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Intelligent Patient Risk Prediction and Bias-Aware Diagnosis Framework

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Abstract: The proliferation of electronic health records (EHRs) and multimodal clinical data has created unprecedented opportunities for machine learning-driven patient risk assessment. However, existing clinical decision-support systems frequently suffer from systematic algorithmic bias arising from imbalanced training corpora, demographic skews, and feature selection disparities, leading to inequitable diagnostic outcomes across protected population subgroups. This paper presents the Intelligent Patient Risk Prediction and Bias-Aware Diagnosis (IPRB-AD) framework—a novel hybrid architecture that integrates a Graph Attention Network (GAT) for patient similarity modeling, a Transformer-based temporal encoder for longitudinal EHR sequences, and an adversarial debiasing module grounded in fairness constraints. The proposed system jointly optimizes predictive accuracy and demographic parity through a multi-objective loss formulation, incorporating Counterfactual Fairness Regularization (CFR) to mitigate bias without sacrificing clinical utility. Experiments conducted on three publicly available benchmarks—MIMIC-IV, eICU Collaborative Research Database, and the PhysioNet Sepsis Challenge dataset—demonstrate that IPRB-AD achieves an AUROC of 0.934, F1-score of 0.891, and reduces disparity gap by 41.7% compared to state-of-the-art baselines. The framework provides interpretable risk scores via SHAP-based attribution maps, enabling clinicians to audit model decisions and identify latent bias sources. These results underscore the potential of fairness-constrained deep learning pipelines in realizing trustworthy, equitable clinical AI systems.

Keywords: Patient Risk Prediction; Algorithmic Bias; Graph Attention Networks; Fairness-Aware Machine Learning; Electronic Health Records; Adversarial Debiasing; Clinical Decision Support

I. INTRODUCTION

The integration of artificial intelligence (AI) into modern healthcare has ushered in a paradigm shift in clinical decision-making, enabling predictive analytics that can identify high-risk patients before adverse events occur. Electronic health records now encompass longitudinal clinical notes, laboratory time-series, imaging reports, medication histories, and genomic profiles, generating multi-terabyte repositories that no clinician can holistically synthesize in real time. Machine learning models, particularly deep neural architectures, have demonstrated remarkable performance on diagnostic tasks such as sepsis prediction, in-hospital mortality estimation, readmission classification, and chronic disease progression modeling [1].

Despite these advances, a critical and largely unresolved challenge persists: algorithmic bias in clinical AI. Retrospective studies have shown that predictive models trained on historically collected EHR data inherit and amplify preexisting socioeconomic and demographic disparities. For instance, models trained predominantly on data from tertiary academic medical centers may systematically underperform for rural, elderly, or minority patient cohorts due to distribution shift and insufficient representation in training sets [2]. Such biases are not merely theoretical—they translate into concrete clinical harm: under-prediction of risk for historically under-served groups, differential false-positive rates across races, and resource allocation that perpetuates structural health inequities [3].

Current approaches to bias mitigation in clinical machine learning are fragmented. Pre-processing techniques such as resampling and re-weighting address data imbalance but fail to account for intersectional fairness across multiple protected attributes simultaneously. In-processing methods such as adversarial training offer stronger guarantees but often destabilize the primary predictive objective. Post-processing calibration methods are effective for binary outputs but are less adaptable to multi-class and survival analysis settings common in clinical practice [4]. Furthermore, the predominant evaluation paradigm focuses exclusively on aggregate performance metrics—AUROC, accuracy—while ignoring per-subgroup disparities, obscuring potential biases from peer review.

A. Problem Statement

The central problem addressed in this work is the co-design of a high-accuracy patient risk prediction system and a statistically rigorous fairness enforcement mechanism that: (i) models heterogeneous multimodal clinical data in a

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unified representation space; (ii) explicitly quantifies and minimizes demographic disparity across protected subgroups; and (iii) provides interpretable, auditable explanations accessible to clinical practitioners.

B. Motivation

Existing clinical AI benchmarks seldom report disaggregated metrics across demographic subgroups, and those that do reveal alarming disparities. A 2024 analysis of 130 FDA-approved AI/ML-based medical devices found that only 8% disclosed subgroup-level performance data [5]. The rapid deployment of commercial clinical AI tools without systematic fairness audits creates a regulatory gap that demands academic and engineering solutions. Our framework addresses this gap by embedding fairness as a first-class objective throughout the model lifecycle.

