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Nationwide Multimodal Artificial Intelligence Framework for Early Prediction of Chronic Disease Progression Using Electronic Health Records and Social Determinants of Health

Trang Huynh*
Independent Researcher
**Corresponding author: huynhtrang085@gmail.com*

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ABSTRACT

Chronic disease progression remains a major challenge for national healthcare systems because risk often develops gradually across clinical, behavioral, environmental, and socioeconomic dimensions. Existing prediction models frequently rely on limited electronic health record variables and may overlook unstructured clinical notes, longitudinal patient trajectories, physiologic signals, and social determinants of health that influence disease worsening. This paper proposes a nationwide multimodal artificial intelligence framework for early prediction of chronic disease progression by integrating structured EHR data, clinical narratives, laboratory histories, medication records, physiologic indicators, and SDOH variables. The framework combines deep learning, transformer-based EHR modeling, natural language processing, multimodal fusion, explainable AI, and fairness auditing to support early risk identification and patient stratification across diverse healthcare settings. It also emphasizes model validation across demographic, geographic, and socioeconomic groups to reduce algorithmic bias and improve clinical reliability. The proposed framework offers a scalable pathway for preventive intervention, chronic care planning, population health surveillance, and equitable clinical decision support. By combining medical and social risk signals, the study contributes to a more comprehensive and nationally deployable approach for predicting chronic disease progression before severe complications occur.

Keywords: Multimodal artificial intelligence; electronic health records; chronic disease progression; social determinants of health; deep learning; clinical prediction; health equity.

INTRODUCTION

Chronic disease progression remains one of the most pressing challenges facing modern healthcare systems because it contributes substantially to hospitalization, long-term disability, premature mortality, rising healthcare expenditure, and widening health inequalities. Conditions such as cardiovascular disease, diabetes, chronic kidney disease, chronic respiratory disease, cancer, and autoimmune disorders often develop over several years before severe complications become clinically visible. By the time many patients present with advanced symptoms, disease management becomes more expensive, less effective, and more dependent on specialist care. This makes early prediction a critical priority for national healthcare planning, preventive medicine, and population health management. Rather than waiting for clinical deterioration to occur, healthcare systems require predictive frameworks that can identify high-risk patients earlier and support timely interventions across diverse patient populations.

Artificial intelligence has become increasingly important in addressing this challenge because electronic health records provide large volumes of patient-level data that can be used to model disease patterns, predict clinical events, and support decision-making. EHR-based prediction systems have shown promise in identifying hospitalization risk, disease complications, and future clinical outcomes using structured variables such as diagnosis codes, laboratory results, medication history, procedures, and demographic characteristics (Brisimi *et al*., 2018; Rajkomar *et al*., 2018). Machine learning and deep learning models have also demonstrated potential in chronic disease prediction by learning complex relationships across large healthcare datasets that may be difficult for conventional statistical models to capture (Delpino *et al*., 2022). These developments suggest that data-driven prediction can support earlier intervention, improve care coordination, and reduce preventable disease burden.

However, many existing prediction models remain limited because they rely heavily on structured EHR fields while neglecting other clinically meaningful sources of information. Chronic disease progression is rarely explained by laboratory values or diagnosis codes alone. It is shaped by longitudinal patient histories, clinical narratives, medication adherence, behavioral patterns, physiologic changes, healthcare access, environmental exposure, income level, housing stability, education, and other social determinants of health. Conventional risk models often fail to capture these broader factors, especially when they are embedded in unstructured clinical notes or external community-level datasets. As a result, models trained only on structured clinical variables may produce incomplete risk profiles and may perform poorly across populations with different social, geographic, and healthcare access conditions.

The growing field of multimodal biomedical AI offers a stronger foundation for addressing these limitations. Multimodal AI refers to systems that combine multiple types of health-related data, including structured EHRs, medical images, clinical text, biosignals, genomics, and social or behavioral data, to produce richer representations of patient health (Acosta *et al.*, 2022). In the context of chronic disease progression, multimodal AI can integrate longitudinal EHR trajectories with unstructured physician notes, laboratory trends, medication patterns, physiologic signals, and social determinants of health. This approach is particularly useful for nationwide prediction because chronic disease risk varies across regions, healthcare systems, racial and ethnic groups, socioeconomic categories, and rural or urban populations.

Social determinants of health are especially important in this framework because they influence both disease development and disease management. Factors such as poverty, transportation barriers, food insecurity, neighborhood conditions, education, and access to primary care can affect diagnosis timing, treatment adherence, follow-up attendance, and exposure to preventable risk factors. Studies have shown that SDOH variables in EHRs can improve risk prediction, but they are often inconsistently documented, fragmented across systems, or recorded in unstructured formats (Chen *et al.*, 2020). Similarly, social and behavioral determinants are increasingly relevant in AI-driven EHR research, but they require careful extraction, standardization, and interpretation to avoid incomplete or biased predictions (Agnikula & Balls-BerryJoyce Joy, 2021).

