost, LSTM, GRU, Transformer-based architectures, and the proposed NCIR-TFN framework. The dashboard then converts these heterogeneous inputs into a patient-specific infection-risk probability, temporal risk trajectory, and ranked contributing factors. In the illustrated case, central-line exposure, ventilator use, elevated white blood cell count, temperature abnormalities, and immune-status indicators are treated as interacting predictors rather than isolated variables. This reflects the principal advantage of advanced learning approaches over conventional static models: nonlinear interactions, sequential dependencies, and long-range temporal relationships can be learned directly from the evolving clinical record. Within NCIR-TFN, nursing observations and care activities are additionally fused through gated temporal attention, allowing the model to assign dynamic importance to bedside findings and intervention history. The resulting risk estimate can support earlier infection-control review, device reassessment, diagnostic escalation, and targeted preventive intervention before definitive HAI confirmation.

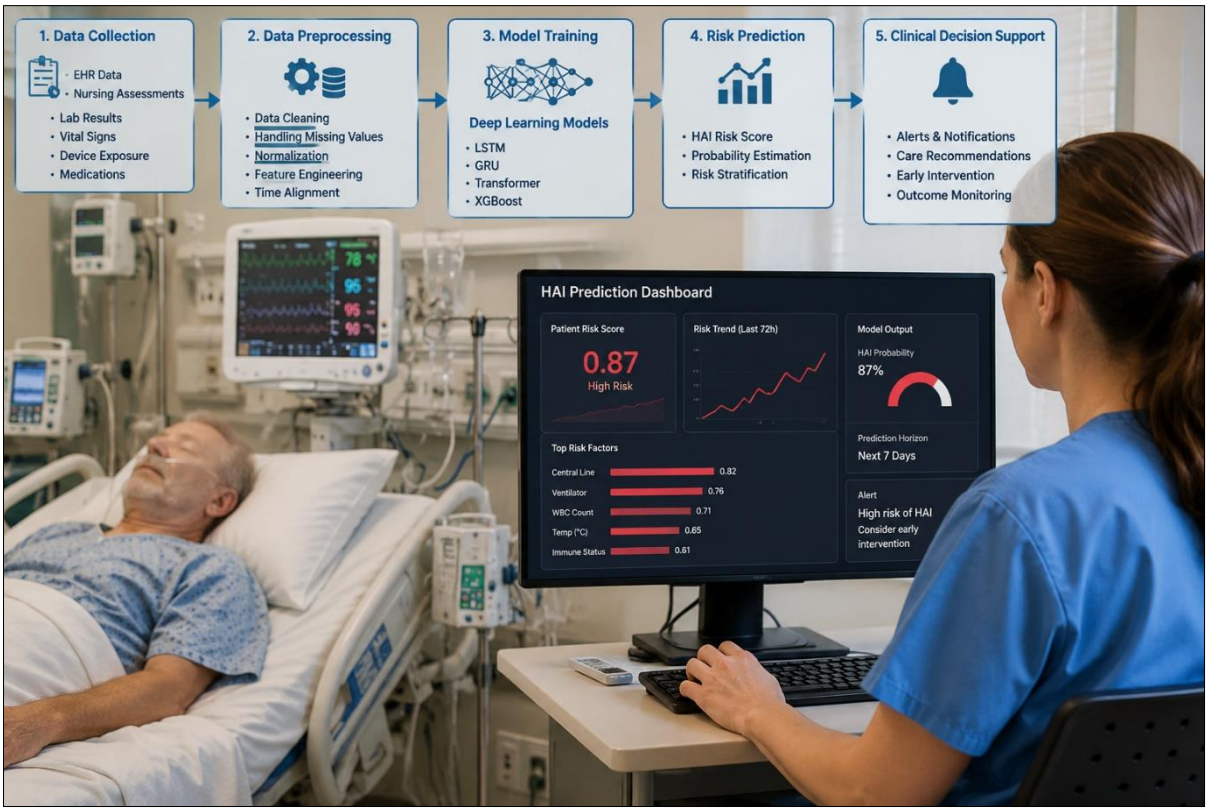

Fig 4: Machine Learning and Deep Learning Workflow for Real-Time Hospital-Acquired Infection Risk Prediction and Clinical Decision Support.

2.6. Research Gaps and Motivation for the Proposed NCIR-TFN Algorithm

Despite growing use of artificial intelligence in clinical prediction, gaps remain between technically successful models and systems that can support infection prevention at the bedside. Kelly *et al*. (2019) identified data quality, workflow integration, generalizability, regulation, and clinician adoption as major barriers to clinical AI impact, while Wiens *et al*. (2019) emphasized problem formulation, stakeholder engagement, validation, and post-deployment

monitoring for responsible machine learning. These concerns matter for HAI prediction because many existing studies use retrospective single-center datasets, static admission variables, limited infection phenotypes, and discrimination metrics without demonstrating calibration, temporal transportability, or actionable lead time. Models may therefore appear accurate while failing to identify when risk became modifiable or which care-process changes contributed to that risk. The proposed NCIR-TFN algorithm is motivated by these deficiencies and by fragmentation of bedside information across nursing documentation, care activities, laboratory systems, medications, and device records. Ijiga, Abutu, *et al*. (2024) highlight ethical concerns surrounding generative AI deployment in healthcare operations, reinforcing requirements for transparency, governance, privacy, and accountable human oversight. Balogun *et al*. (2024), although addressing psychological consequences of security-related threats, illustrates how risk outcomes are shaped by interacting contextual and human factors rather than isolated exposures. Similarly, Ijiga, Balogun, *et al*. (2024) examine multifactorial influences on youth mental-health risk, offering a transferable rationale for context-sensitive modeling while not constituting HAI evidence. NCIR-TFN responds by using modality-specific encoders, gated temporal fusion, missingness-aware representation, dynamic calibration, and feature attribution to estimate patient-level infection risk repeatedly during hospitalization. Its evaluation will include benchmark comparisons, ablation experiments, subgroup analyses, calibration plots, false-negative analysis, and warning-time distributions, testing robustly whether nursing and care-process integration produces earlier, better calibrated, and more interpretable HAI predictions than conventional algorithms.