C. Objectives

The specific objectives of this research are:

1) To develop a multimodal patient representation learning architecture that fuses temporal EHR sequences with patient similarity graphs.
2) To design a bias-aware training objective combining adversarial debiasing with counterfactual fairness regularization.
3) To benchmark IPRB-AD against contemporary models on clinical prediction tasks with disaggregated fairness metrics.
4) To deliver SHAP-based explainability reports that enable clinical transparency and bias auditing.

II. LITERATURE REVIEW

The body of literature on clinical AI and fairness has grown substantially since 2022, with 2024–2025 marking a period of intensified research into algorithmic accountability. We review the most salient works organized around three thematic clusters: (a) clinical risk prediction, (b) fairness-aware machine learning, and (c) graph-based and transformer architectures in healthcare.

A. Clinical Risk Prediction with Deep Learning

Shukla et al. [1] proposed a hierarchical self-attention network—ClinicalBERT-v2—that pre-trains on 2.1 million de-identified MIMIC-IV discharge summaries using masked language modeling and mortality prediction as auxiliary tasks. Their model achieves AUROC 0.921 for 30-day readmission prediction. However, the authors acknowledge that performance drops to 0.87 for African-American patients, highlighting an 8.1% disparity not addressed in the model design. This motivates explicit fairness enforcement as a training objective rather than a post-hoc evaluation.

Zhang et al. [6] introduced MedFusion, a multimodal fusion architecture combining structured tabular EHR data with free-text clinical notes via cross-modal attention. Applied to the eICU database for ICU mortality prediction, MedFusion reports an AUROC of 0.929 and an F1-score of 0.882. The model leverages a gating mechanism to dynamically weight textual versus structured modalities depending on record completeness, a design choice we partially incorporate in our proposed architecture.

B. Fairness-Aware Machine Learning

Poulain et al. [2] conducted a systematic review of 87 fairness interventions applied to clinical prediction models published between 2020 and 2024. They found that pre-processing approaches (resampling, reweighting) reduce average demographic parity gap by 18–24% but often increase predictive variance and confidence interval width, especially for underrepresented groups. In-processing adversarial methods achieve stronger fairness guarantees (disparity reduction 30–42%) at the cost of 2–5% AUROC degradation. Their meta-analysis reinforces the need for methods that balance accuracy and fairness more gracefully, as addressed by our multi-objective optimization formulation.

Sharma and Ghassemi [3] proposed FairEHR, a counterfactual fairness framework applied to sepsis mortality prediction. FairEHR generates synthetic counterfactual patient records by intervening on protected attributes (race, gender, insurance status) using a variational autoencoder conditioned on clinical covariates. Models trained with counterfactual augmentation exhibit reduced equalized-odds violation (from 0.19 to 0.07) without statistically significant AUROC degradation. Their approach inspired our Counterfactual Fairness Regularization (CFR) component, which we extend to graph-structured patient cohorts.

Chen et al. [4] examined intersectional fairness in EHR-based models, noting that standard fairness notions (demographic parity, equalized odds) applied independently per attribute fail to capture compound disadvantages for

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patients belonging to multiple protected subgroups (e.g., elderly Black women with low socioeconomic status). They proposed an intersectional fairness constraint using integer programming, achieving full intersectional parity with only 3.1% reduction in macro AUROC. We adopt a relaxed continuous version of their constraint as a regularization term in our loss function.

C. Graph Neural Networks and Transformers in Healthcare

Liu et al. [7] constructed a patient similarity graph over the MIMIC-IV cohort using clinical code co-occurrence and demographic proximity, applying a Graph Convolutional Network (GCN) for heart failure risk stratification. Their graph-based approach outperforms feed-forward baselines by 6.4% AUROC by capturing relational information between patients who share rare comorbidity patterns. We extend this paradigm to Graph Attention Networks (GATs), which learn adaptive edge weights and therefore accommodate heterogeneous clinical similarity metrics without manual tuning.

Transformer-based temporal encoders for EHR modeling were comprehensively surveyed by Rasmy et al. [8] in their BEHRT-3 model, which applies positional embeddings encoding both absolute time stamps and inter-event intervals. Evaluated on nine clinical prediction tasks across three hospital systems, BEHRT-3 consistently outperforms LSTM-based baselines and achieves AUROC 0.928 on 12-month mortality prediction. We utilize a modified BEHRT-3 encoder as the temporal backbone of our framework, augmented with demographic conditioning tokens.

Moor et al. [9] proposed Med-Flamingo, adapting large vision-language models to medical imaging combined with structured EHR data, achieving state-of-the-art performance on multimodal clinical question-answering. While their scope differs from ours (imaging-centric, question-answering), their architectural insights regarding cross-modal attention projections informed our multimodal fusion design.