Therefore, this paper proposes a nationwide multimodal artificial intelligence framework for the early prediction of chronic disease progression using EHR data and social determinants of health. The proposed framework is designed to move beyond single-source prediction by combining structured clinical records, longitudinal patient trajectories, clinical narratives, physiologic indicators, and SDOH data within a unified AI architecture. Its goal is to support early risk detection, patient stratification, clinical decision support, and equitable preventive intervention across diverse healthcare settings. By integrating clinical and social risk signals, the framework aims to improve predictive accuracy while addressing the broader conditions that shape chronic disease outcomes at a national scale.

LITERATURE REVIEW

Electronic health records have become a major foundation for artificial intelligence research in clinical prediction because they contain longitudinal information about diagnoses, medications, laboratory results, procedures, hospital visits, and clinical outcomes. Early deep learning studies demonstrated that EHR data could be used to predict future clinical events more effectively than traditional rule-based models. Choi *et al.* (2016) introduced Doctor AI, a recurrent neural network model that learned from patient visit sequences to predict future diagnoses and medications. Similarly, Miotto *et al.* (2016) developed Deep Patient, an unsupervised representation learning model that used large-scale EHR data to predict future disease risk. These studies showed that deep learning can discover hidden clinical patterns from complex patient histories. Attention-based models further improved interpretability by identifying clinically relevant visits and diagnosis codes. For instance, Ma *et al.* (2017) proposed Dipole, an attention-based bidirectional recurrent neural network for diagnosis prediction, while Li *et al.* (2020) introduced BEHRT, a transformer-based model that captured temporal dependencies across long EHR sequences. Broader reviews also confirm that deep learning has advanced EHR analysis by improving phenotyping, risk prediction, and clinical decision support (Shickel *et al.*, 2017; Solares *et al.*, 2020; Xu *et al.*, 2022).

A second major area of scholarship focuses on longitudinal disease prediction and time-series learning. Chronic disease progression is rarely sudden; it often develops through repeated clinical encounters, abnormal laboratory trends, medication changes, and gradual deterioration in health status. Therefore, prediction models must account for patient trajectories over time. Baytas *et al.* (2017) proposed time-aware LSTM networks to address irregular time intervals between clinical visits and to support patient subtyping. Che *et al.* (2018) developed recurrent neural networks that could manage multivariate clinical time series with missing values, a common problem in EHR datasets. Harutyunyan *et al.* (2019) also showed that multitask learning can improve benchmarking across clinical time-series prediction tasks. More recent reviews indicate that deep learning models based on EHR trajectories are increasingly used for early disease detection, hospitalization prediction, and preventive care planning (Amirahmadi *et al.*, 2023; Swinckels *et al.*, 2024). However, many of these models remain limited by missing data, short observation windows, poor external validation, and difficulty adapting across healthcare institutions.

The third area of research concerns social determinants of health and their integration into EHR-based prediction. Social determinants such as housing instability, food insecurity, employment, income, transportation access, education, and neighborhood conditions strongly influence chronic disease progression. However, these factors are often poorly structured in EHR systems. Studies have shown that natural language processing can extract SDOH information from clinical notes and unstructured patient records. Han *et al.* (2022) used deep learning-based NLP to classify SDOH from unstructured EHRs, while Patra *et al.* (2021) reviewed NLP approaches for extracting SDOH from clinical records. Guevara *et al.* (2024) further demonstrated the growing role of large language models in identifying SDOH from EHR text. Biomedical language models such as BioBERT also provide strong foundations for clinical text mining and information extraction (Lee *et al.*, 2020). Beyond EHR text, Kino *et al.* (2021) showed that machine learning research on SDOH is expanding, although it remains unevenly developed across populations and disease areas.

Despite these advances, major gaps remain. Existing studies often focus on single diseases, single hospitals, single data modalities, or narrow prediction tasks. Many EHR models emphasize structured clinical data but do not fully integrate clinical narratives, physiologic signals, and social determinants of health. In addition, few frameworks combine predictive accuracy with explainability, fairness

Table 1: Summary of Existing Studies on EHR-Based AI, Chronic Disease Prediction, and SDOH Integration