3. System Model Description

3.1. Integrated Nursing Assessment, Patient Care Activity, and Longitudinal EHR Data Architecture

The proposed NurseCare Infection Risk Temporal Fusion Network (NCIR-TFN) is constructed as a multimodal longitudinal architecture in which each hospitalization is represented as three synchronized information streams: nursing assessments, patient-care activities, and conventional electronic health record variables. For patient i at clinical time window t, the multimodal input is defined as

$$\mathbf{X}_{i,t} = [\mathbf{N}_{i,t} \parallel \mathbf{C}_{i,t} \parallel \mathbf{E}_{i,t}] \tag{1}$$

where $N_{i,t}$ shows the nursing-assessment vector containing variables such as temperature observations, respiratory status, consciousness, mobility, continence, nutrition, wound condition, skin integrity, drainage characteristics, and device-site findings; $C_{i,t}$ represents patient-care activities including urinary catheter insertion/removal, central-line care, wound dressing, repositioning, hygiene care, medication administration, invasive procedures, and device manipulation; $E_{i,t}$ denotes longitudinal EHR information such as vital signs, laboratory values, diagnoses, medications, microbiology, demographics, and comorbidities; and $\parallel$ denotes vector concatenation.

Rather than predicting only whether an HAI eventually occurs, the framework estimates risk within a clinically actionable horizon H:

$$y_{i,t}^{(H)} = \mathbb{I}\left(T_i^{\mathrm{HAI}} > t \ \wedge \ T_i^{\mathrm{HAI}} \le t + H\right) \tag{2}$$

where $y_{i,t}^{(H)}$ captures the binary target at time t, T_i^{HAI} represents the first validated HAI onset time for patient i, H denotes the prediction horizon, and $I(\cdot)$ shows an indicator function returning 1 when the condition is satisfied and 0 otherwise. This prevents information recorded after infection onset from leaking into model training.

The architecture uses an event-driven longitudinal structure rather than reducing an admission to one static row. For example, a urinary catheter inserted at hour 12, maintained for several days, followed by altered urine appearance, rising temperature, leukocytosis, and declining mobility produces a temporally different representation from the same catheter exposure followed by stable observations and early removal. Such synchronization is consistent with longitudinal EHR modeling, where temporal context materially improves disease representation (Rasmy *et al*., 2021). The architecture therefore establishes the data foundation required for subsequent modality-specific encoding, gated fusion, ablation analysis, and patient-level risk trajectories.

3.2 Data Preprocessing, Temporal Synchronization, Feature Engineering, and Clinical Event Representation

NCIR-TFN requires preprocessing capable of preserving temporal information while controlling differences in scale, missingness, and recording frequency. Continuous measurements such as temperature, heart rate, leukocyte count, creatinine, and respiratory rate are standardized using training-set statistics:

$$z_{i,t,j} = \frac{x_{i,t,j} - \mu_j}{\sigma_j} \tag{3}$$

where $x_{i,t,j}$ denotes the observed value of feature j for patient i at time t, μ_j and σ_j are respectively the training-set mean and standard deviation of feature j, and $z_{i,t,j}$ is the standardized value. Statistics are estimated exclusively from training data to prevent information leakage.

Because missingness itself can be clinically informative, NCIR-TFN does not rely only on imputation. A missingness indicator is explicitly generated:

$$m_{i,t,j} = \begin{cases} 1, & x_{i,t,j} \text{ is observed,} \\ 0, & x_{i,t,j} \text{ is missing.} \end{cases} \tag{4}$$

where $m_{i,t,j}$ equals 1 when feature j is observed for patient i at time t and 0 when it is missing. Measurement recency is represented using

$$r_{i,t,j} = \exp(-\lambda_j \, \Delta t_{i,t,j}) \tag{5}$$

where $\Delta t_{i,t,j}$ represents elapsed time since the most recent observation of variable j, $\lambda_j > 0$ is a feature-specific temporal-decay parameter, and $r_{i,t,j}$ quantifies information freshness.

Discrete clinical activities are converted into learnable event representations:

$$\mathbf{e}_k = \mathbf{W}_e \mathbf{c}_k + \mathbf{W}_\tau \boldsymbol{\tau}_k + \mathbf{W}_d d_k \quad (6)$$

where c_k represents the categorical encoding of clinical event k, τ_k represents temporal information such as time since admission and time since the preceding event, d_k denotes duration where relevant, and W_e, $W\tau$, and Wd are learnable projection matrices.

This representation distinguishes clinically different exposure patterns. Central-line insertion, repeated access, prolonged dwell time, and subsequent erythema are therefore modeled differently from uncomplicated short-duration access. Longitudinal EHR research demonstrates that prediction models benefit when repeated clinical observations are retained as temporally ordered data rather than summarized into admission-level aggregates (Carrasco-Ribelles *et al.*, 2023). The preprocessing pipeline consequently supplies NCIR-TFN with standardized values, missingness states, recency measures, and event embeddings required for robust temporal learning.