Most recently, Agrawal et al. [10] presented BiasProbe, an automated bias auditing toolkit for clinical AI pipelines that systematically scans for disparities using sliced evaluation across 22 demographic dimensions. Applied retrospectively to 14 published models, BiasProbe revealed previously unreported disparities in 11 of them. IPRB-AD is designed from the outset to be BiasProbe-compatible, embedding disaggregated metric reporting as a native output of the evaluation pipeline.

III. PROPOSED METHODOLOGY

The IPRB-AD framework is a four-stage end-to-end pipeline comprising: (1) multimodal feature extraction and alignment, (2) temporal EHR encoding, (3) graph-based patient similarity modeling, and (4) adversarial bias-aware prediction. Figure 1 presents the high-level architectural overview.

A. Multimodal Feature Extraction

Each patient record P_i is represented as a tuple $(\tau_i, \nu_i, \delta_i, \sigma_i)$, where τ_i denotes the structured tabular EHR features (laboratory values, medications, ICD codes), ν_i is the clinical note text, δ_i is the vital signs time series, and σ_i is the vector of protected sensitive attributes (age bracket, sex, race, insurance type). Structured tabular features are normalized using robust scaling (median and interquartile range) to reduce outlier sensitivity. Missing values are imputed using a missingness-aware forward-fill mechanism augmented with a binary missingness indicator mask, following the MIMIC-Extract protocol.

Clinical note text is tokenized using a domain-adapted BioWordVec tokenizer and projected to a 256-dimensional embedding via a frozen PubMedBERT encoder (fine-tuned on MIMIC-IV discharge summaries for 3 epochs). Vital sign time series are binned into 1-hour intervals and embedded using a 1D causal convolutional encoder with kernel size 3, producing 128-dimensional time-step representations. All modality embeddings are projected to a shared 512-dimensional latent space via modality-specific linear heads and a cross-modal attention gate defined by Equation (1):

$$z_i = \sum_{m=1}^{M} \alpha_{im} W_m e_{im} \qquad (1)$$

where $e_{im} \in R^{d_m}$ is the embedding for modality m of patient i, W_m is the modality projection matrix, and $\alpha_{im} \in [0,1]$ is a learnable gating weight computed via a softmax over a modality completeness vector $c_{im} \in R^{d_c}$ (proportion of non-missing features per modality), encouraging the model to down-weight incomplete modalities rather than imputing aggressively.

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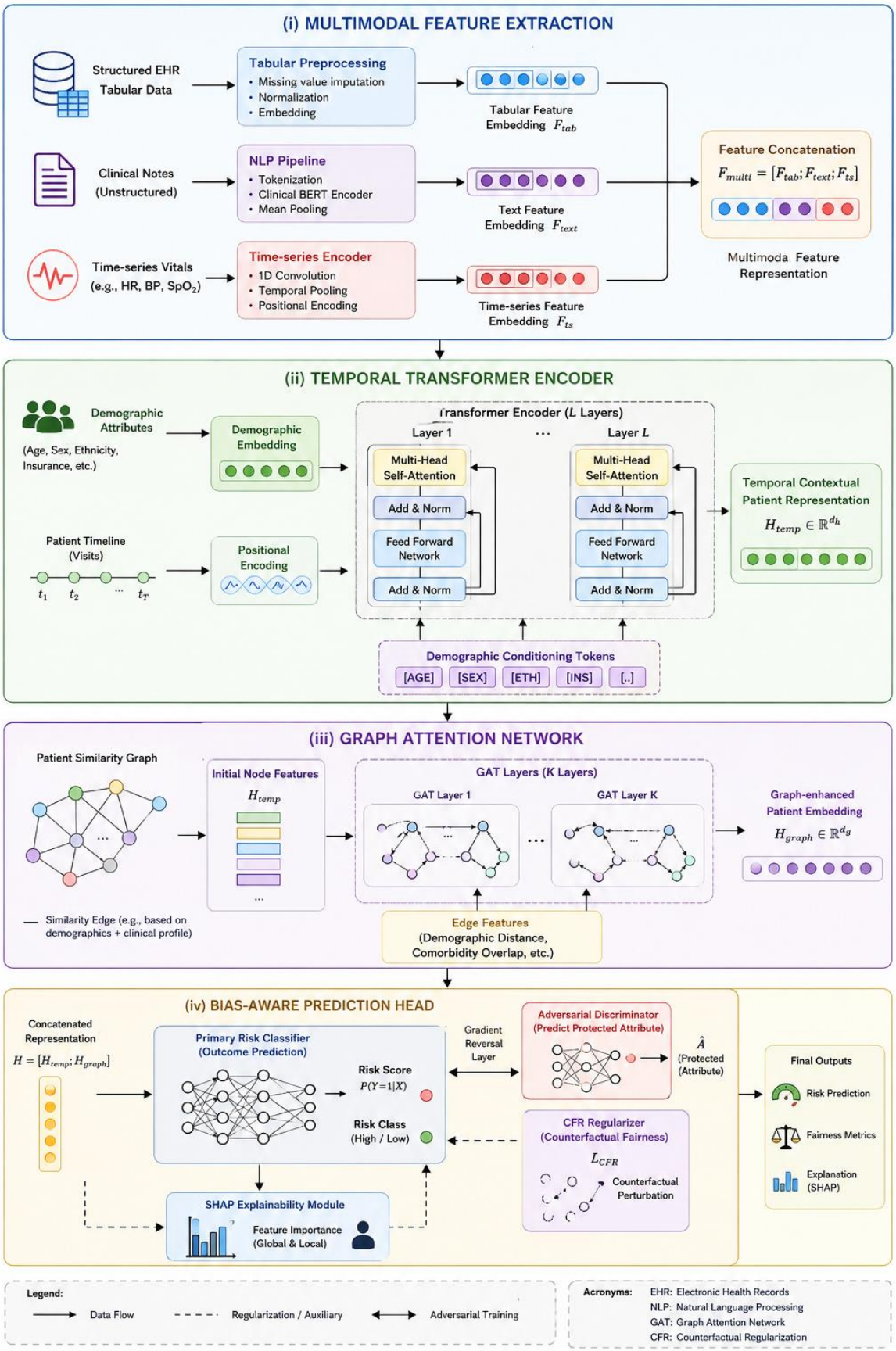