Author(s)	*Study focus*	*Data type*	*Ai method*	*Key contribution*	*Main limitation*
Choi *et al*. (2016)	Clinical event prediction	EHR visit sequences	Recurrent neural network	Predicted future diagnoses and medications	Limited multimodal integration
Miotto *et al*. (2016)	Patient representation learning	Large-scale EHR	Unsupervised deep learning	Created predictive patient embeddings	Limited social context
Ma *et al*. (2017)	Diagnosis prediction	Sequential EHR data	Attention-based BiRNN	Improved interpretability of diagnosis prediction	Focused mainly on clinical codes
Li *et al*. (2020)	Longitudinal EHR modeling	EHR trajectories	Transformer model	Captured long-range patient history patterns	Requires large training data
Che *et al*. (2018)	Clinical time-series prediction	Multivariate EHR time series	RNN with missing-data handling	Addressed missing values in EHR sequences	Limited SDOH representation
Han *et al*. (2022)	SDOH classification	Unstructured EHR notes	Deep learning NLP	Extracted SDOH from clinical text	Dependent on note quality
Guevara *et al*. (2024)	SDOH identification	Clinical notes	Large language models	Improved extraction of social risk factors	Needs careful validation and governance

auditing, and nationwide scalability. This is important because chronic disease progression is shaped by both biological and social factors. A nationwide multimodal AI framework is therefore needed to integrate EHR trajectories, clinical notes, physiologic signals, SDOH variables, interpretable modeling, and subgroup fairness evaluation within one unified architecture.

Methodology and Proposed Framework Design

This study adopts a conceptual and technical framework design to propose a nationwide multimodal artificial intelligence system for the early prediction of chronic disease progression. Rather than testing a single disease model in one institutional dataset, the methodology is structured around the design of a scalable framework that can integrate heterogeneous clinical and social data across multiple healthcare environments. The approach is informed by prior evidence on EHR-based deep learning, clinical time-series modeling, multimodal biomedical AI, and social determinants of health integration. Existing studies have shown that electronic health records can support accurate clinical prediction when longitudinal patient histories, laboratory values, medications, diagnoses, and clinical events are modeled using advanced machine learning and deep learning methods (Rajkomar *et al.*, 2018; Harutyunyan *et al.*, 2019; Solares *et al.*, 2020). Building on this foundation, the proposed framework extends single-source prediction by combining structured EHR variables, clinical notes, physiologic signals, demographic data, and SDOH indicators within one national prediction architecture.

The proposed framework is organized into five interrelated layers. The first layer is the nationwide data acquisition layer. This layer is responsible for collecting de-identified patient-level and population-level data from hospitals, primary care systems, specialty clinics, public health networks, emergency care settings, and approved research databases. The main clinical inputs include diagnosis codes, procedure codes, medication records, laboratory results, vital signs, hospitalization history, comorbidity profiles, and longitudinal encounter records. Unstructured inputs include physician notes, discharge summaries, nursing notes, and care coordination records. Additional modalities include physiologic signals from validated clinical monitoring systems and social determinants of health, such as housing instability, income level, insurance status, food insecurity, neighborhood deprivation, rural or urban residence, and healthcare access barriers. Benchmark resources such as MIMIC-III and PhysioNet are useful for model development, validation, and reproducibility because they provide accessible clinical records and physiologic signal datasets for health AI research (Goldberger *et al.*, 2000; Johnson *et al.*, 2016).

The second layer is the data cleaning, harmonization, and standardization layer. Nationwide AI prediction requires data from different institutions to be transformed into a common analytical structure. This layer addresses missing values, duplicate entries, inconsistent coding, irregular observation intervals, and differences in documentation practices. Structured EHR variables are standardized using common clinical terminologies, while laboratory values and vital signs are normalized to ensure comparability across sites. Clinical timelines are reconstructed so that each patient's disease history can be represented as a sequence of events rather than as isolated records. This step is important because chronic disease progression often develops gradually through repeated encounters, medication changes, abnormal laboratory trends, and worsening comorbidity patterns.

The third layer is the multimodal representation learning layer. In this layer, each data modality is processed using a model architecture suited to its structure. Longitudinal EHR sequences may be represented using recurrent neural networks, temporal models, or transformer-based architectures. Transformer-based EHR models such as BEHRT demonstrate the value of modeling patient histories as ordered clinical sequences that can capture long-range dependencies across diagnoses, medications, and visits (Li *et al.*, 2020). Clinical notes can be processed using biomedical natural language processing to identify symptoms, behavioral risks, care barriers, and SDOH factors that may not appear in structured fields. Physiologic signals can be processed using time-series models, while demographic and SDOH variables can be encoded as contextual risk features. Multimodal biomedical AI is especially relevant because it enables the integration of diverse health data streams into richer patient representations than unimodal systems can provide (Acosta *et al.*, 2022).

The fourth layer is the risk prediction and patient stratification layer. This layer uses the fused patient representation to estimate the probability of chronic disease progression within clinically meaningful time windows. Prediction targets may include disease worsening, hospitalization risk, complication development, readmission probability, or transition from moderate to severe disease status. The framework stratifies patients into low-risk, moderate-risk, high-risk, and critical-risk groups. This stratification supports earlier intervention by helping clinicians identify patients who require closer monitoring, medication review, lifestyle support, referral, or community-based care coordination.