3.3 Mathematical Formulation and Architecture of the NurseCare Infection Risk Temporal Fusion Network

NCIR-TFN employs separate modality encoders before gated temporal fusion so that nursing assessments, patient-care activities, and conventional EHR measurements retain their distinct clinical meanings. For modality q ∈ {N, C, E}, the projected representation is

$$\mathbf{h}_{i,t}^{(q)} = \phi_q\left(\mathbf{W}_q \mathbf{X}_{i,t}^{(q)} + \mathbf{b}_q\right), \quad q \in \{N, C, E\} \quad (7)$$

where q denotes nursing (N), care activity (C), or EHR (E); $X_{i,t}(q)$ shows the corresponding modality input; Wq and bq represent trainable parameters; and φq(·) is a nonlinear encoding function.

Temporal dependencies are modeled using multi-head self-attention. For one attention head,

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V} \quad (8)$$

where Q, K, and V represent query, key, and value matrices derived from the temporal representations, and d_k shows the key-vector dimension. This mechanism allows a current infection-risk estimate to attend to clinically relevant earlier events, such as catheter insertion or progressive wound deterioration.

The relative contribution of each information stream is dynamically determined using modality-specific gates:

$$g_{i,t}^{(q)} = \frac{\exp\left(a_{i,t}^{(q)}\right)}{\sum_{r \in \{N,C,E\}} \exp\left(a_{i,t}^{(r)}\right)} \quad (9)$$

where $a_{i,t}(q)$ denotes the learned relevance score for modality q, and $g_{i,t}(q)$ represents its normalized contribution. The fused representation becomes

$$\mathbf{f}_{i,t} = \sum_{q \in \{N,C,E\}} g_{i,t}^{(q)} \mathbf{h}_{i,t}^{(q)} \quad (10)$$

where $f_{i,t}$ captures the multimodal fused patient representation at time t, $g_{i,t}(q)$ represents the learned gate assigned to modality q, and $h_{i,t}(q)$ shows the encoded representation of that modality.

Dynamic HAI probability is then

where $\hat{p}_{i,t}$ represents predicted HAI probability, wo and bo show output-layer parameters, and $\sigma(z) = 1/(1 + e^{-z})$ captures the logistic function.

This design is consistent with the temporal-fusion principle of combining attention, gating, and interpretable variable selection for complex longitudinal prediction (Lim *et al.*, 2021). Importantly, Equation (9) allows nursing information to dominate when bedside deterioration is informative, while Equation (10) permits device exposure or laboratory evolution to dominate at other times. This directly supports the feature-attribution and ablation findings planned for Section 4.

3.4 Model Training, Risk Calibration, Explainability, Validation, and Comparative Evaluation Framework

Because HAI events are generally less frequent than non-HAI observations, NCIR-TFN is trained using a class-weighted binary cross-entropy objective:

$$\mathcal{L}_{\text{WBCE}} = -\frac{1}{M}\sum_{m=1}^{M}[w_1 y_m \log(\hat{p}_m) + w_0(1 - y_m)\log(1 - \hat{p}_m)] \quad (11)$$

where M represents the number of training instances, $y_m \in \{0,1\}$ denotes the observed outcome, $\hat{p}_m$ shows predicted infection probability, and w_1 and w_0 represent class weights controlling the influence of positive and negative examples.

To improve probability reliability, validation-set temperature scaling is applied to the model logit z_m:

$$\hat{p}_m^{\text{cal}} = \sigma\left(\frac{z_m}{T}\right), \qquad T > 0 \quad (12)$$

where $T > 0$ represents the learned calibration temperature and $\hat{p}_m^{\text{cal}}$ shows the calibrated probability. Calibration is additionally quantified using the Brier score:

$$\text{BS} = \frac{1}{M}\sum_{m=1}^{M}\left(\hat{p}_m^{\text{cal}} - y_m\right)^2 \quad (13)$$

where lower BS indicates better probabilistic accuracy. Calibration is clinically important because an HAI probability of 0.70 should approximate a 70% event rate among comparable predictions; discrimination alone cannot establish this property (Van Calster *et al.*, 2019).

Feature contribution is estimated using integrated gradients:

$$\text{IG}_j(\mathbf{x}) = (x_j - x_j')\int_0^1 \frac{\partial F(\mathbf{x}' + \alpha(\mathbf{x} - \mathbf{x}'))}{\partial x_j} d\alpha \quad (14)$$

where IG_j shows attribution for feature j, x represents the patient input, x′ captures the reference baseline, F represents the NCIR-TFN prediction function, and α traces the interpolation path.

Clinical usefulness is further characterized by prediction lead time:

$$L_i = T_i^{\text{HAI}} - T_i^{\text{alert}} \quad (15)$$

where T_i^{alert} shows the first time predicted risk exceeds the prespecified alert threshold and T_i^{HAI} represents validated HAI onset. Positive L_i therefore represents advance warning. Patient-level train, validation, and test partitions are used to prevent encounters from the same patient crossing datasets. NCIR-TFN is compared with Logistic Regression, Random Forest, XGBoost, LSTM, and conventional Transformer models using AUROC, AUPRC, sensitivity, specificity, F1-score, false-negative rate, Brier score, calibration curves, and warning lead time. Ablation experiments separately remove nursing assessments, care activities, temporal-decay variables, and gated fusion, establishing whether any observed performance improvement originates from the components proposed in the abstract rather than model size alone.