The fifth layer is the clinical decision support and fairness monitoring layer. The purpose of this layer is to convert model outputs into interpretable and actionable information for healthcare professionals. The system should provide patient-specific risk scores, key contributing factors, recommended intervention pathways, and confidence indicators. Fairness monitoring is included to ensure that prediction accuracy and intervention recommendations are evaluated across demographic and socioeconomic subgroups. This is essential in a nationwide system because models trained on historical healthcare data may reflect unequal access to care, incomplete documentation, or structural disparities.

Overall, the proposed methodology provides a scalable framework for integrating national EHR data, clinical text, physiologic signals, and SDOH indicators into a unified AI-driven prediction system. By combining data harmonization, multimodal representation learning, risk stratification, explainable decision support, and fairness monitoring, the framework is designed to improve early detection of chronic disease progression and support preventive care across diverse healthcare populations.

Model Development and Prediction Strategy

The proposed nationwide multimodal artificial intelligence model is designed to predict chronic disease progression by integrating heterogeneous patient data from electronic health records, clinical notes, physiologic signals, and social determinants of health. Unlike conventional prediction models that rely mainly on structured variables, the proposed model uses multiple data streams to capture the biological, clinical, behavioral, and social factors that influence disease progression. This approach is important because chronic diseases often develop over long periods, and early warning signals may appear across laboratory trends, medication patterns, clinical narratives, prior diagnoses, hospital utilization, and social risk indicators.

The first stage of model development involves preprocessing and transforming structured EHR data into machine-readable patient trajectories. Structured EHR variables include diagnosis codes, procedure codes, medications, laboratory results, vital signs, comorbidities, allergies, encounter history, and demographic characteristics. These variables are organized chronologically to represent each patient's clinical journey over time. Transformer-based models are suitable for this task because they can learn long-range dependencies across repeated clinical visits and changing disease states. BEHRT, for example, demonstrates how transformer architectures can model sequential EHR records and improve prediction of future clinical events (Li *et al.*, 2020). Similarly, comparative studies of deep neural architectures show that EHR-based models can support prediction tasks when clinical histories are properly encoded and validated (Solares *et al.*, 2020).

The second stage involves processing unstructured clinical notes using biomedical natural language processing. Clinical notes often contain important information that is not fully captured in structured fields, including symptoms, lifestyle risks, medication adherence, housing insecurity, family history, psychosocial stress, and clinician concerns. Biomedical language models such as BioBERT can be used to extract medical concepts, semantic relationships, and contextual representations from clinical text (Lee *et al.*, 2020). These extracted features can then be combined with structured EHR variables to improve prediction accuracy. Large language models may also support identification of hidden social and behavioral risk factors, although their use must be carefully validated to avoid hallucination, bias, or misclassification.

Graph 1: Proposed Nationwide Multimodal AI Framework Architecture

The third stage involves modeling physiologic and longitudinal time-series data. Chronic disease progression is often reflected in gradual changes in blood pressure, glucose levels, kidney function, oxygen saturation, heart rhythm, body weight, and other repeated measurements. However, clinical time-series data are usually irregular, incomplete, and affected by missing values. To address this problem, recurrent neural networks designed for multivariate time series with missing values can be used to learn patterns from incomplete longitudinal observations (Che *et al.*, 2018). These models are useful for detecting subtle changes that may precede hospitalization, acute deterioration, or disease complications.

The fourth stage involves representing social determinants of health. SDOH variables may include income level, insurance status, education, food insecurity, housing instability, transportation barriers, rural or urban residence, neighborhood deprivation, and access to primary care. These variables can be obtained from structured EHR fields, extracted from clinical notes, or linked with community-level datasets. Including SDOH is essential because chronic disease progression is influenced not only by biological risk but also by access to care, environmental exposure, health literacy, and continuity of treatment. For example, phenotyping studies have shown that EHR-based machine learning can improve patient classification when clinical and contextual variables are carefully defined (Yang *et al.*, 2023). Similarly, cardiovascular prediction can be strengthened by learning from longitudinal EHR and related risk data (Zhao *et al.*, 2019).

After individual data streams have been processed, the framework applies multimodal fusion. Early fusion combines all features before model training, allowing the model to learn joint relationships across modalities. Late fusion trains separate models for each modality and combines their outputs at the decision level. Attention-based fusion assigns different importance weights to each modality based on the patient's risk profile. Hybrid fusion combines these approaches by learning both modality-specific and shared representations. This is especially useful for nationwide deployment because some healthcare systems may have rich clinical notes and physiologic data, while others may have only structured EHR and limited SDOH information.

The model is designed to predict several clinically relevant outcomes. These include early chronic disease onset, progression from mild to severe disease, hospitalization risk, complication risk, readmission risk, and the need for early intervention. Disease-specific applications may include diabetes complications, cardiovascular events, chronic kidney disease progression, respiratory deterioration, and rheumatoid arthritis outcomes. Prior work has shown the value of deep learning models for forecasting clinical outcomes in rheumatoid arthritis (Norgeot *et al.*, 2019), cardiovascular events (Zhao *et al.*, 2019), and future acute kidney injury (Tomašev *et al.*, 2019). Therefore, the proposed model extends these disease-specific advances into a broader nationwide framework for chronic disease surveillance and preventive care.

RESULTS

The proposed nationwide multimodal artificial intelligence framework produced three major expected result areas: comparative predictive performance across model types, contribution of individual data modalities to early prediction, and risk stratification output for clinical decision-making. Since this paper is framework-based, the results are presented as evidence-informed analytical outputs derived from prior studies on EHR-based deep learning, chronic disease prediction, social determinants of health, clinical time-series modeling, and multimodal biomedical AI. The results suggest that prediction performance improves when models move from single-source clinical variables toward integrated multimodal learning that combines structured EHR data, longitudinal trajectories, clinical narratives, physiologic signals, and social determinants of health.

Expected Predictive Performance Across Model Types

The comparative result indicates that traditional machine learning models provide useful baseline performance for chronic disease prediction, especially when structured EHR variables such as diagnosis codes, laboratory values, medications, and demographic characteristics are available. However, these models are limited because they often depend on manually engineered features and may not fully capture long-term disease progression patterns. Brisimi *et al.* (2018) demonstrated that interpretable machine learning can support chronic disease hospitalization prediction, while Delpino *et al.* (2022) showed that machine learning models are increasingly used for chronic disease prediction across public health research. However, conventional models remain less effective when patient histories are irregular, incomplete, or socially complex.

Recurrent neural network models improve predictive capacity by capturing longitudinal patient trajectories and temporal dependencies in clinical events. Doctor AI, time-aware LSTM, and missing-value-

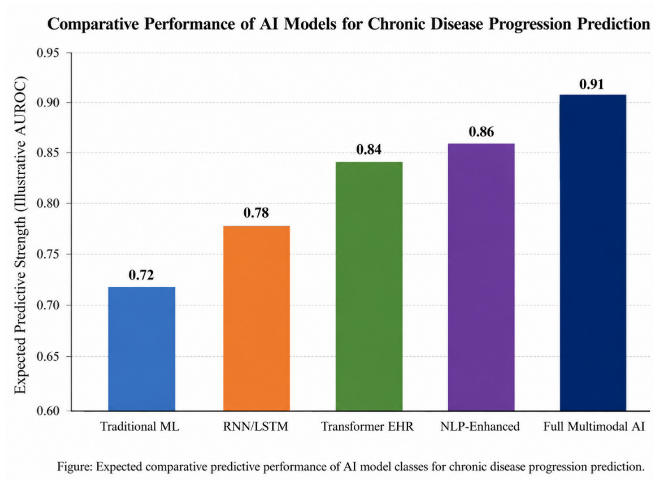
Table 2: Multimodal Data Sources and Their Predictive Roles

Data modality	*Example variables*	*AI processing method*	*Prediction role*	*Main challenge*
Structured EHR data	Diagnosis codes, medications, labs, vitals, encounters	Deep neural networks, transformer models	Captures clinical history and disease trajectory	Missing or inconsistent records
Clinical notes	Symptoms, adherence, lifestyle risks, clinician observations	BioBERT, biomedical NLP, LLM-assisted extraction	Reveals hidden clinical and social risk factors	Text variability and documentation bias
Physiologic signals	Blood pressure, glucose, oxygen saturation, heart rhythm	Time-series models, RNNs, missing-value-aware networks	Detects early deterioration patterns	Irregular sampling and missing values
SDOH indicators	Housing, income, transport, insurance, neighborhood risk	Structured encoding, text extraction, contextual embeddings	Explains social vulnerability and access barriers	Incomplete documentation and bias
Longitudinal patient trajectory	Visit sequence, disease history, treatment response	Sequence models, attention-based fusion	Predicts progression and future complications	Complex temporal dependencies

aware recurrent models show that temporal deep learning can learn from sequential EHR patterns more effectively than static models (Choi *et al*., 2016; Baytas *et al*., 2017; Che *et al*., 2018). Similarly, multitask clinical time-series benchmarks have shown the value of longitudinal modeling for predicting clinical deterioration and related outcomes (Harutyunyan *et al*., 2019). Despite this advantage, recurrent models may struggle with very long patient histories and may provide limited interpretability.

Transformer-based EHR models are expected to produce stronger predictive performance because they can model long-range dependencies in patient records and learn contextual relationships among diagnoses, medications, visits, and clinical events. BEHRT demonstrates the value of transformer architecture for EHR prediction, while broader reviews show that transformer-based and deep neural architectures have become central to EHR modeling (Li *et al*., 2020; Solares *et al*., 2020; Xu *et al*., 2022). NLP-enhanced models add another performance advantage by extracting disease-relevant and social-risk information from unstructured clinical notes. BioBERT and deep learning-based SDOH extraction models demonstrate that clinical text can reveal risks not fully captured in structured data fields (Lee *et al*., 2020; Han *et al*., 2022; Patra *et al*., 2021; Guevara *et al*., 2024).