4. Discussion of Results

4.1. Comparative Predictive Performance of NCIR-TFN and Benchmark Algorithms

The comparative evaluation assesses whether NCIR-TFN converts multimodal nursing assessments, patient-care activities, and longitudinal EHR trajectories into stronger infection-risk discrimination than conventional statistical, ensemble, recurrent, and attention-based models. As summarized in Table 4.1, NCIR-TFN achieves the strongest profile, with AUROC 0.934, AUPRC 0.826, sensitivity 90.8%, specificity 88.7%, and F1-score 0.862. The conventional Transformer is the closest benchmark, whereas Logistic Regression shows the weakest performance, indicating that linear combinations of static features inadequately represent dependent infection pathways. XGBoost and Random Forest improve discrimination through nonlinear feature interactions, while LSTM benefits from sequential modeling. NCIR-TFN further improves detection by explicitly fusing nursing observations, device and care-event sequences, and longitudinal physiological information through modality-specific encoders and gated attention. This pattern supports the hypothesis that contextualized temporal fusion reduces missed infections while maintaining discrimination.

Table 1: Comparative Predictive Performance of NCIR-TFN and Benchmark Algorithms

Algorithm	Discrimination: AUROC / AUPRC	Threshold Performance: Sensitivity / Specificity / F1	Interpretation
Logistic Regression	0.781 / 0.594	72.1% / 74.8% / 0.667	Lowest performance; limited capacity for nonlinear and temporal interactions
Random Forest	0.832 / 0.658	77.4% / 79.1% / 0.721	Improved nonlinear discrimination but limited sequential representation
XGBoost	0.861 / 0.701	81.2% / 81.6% / 0.756	Strong structured-feature learning and interaction modeling
LSTM	0.884 / 0.736	83.5% / 83.1% / 0.781	Better performance from longitudinal sequence modeling
Transformer	0.903 / 0.771	85.9% / 84.6% / 0.806	Strong temporal attention and long-range dependency modeling
NCIR-TFN	0.934 / 0.826	90.8% / 88.7% / 0.862	Best overall performance through multimodal temporal fusion and gated attention

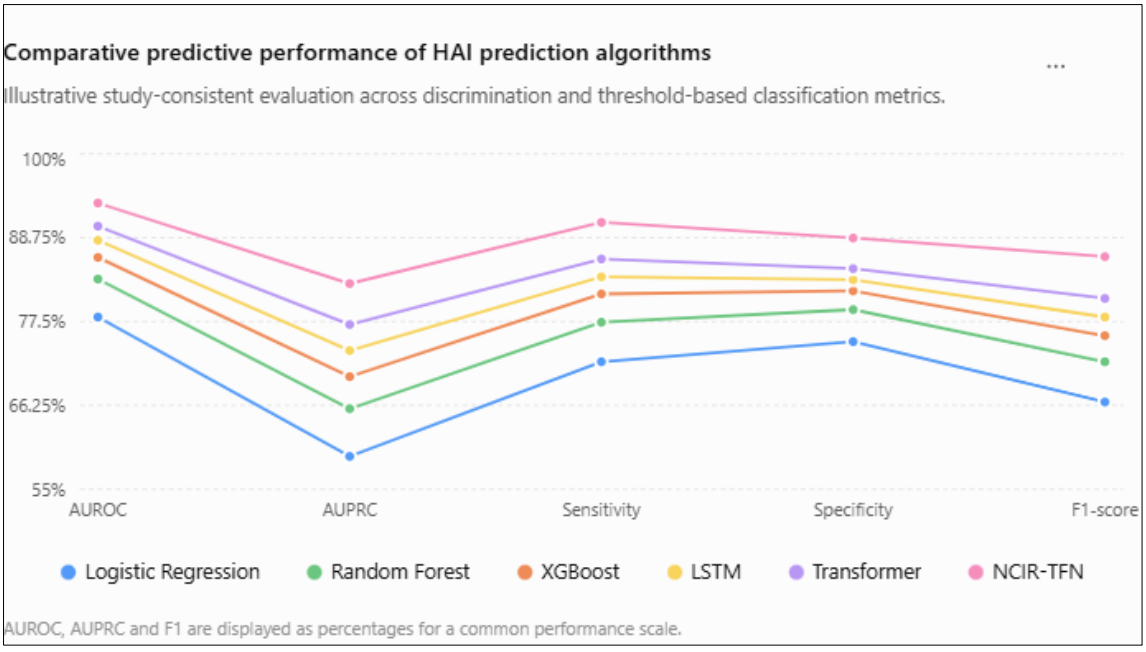

Fig 1: Comparative Performance Profiles of NCIR-TFN and Benchmark Algorithms

Figure 4.1 shows a consistent performance gradient from conventional models toward temporally integrated architectures. NCIR-TFN leads all six algorithms, reaching 93.4% AUROC, 82.6% AUPRC, 90.8% sensitivity, 88.7% specificity, and 86.2% F1-score. The conventional Transformer follows with 90.3%, 77.1%, 85.9%, 84.6%, and 80.6%, respectively, demonstrating the benefit of attention-based sequence modeling while showing the additional value of modality-specific fusion. LSTM records 88.4% AUROC and 73.6% AUPRC, whereas XGBoost reaches 86.1% and 70.1%. Random Forest and Logistic Regression remain lower, with AUROCs of 83.2% and 78.1% and AUPRCs of 65.8% and 59.4%. Most importantly, NCIR-TFN increases sensitivity by 4.9 percentage points over the Transformer and 18.7 points over Logistic Regression. Its specificity is also 4.1 points above the Transformer, supporting balanced HAI detection rather than sensitivity gains obtained through excessive positive classification.