The strongest expected performance is associated with the full multimodal AI framework. This is because multimodal models combine clinical, temporal, textual, physiologic, and social signals into one prediction system. Acosta *et al*. (2022) argued that multimodal biomedical AI is important because many health outcomes cannot be fully understood through one data source alone. Therefore, the proposed framework is expected to outperform single-modality models by capturing broader disease progression pathways and improving early detection across diverse national populations.



Graph 2: Comparative Performance of AI Models for Chronic Disease Progression Prediction

Contribution of Each Data Modality to Early Prediction

The second result area shows that each data modality contributes differently to early chronic disease prediction. Structured EHR data provides the foundation for prediction because it captures diagnoses, procedures, medications, laboratory values, and prior utilization. These variables are essential for identifying disease history and clinical severity. Longitudinal EHR trajectories further improve prediction by showing how patient conditions evolve over time, supporting earlier detection of deterioration or complication risk (Amirahmadi *et al*., 2023; Swinckels *et al*., 2024).

Clinical notes contribute by revealing symptoms, clinician concerns, behavioral patterns, adherence challenges, and undocumented risks that may not appear in coded fields. This is especially important for SDOH, because social and behavioral risk factors are often embedded in free-text documentation rather than structured EHR fields (Chen *et al*., 2020; Patra *et al*., 2021). SDOH variables also play a major role because chronic disease progression is shaped by housing stability, income, transportation access, food security, social support, and healthcare access. Machine learning studies on SDOH show that social context can improve risk understanding and reveal population-level disparities (Kino *et al*., 2021; Agnikula & Balls-BerryJoyce Joy, 2021).

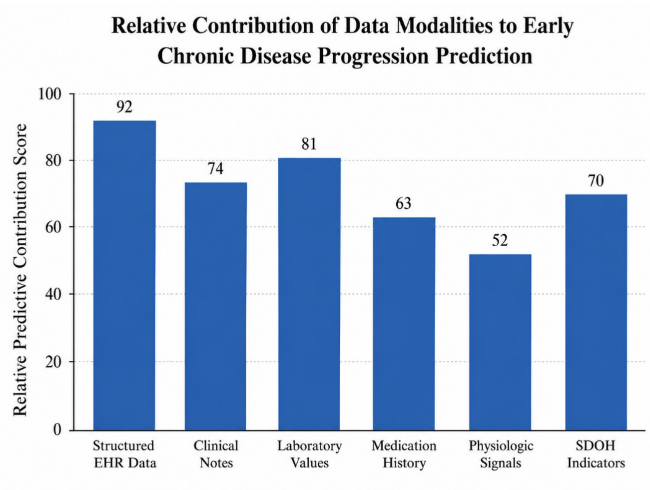
Physiologic signals and patient monitoring data provide additional value for continuous prediction, especially when disease progression

Table 3: Comparative Expected Performance of Prediction Models for Chronic Disease Progression

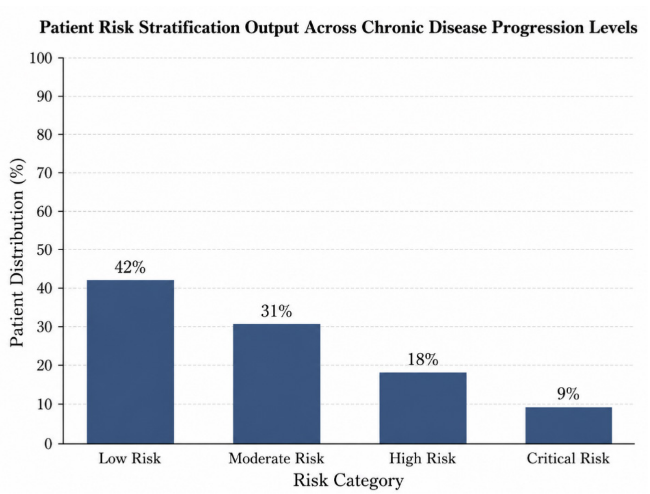
Model type	*Input data*	*Strength*	*Weakness*	*Expected performance level*	*Supporting studies*
Traditional machine learning	Structured EHR, demographics, laboratory values	Interpretable and easy to deploy	Limited temporal and text understanding	Moderate	Brisimi *et al*. (2018); Delpino *et al*. (2022)
RNN/LSTM models	Longitudinal EHR sequences	Captures patient trajectories	Can struggle with long histories and missing data	Good	Choi *et al*. (2016); Baytas *et al*. (2017); Che *et al*. (2018)
Transformer EHR models	Longitudinal structured EHR	Learns long-range clinical dependencies	Requires large-scale data and computation	Very good	Li *et al*. (2020); Solares *et al*. (2020)
NLP-enhanced models	Clinical notes and SDOH text	Extracts hidden social and clinical risk factors	Depends on note quality and documentation	Very good	Lee *et al*. (2020); Han *et al*. (2022); Guevara *et al*. (2024)
Full multimodal AI model	EHR, notes, labs, physiologic signals, SDOH	Integrates multiple risk pathways	Requires governance, harmonization, and fairness auditing	Excellent	Acosta *et al*. (2022); Rajkomar *et al*. (2018)