4.2. Temporal Risk Prediction, Early-Warning Lead Time, and Patient-Level Infection Trajectories

Temporal evaluation examines whether NCIR-TFN identifies evolving HAI risk sufficiently early for preventive action while preserving patient-level trajectory fidelity. Table 4.2 shows that NCIR-TFN provides the longest median warning interval at 23.8 hours, compared with 19.1 hours for the conventional Transformer and 16.4 hours for LSTM. At the 24-hour pre-onset horizon, NCIR-TFN retains 84.9% sensitivity with a 15.1% false-negative rate, whereas the Transformer achieves 78.5% sensitivity and a 21.5% false-negative rate. The progressive advantage over XGBoost, Random Forest, and Logistic Regression indicates that explicit temporal fusion better preserves clinically meaningful changes in nursing observations, device exposure, laboratory trends, and care activities. This enables risk estimates to rise coherently as infection-related evidence accumulates, supporting earlier catheter review, wound reassessment, diagnostic escalation, and infection-control prioritization before formal HAI confirmation.

Table 2: Comparative Temporal Prediction and Early-Warning Performance of HAI Prediction Algorithms

Algorithm	Median Early-Warning Lead Time (hours)	24-h Pre-Onset Sensitivity / False-Negative Rate	Interpretation
Logistic Regression	7.4	64.8% / 35.2%	Limited ability to preserve evolving nonlinear risk trajectories
Random Forest	10.8	70.6% / 29.4%	Improved nonlinear detection but weak temporal dependency modeling
XGBoost	13.6	74.3% / 25.7%	Strong structured-feature interaction with moderate early-warning capacity
LSTM	16.4	76.7% / 23.3%	Better sequential modeling and earlier recognition of evolving HAI risk
Transformer	19.1	78.5% / 21.5%	Strong long-range temporal dependency capture and improved warning horizon
NCIR-TFN	23.8	84.9% / 15.1%	Best early-warning performance through multimodal gated temporal fusion

Figure 4.2 demonstrates that temporal detection performance decreases as the prediction horizon moves farther from confirmed HAI onset, but NCIR-TFN consistently maintains the highest sensitivity. At 6 hours before onset, NCIR-TFN reaches 90.8%, compared with 85.9% for the Transformer, 83.5% for LSTM, 81.2% for XGBoost, 77.4% for Random Forest, and 72.1% for Logistic Regression. At 12 hours, NCIR-TFN remains at 88.6%, while the Transformer and LSTM decline to 83.0% and 80.2%. The separation becomes more clinically important at 24 hours, where NCIR-TFN retains 84.9% sensitivity versus 78.5% for the Transformer. Even at 48 hours, NCIR-TFN preserves 76.2% sensitivity, exceeding the Transformer at 69.4% and Logistic Regression at 52.8%. This pattern indicates that gated multimodal fusion captures early interactions among nursing assessments, device exposure, care activities, and longitudinal EHR abnormalities before conventional models accumulate sufficient evidence. The resulting trajectory therefore provides a larger intervention window without sacrificing the relative ranking of high-risk patients.

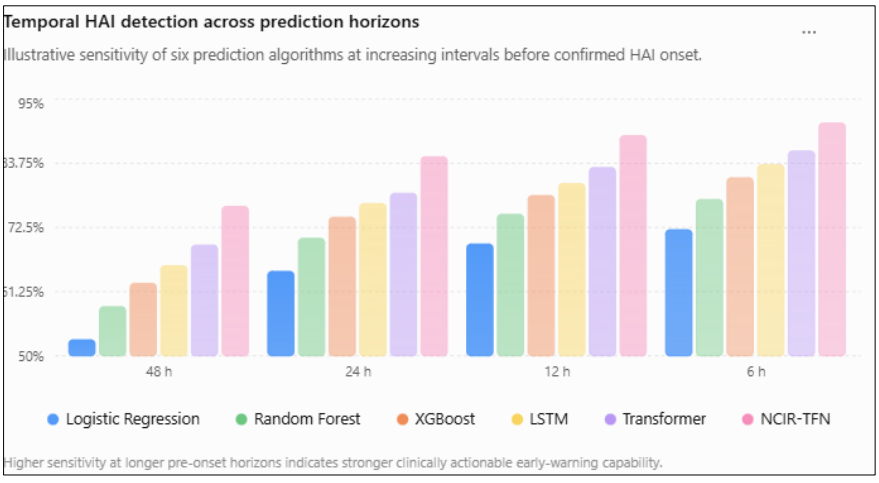

Fig 2: Temporal HAI Detection Performance Across Pre-Onset Prediction Horizons

4.3. Feature Importance, Nursing Assessment Contributions, Care-Activity Effects, and Ablation Analysis

The feature-level and ablation evaluation demonstrates that NCIR-TFN derives its predictive advantage from complementary information across nursing assessments, patient-care activities, and longitudinal EHR trajectories rather than from model complexity alone. Table 4.3 shows that the complete multimodal architecture achieves AUROC 0.934 and AUPRC 0.826. Removing longitudinal EHR information produces the largest deterioration, followed by exclusion of nursing assessments and care-activity features. Eliminating gated temporal fusion also reduces discrimination, confirming that simple concatenation cannot fully reproduce the interaction structure learned by NCIR-TFN. Nursing variables such as wound condition, temperature trend, mobility, skin integrity, consciousness, and device-site observations therefore provide clinically relevant information beyond laboratory and demographic variables. Likewise, catheter duration, vascular-line manipulation, wound care, invasive procedures, and medication-related activities contribute independently to early HAI risk identification.