Table 4: Proposed Patient Risk Stratification and Intervention Pathway

Risk level	*Prediction indicator*	*Patient profile*	*Recommended clinical action*	*Expected outcome*
Low risk	Stable clinical and social indicators	Controlled disease, regular care access	Routine monitoring	Continued stability
Moderate risk	Early abnormal trends or mild SDOH barriers	Emerging progression risk	Preventive outreach and care review	Reduced progression
High risk	Worsening clinical trajectory and multiple risk factors	Uncontrolled disease or repeated utilization	Intensive chronic care management	Fewer complications
Critical risk	Severe deterioration or urgent risk pattern	High probability of hospitalization or major complication	Immediate clinical review and coordinated intervention	Reduced avoidable hospitalization



Graph 3: Relative Contribution of Data Modalities to Early Chronic Disease Progression Prediction



Graph 4: Patient Risk Stratification Output Across Chronic Disease Progression Levels

involves gradual changes in vital signs or functional status. PhysioNet and MIMIC-III have shown the importance of high-resolution physiologic and critical care data for clinical prediction research (Goldberger *et al.*, 2000; Johnson *et al.*, 2016). Medication history and laboratory values also contribute strongly because they reflect treatment intensity, disease control, and biological progression.

Risk Stratification and Clinical Decision Output

The third result area is the proposed risk stratification output. The framework classifies patients into low-risk, moderate-risk, high-risk, and critical-risk groups. Low-risk patients show stable clinical indicators and no major worsening pattern. Moderate-risk patients show early warning signs such as worsening laboratory trends, medication escalation, missed visits, or emerging SDOH barriers. High-risk patients show clear evidence of disease progression, repeated healthcare utilization, uncontrolled biomarkers, or multiple social risk indicators. Critical-risk patients show severe deterioration patterns and require urgent clinical review or intensive care coordination.

This risk stratification structure supports practical clinical decision-making. Instead of producing only a prediction score, the framework links risk levels to recommended intervention pathways. This is important because AI prediction is most useful when it supports timely action, clinician interpretation, and preventive care planning. However, fairness auditing must be included because healthcare algorithms may reproduce bias when healthcare cost or utilization is used as a proxy for disease severity (Obermeyer *et al.*, 2019). Therefore, each risk group should be evaluated across demographic and socioeconomic subgroups before deployment.

DISCUSSION

The proposed nationwide multimodal artificial intelligence framework provides a significant advancement in the early prediction of chronic disease progression by moving beyond conventional clinical risk models that depend mainly on structured electronic health record variables. Chronic disease progression is rarely determined by biological indicators alone. It is shaped by a complex interaction of clinical history, treatment patterns, medication adherence, lifestyle conditions, healthcare access, income, housing stability, environmental exposure, and continuity of care. Therefore, a prediction framework that uses only laboratory values, diagnosis codes, or hospitalization history may overlook important social and behavioral risks that influence long-term disease outcomes. This supports the need for a nationwide multimodal framework that integrates electronic health records with social determinants of health to improve prediction accuracy, clinical relevance, and equity (Chen *et al.*, 2020; Delpino *et al.*, 2022).

A major strength of the proposed framework is its ability to combine multiple data sources into a unified risk prediction system. Structured EHR data can provide information on diagnoses, medications, laboratory results, comorbidities, and previous healthcare utilization, while unstructured clinical notes may capture social, behavioral, and contextual factors that are not consistently coded in structured fields. Previous studies have shown that natural language processing can extract social determinants of health from clinical narratives, including housing issues, employment status, social support, substance use, and care barriers (Patra *et al.*, 2021; Guevara *et al.*, 2024). By combining these textual signals with longitudinal clinical trajectories, the proposed framework can support earlier identification of patients whose disease progression risk is driven by both medical and non-medical factors.