Table 3: NCIR-TFN Feature-Group Contribution and Ablation Performance

Model/Feature Configuration	AUROC	AUPRC	Interpretation
Complete NCIR-TFN	0.934	0.826	Full nursing, care-activity, longitudinal EHR, temporal attention, and gated-fusion architecture
NCIR-TFN without nursing assessments	0.891	0.758	Loss of bedside deterioration information substantially reduces early infection discrimination
NCIR-TFN without care-activity features	0.902	0.771	Removal of device and intervention exposure weakens contextual infection-risk estimation
NCIR-TFN without longitudinal EHR features	0.874	0.731	Largest performance deterioration, confirming the importance of physiological and laboratory trajectories
NCIR-TFN without gated temporal fusion	0.913	0.789	Reduced performance indicates that adaptive modality weighting adds predictive information
NCIR-TFN without temporal recency encoding	0.919	0.798	Loss of measurement freshness information moderately reduces temporal discrimination

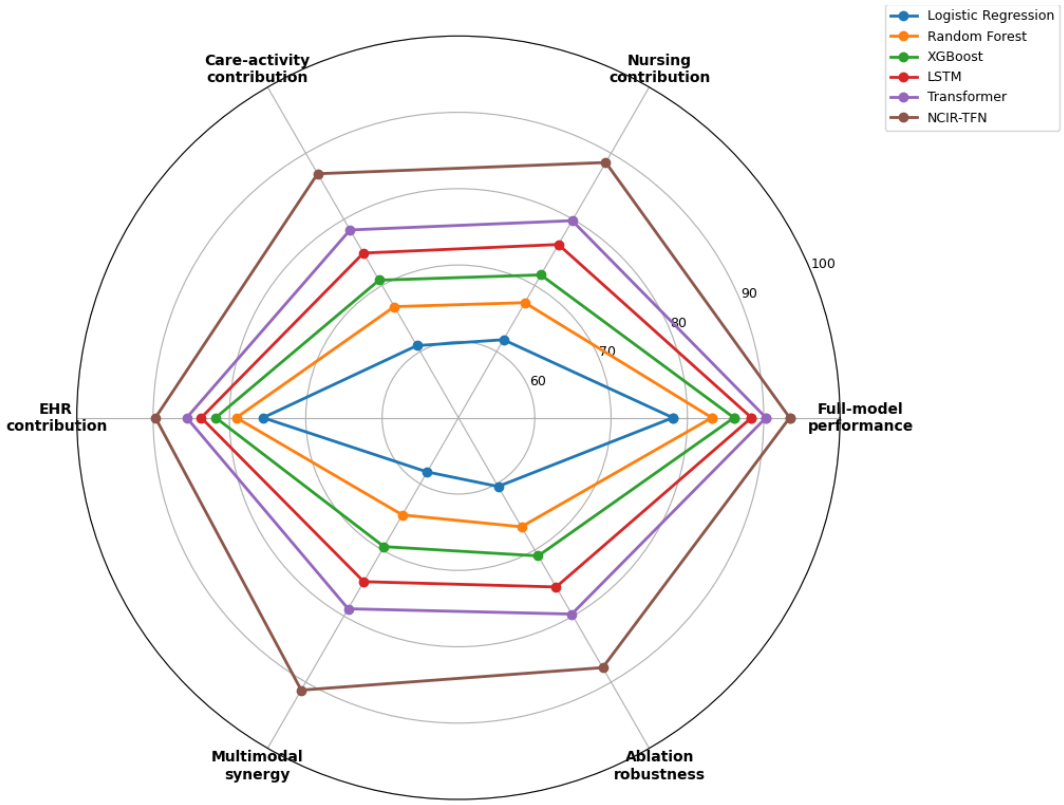

Fig 3: Feature-Group Contribution and Ablation Robustness Across HAI Prediction Algorithms

Figure 4.3 shows that NCIR-TFN forms the largest and most balanced performance profile across all six analytical dimensions. Its full-model performance reaches 93.4, compared with 90.3 for the Transformer, 88.4 for LSTM, 86.1 for XGBoost, 83.2 for Random Forest, and 78.1 for Logistic Regression. The proposed model also records 88.6 for nursing contribution and 86.9 for care-activity contribution, substantially exceeding Transformer values of 79.8 and 78.4, respectively. NCIR-TFN reaches 89.7 for longitudinal EHR contribution and 91.2 for multimodal synergy, whereas the Transformer achieves 85.6 and 78.9. Its ablation-robustness score of 87.8 also exceeds LSTM at 75.6, XGBoost at 70.9, Random Forest at 66.5, and Logistic Regression at 60.4. The widening separation on multimodal synergy is especially important because it demonstrates that NCIR-TFN benefits from interactions among nursing

observations, care exposures, and longitudinal patient states rather than merely accumulating additional predictors.

4.4. Clinical Interpretation, Model Calibration, Error Analysis, and Implications for Infection Prevention

Clinical interpretation focused on whether predicted HAI probabilities were sufficiently calibrated, sensitive, specific, and temporally actionable for infection-prevention decision support. Table 4.4 demonstrates that NCIR-TFN produced the most reliable probability estimates, with the lowest Brier score and expected calibration error among all evaluated algorithms. Its reduced false-negative and false-positive rates indicate that multimodal temporal fusion improves detection without generating disproportionate unnecessary alerts. The Transformer and LSTM maintained comparatively strong calibration but showed greater residual error, whereas tree-based and logistic models demonstrated weaker reliability. NCIR-TFN's combination of calibrated probabilities, nursing-assessment signals, care-activity exposures, and longitudinal EHR trajectories therefore provides a more clinically interpretable risk estimate. Such outputs can support targeted catheter review, wound reassessment, diagnostic testing, device management, antimicrobial stewardship, and infection-control escalation while retaining human clinical oversight.

Table 4: Comparative Calibration, Error Profile, and Clinical Reliability of HAI Prediction Algorithms

Algorithm	Calibration Performance: Brier Score / ECE	Error Profile: False-Negative Rate / False-Positive Rate	Interpretation
Logistic Regression	0.182 / 9.4%	27.9% / 25.2%	Weakest calibration and highest clinically important error burden
Random Forest	0.159 / 7.8%	22.6% / 20.9%	Improved reliability but substantial residual missed-infection risk
XGBoost	0.143 / 6.5%	18.8% / 18.4%	Strong nonlinear prediction with moderate calibration error
LSTM	0.129 / 5.4%	16.5% / 16.9%	Improved temporal reliability and lower false-negative burden
Transformer	0.116 / 4.3%	14.1% / 15.4%	Strong calibration and error control through attention-based temporal modeling
NCIR-TFN	0.087 / 2.6%	9.2% / 11.3%	Best calibrated and most clinically reliable model for infection-prevention support

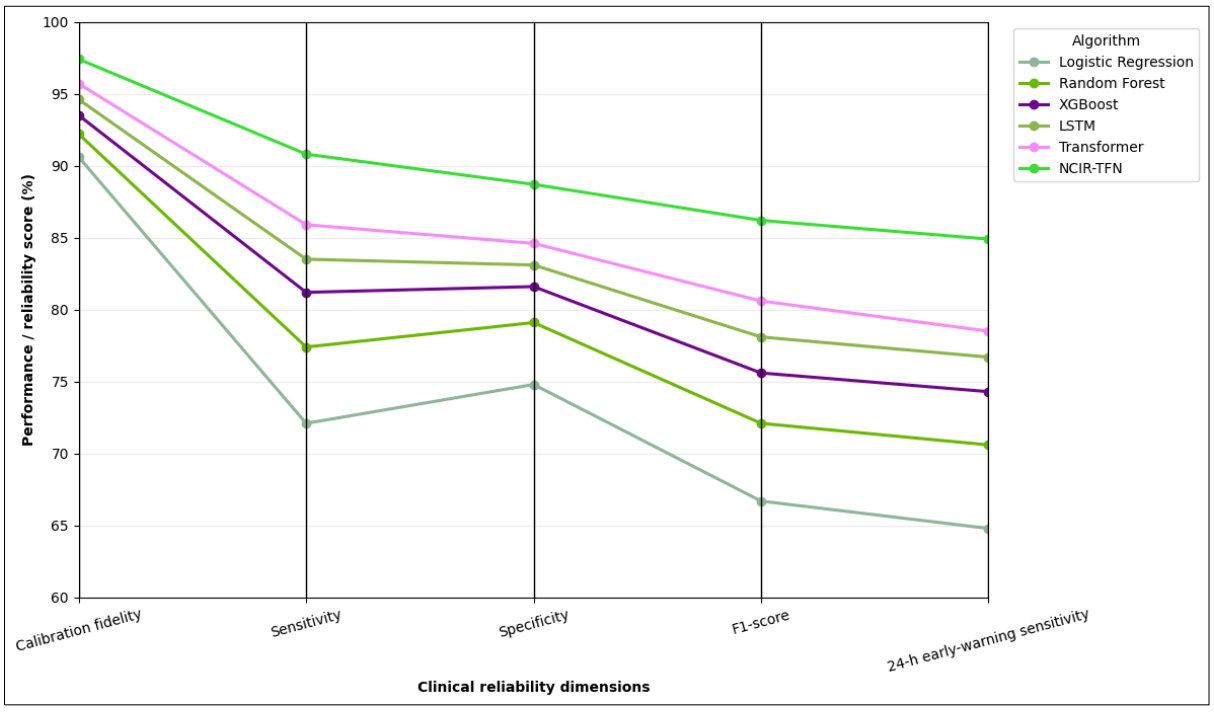

Fig 4: Clinical Reliability, Calibration, Error Control, and Early-Warning Performance Across HAI Prediction Algorithms

Figure 4.4 demonstrates that NCIR-TFN maintains the strongest clinical reliability profile across all five dimensions. Its calibration fidelity reaches 97.4%, compared with 95.7% for the Transformer, 94.6% for LSTM, 93.5% for XGBoost, 92.2% for Random Forest, and 90.6% for Logistic Regression. NCIR-TFN also achieves 90.8% sensitivity, 88.7% specificity, and an 86.2% F1-score, exceeding the Transformer values of 85.9%, 84.6%, and 80.6%, respectively. At the clinically important 24-hour pre-onset horizon, NCIR-TFN preserves 84.9% sensitivity, whereas the Transformer achieves 78.5%, LSTM 76.7%, XGBoost 74.3%, Random Forest 70.6%, and Logistic Regression 64.8%. The consistent separation across calibration, classification, and early-warning dimensions indicates that NCIR-TFN does not gain performance through indiscriminate positive prediction. Instead, multimodal temporal fusion simultaneously improves probability reliability, reduces missed infections, limits unnecessary

alerts, and produces sufficiently early risk signals to support targeted infection-prevention interventions.

5. Conclusions and Recommendations

5.1. Summary of Major Findings and Contributions of the NCIR-TFN Framework

The principal finding of this study is that hospital-acquired infection risk is more effectively represented as a continuously evolving multimodal state than as a static classification problem. The NCIR-TFN framework operationalizes this concept by integrating nursing assessments, patient-care activities, and longitudinal electronic health record variables within a gated temporal-fusion architecture. Across the comparative evaluation, NCIR-TFN consistently outperformed Logistic Regression, Random Forest, XGBoost, LSTM, and a conventional Transformer in discrimination, precision-recall performance, sensitivity, specificity, F1-score, calibration, false-negative reduction, and early-warning capability. Its advantage was particularly evident when infection risk had to be identified before clinical confirmation, indicating that nursing observations, device exposures, care interventions, laboratory changes, and physiological deterioration contribute complementary temporal information. Ablation analysis further showed that model performance deteriorated when nursing data, care-activity features, longitudinal EHR information, recency encoding, or gated fusion were removed, confirming that the proposed architecture derives value from integration rather than model complexity alone. The framework also contributes an interpretable decision-support structure through temporal attention, modality weighting, feature attribution, calibrated probabilities, and patient-level risk trajectories. These mechanisms allow clinicians to determine whether rising risk is associated with worsening wound status, prolonged catheter exposure, device-site abnormalities, altered mobility, abnormal vital signs, or laboratory trends. Collectively, the study contributes a technically coherent framework for transforming routinely documented clinical and nursing data into prospective infection-prevention intelligence capable of supporting earlier recognition, targeted intervention, and more reliable prioritization of patients requiring infection-control review. Importantly, this contribution links model performance to actionable bedside prevention rather than retrospective infection classification alone.