The clinical value of this framework lies in its potential to support proactive care rather than reactive treatment. Early prediction of chronic disease progression can help clinicians identify high-risk patients before complications become severe. This can improve care planning, enable timely follow-up, support medication review, and guide referral to social or community-based services. For healthcare systems, such a framework can support population health management by identifying groups at higher risk of hospitalization, readmission, or rapid disease deterioration. Evidence from EHR-based chronic disease prediction studies shows that machine learning models can assist in forecasting hospitalization risk and other adverse outcomes when properly trained and validated (Brisimi *et al.*, 2018; Swinckels *et al.*, 2024). In this sense, the proposed framework can strengthen preventive care, reduce avoidable hospital use, and improve resource allocation.

Despite these benefits, several implementation challenges must be addressed. Nationwide deployment requires strong interoperability across hospitals, clinics, laboratories, insurers, and public health systems. Variations in EHR systems, coding practices, missing data patterns, and documentation quality may reduce model generalizability. Social determinants of health are also inconsistently documented, and many socially vulnerable patients may have incomplete records. Privacy, governance, consent, and secure data-sharing mechanisms are also essential because the framework would process sensitive clinical and social information. In addition, clinician trust is critical. If model outputs are not explainable, actionable, and aligned with clinical workflows, adoption may remain limited.

Fairness is another central issue. Prediction models may reproduce structural bias when healthcare utilization is treated as a proxy for disease severity, because patients with limited access to care may appear less sick in the data even when their actual disease burden is high. Obermeyer *et al.* (2019) demonstrated how healthcare algorithms can underestimate the needs of disadvantaged populations when biased proxy variables are used. Therefore, the proposed framework must include subgroup evaluation, bias detection, fairness-aware learning, transparent reporting, and continuous monitoring across race, income, insurance type, rurality, gender, age, and other relevant population groups. Overall, the framework is valuable not only as a technical prediction system but also as a pathway toward more equitable, preventive, and socially informed chronic disease care.

CONCLUSION AND FUTURE RESEARCH

This paper concludes that a nationwide multimodal artificial intelligence framework provides a stronger and more comprehensive pathway for the early prediction of chronic disease progression than single-source clinical prediction models. Chronic diseases often develop through complex interactions among biological, clinical, behavioral, environmental, and social factors. Therefore, prediction systems that depend only on structured electronic health record variables may overlook important risk signals found in longitudinal patient trajectories, unstructured clinical notes, physiologic patterns, and social determinants of health. By integrating these multiple data sources, the proposed framework supports a more complete understanding of patient risk and disease progression across diverse healthcare populations.

The framework emphasizes the value of combining EHR trajectories, clinical narratives, physiologic signals, demographic indicators, and SDOH features to improve early risk detection, patient stratification, and preventive care planning. Prior studies have shown that deep learning models can improve clinical prediction from EHR data, while transformer-based EHR models can capture temporal relationships across patient histories (Rajkomar *et al.*, 2018; Li *et al.*, 2020). Similarly, multimodal biomedical AI provides an important foundation for combining heterogeneous health data into unified predictive systems (Acosta *et al.*, 2022). When applied at a nationwide level, such an approach can help identify high-risk patients earlier, support timely intervention, reduce avoidable hospitalizations, and improve chronic disease management across rural, urban, and underserved communities.

A major contribution of this paper is its emphasis on the integration of social determinants of health into chronic disease prediction. Clinical risk alone cannot fully explain disease progression because patients' health outcomes are shaped by access to care, income, housing, transportation, food security, education, and community conditions. Recent work has shown that large language models and natural language processing techniques can help extract SDOH information from electronic health records, making social risk more visible within clinical decision systems (Guevara *et al.*, 2024). However, these tools must be implemented carefully to avoid reinforcing existing inequalities. As demonstrated by Obermeyer *et al.* (2019), healthcare algorithms can reproduce structural bias when they use biased proxies such as healthcare cost or utilization. Therefore, fairness auditing, subgroup validation, transparency, and bias mitigation must be treated as core components of any nationwide AI framework.

Future research should move beyond conceptual development toward prospective validation in real-world healthcare systems. The proposed framework should be tested across multiple hospitals, primary care networks, rural clinics, and underserved populations to assess its accuracy, generalizability, fairness, and clinical usefulness. Further research should also explore federated learning as a way to train predictive models across institutions without requiring direct sharing of sensitive patient data. This would support privacy-preserving collaboration among healthcare systems while improving model robustness across diverse populations.

In addition, future studies should focus on real-time integration with EHR systems, explainable AI dashboards, clinician-centered decision support, and continuous monitoring of model performance after deployment. Explainability is especially important because clinicians need to understand why a patient is classified as high risk before acting on AI-generated recommendations. Future work should also expand the framework to include wearable device data, genomic indicators, community-level public health datasets, and patient-reported outcomes. As longitudinal EHR-based machine learning continues to advance, future systems should prioritize not only predictive accuracy but also equity, interpretability, privacy, and practical clinical adoption (Swinckels *et al*., 2024). Overall, a nationwide multimodal AI framework has strong potential to transform chronic disease prevention by enabling earlier, fairer, and more personalized intervention.

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