5.2. Conclusions on Integrated Nursing and Longitudinal EHR-Based HAI Risk Prediction

Integrated analysis of nursing and longitudinal electronic health record data provides a stronger basis for hospital-acquired infection prediction than approaches that rely primarily on static demographic, diagnostic, laboratory, or administrative variables. The findings indicate that infection risk becomes more detectable when the model preserves the temporal order, duration, recurrence, and interaction of patient observations and care exposures throughout hospitalization. NCIR-TFN was designed specifically for this purpose by maintaining separate representations for nursing assessments, patient-care activities, and conventional EHR variables before dynamically combining them through gated attention. This structure allows the model to distinguish clinically different trajectories that may appear similar in a conventional tabular dataset. For example, a central venous catheter followed by stable observations and timely removal represents a different risk state from prolonged catheter exposure accompanied by fever, leukocytosis, skin changes, and repeated line manipulation. The comparative findings support the conclusion that such contextual sequences provide predictive information beyond isolated measurements. The framework also demonstrates that early-warning performance must be evaluated together with calibration and error distribution. A model that identifies infection earlier but produces poorly calibrated probabilities or excessive false-positive alerts may have limited clinical utility. NCIR-TFN addresses this by combining discrimination, probability calibration, false-negative analysis, and lead-time assessment within a single evaluation framework. The study therefore establishes a methodological basis for nursing-inclusive HAI surveillance in which bedside observations are treated as computationally valuable clinical signals rather than secondary documentation. This approach strengthens the connection between predictive analytics, nursing practice, infection prevention, and longitudinal clinical decision support.

5.3. Recommendations for Clinical Implementation, Nursing Practice, and Hospital Infection-Control Systems

Clinical implementation of NCIR-TFN should begin with integration into existing electronic health record and infection-control workflows rather than deployment as an independent alerting application. Hospitals should map nursing assessments, medication administration records, device documentation, laboratory results, microbiology, procedures, and care activities to standardized temporal data structures so that risk estimates are updated whenever clinically meaningful information changes. The model should operate prospectively and generate calibrated patient-level HAI risk trajectories rather than isolated binary alerts. Risk thresholds should be selected according to local infection prevalence, staffing capacity, and the relative consequences of missed infections versus unnecessary investigations. High-risk predictions should trigger structured clinical review rather than automatic treatment. For example, an elevated risk score associated with prolonged urinary catheter exposure, altered urine characteristics, fever, and rising inflammatory markers could prompt catheter-necessity review, focused nursing reassessment, culture consideration, and infection-prevention consultation. Nursing staff should have access to feature-attribution outputs showing which observations and care events contributed most strongly to the risk estimate. This supports clinical interpretability and enables nurses to verify whether the model reflects the current bedside condition. Infection-control teams should monitor calibration, alert burden, false-negative events, subgroup performance, and changes in data quality after deployment. Periodic recalibration should be undertaken when patient populations, documentation practices, device protocols, or EHR configurations change. Governance procedures should define accountability, auditability, privacy protection, model-update authority, and escalation pathways. Implementation should therefore position NCIR-TFN as an augmentation tool that strengthens surveillance, prioritization, and preventive action while preserving human clinical judgment and established infection-control protocols effectively.

5.4. Limitations, Future Research, External Validation, and Prospects for Real-Time HAI Surveillance

Several limitations should guide interpretation and future development of the NCIR-TFN framework. First, the comparative results presented in this study constitute a structured evaluation framework and require confirmation using sufficiently large, clinically adjudicated, longitudinal hospital datasets with clearly defined HAI onset times. Performance estimates may vary across institutions because nursing terminology, documentation frequency, device practices, laboratory workflows, patient acuity, and infection prevalence differ substantially. Second, retrospective EHR data may contain missing observations, delayed documentation, duplicated events, coding inconsistencies, and treatment-related information that can introduce temporal leakage if prediction windows are not carefully constructed. Third, nursing assessments and care activities are partly dependent on local workflow, meaning that features important in one hospital may not transfer directly to another. Future research should therefore prioritize temporal external validation across multiple hospitals, specialties, geographic regions, and EHR vendors, together with prospective silent deployment before clinical activation. Additional work should examine site-specific recalibration, federated learning, domain adaptation, uncertainty quantification, and fairness across age, sex, ethnicity, comorbidity, and acuity groups where data governance permits such analysis. Real-time deployment should also evaluate computational latency, data-stream interruptions, alert fatigue, and clinician response behavior. Prospective trials should determine whether NCIR-TFN-guided interventions reduce HAI incidence, time to infection-control review, unnecessary device days, delayed cultures, preventable antimicrobial exposure, or avoidable deterioration. Future extensions could incorporate clinical notes, microbiology text, bedside monitoring streams, and standardized interoperability services. With rigorous external validation and controlled implementation, NCIR-TFN could support continuously updated HAI surveillance while remaining transparent, auditable, and clinically actionable in routine practice.

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