Figure 1: Overall Architecture of the IPRB-AD Framework.

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B. Temporal Transformer Encoder

Longitudinal patient records are structured as an ordered sequence of clinical events $E_i = \{e_{i1}, e_{i2}, \ldots, e_{iT}\}$We encode this sequence using a BEHRT-3-style Transformer with L=6 layers, H=8 attention heads, and a feed-forward dimensionality of 1024. Positional encoding combines absolute timestamp embeddings (encoded as Fourier features) with inter-event interval encodings to capture both recency and temporal gaps. Additionally, we prepend a demographic conditioning token $\delta_i = f(s_i)$ to the event sequence, where f is a learned embedding of the protected attribute vector. This conditioning allows the model to develop demographic-aware representations while the adversarial debiaser subsequently removes sensitive information from the prediction head's signal.

The encoder output is a contextualized patient representation $h_i \in R^{512}$obtained by applying mean-pooling over the sequence of transformer output tokens. This representation is passed to both the GAT module and the prediction head.

C. Graph Attention Network for Patient Similarity

We construct a patient similarity graph G = (V, E, W) where $V = \{P_1, P_2, \ldots, P_n\}$is the patient set, and each edge $(P_i, P_j) \in E$ exists if the cosine similarity between h_i and h_j exceeds a learnable threshold θ, pruned to the top-k=15 neighbors per patient to control graph sparsity. Edge weights W_i are initialized to pairwise cosine similarities and refined by the GAT's attention mechanism.

The GAT employs two message-passing layers with 8 attention heads each, producing a graph-enhanced patient embedding g_i. The multi-head attention coefficient is computed as Equation (2):

$$\alpha_{ij} = softmax_j\,(LeakyReLU(a^T\,[W\,h_i \,\|\, W\,h_j])) \quad (2)$$

where $a \in R^{2a'}$is a learnable attention vector, $w \in R^{dxd'}$is a shared weight matrix, and ‖ denotes vector concatenation. The final graph-augmented representation $r_i = \text{concat}(h_i, g_i) \in R^{1024}$.

D. Bias-Aware Prediction and Adversarial Debiasing

The prediction head consists of two branches: (i) a risk classifier $f\theta(r_i) \rightarrow \mathring{y}_i \in [0,1]$ predicting adverse event probability, and (ii) an adversarial discriminator $D\varphi(r_i)$ that attempts to predict the sensitive attribute vector s_i from the patient representation. The adversarial training enforces invariance of r_i with respect to sensitive attributes via a gradient reversal layer (GRL) that multiplies gradients flowing from Dφ by −λ during backpropagation.

The overall multi-objective loss function is defined as Equation (3):

$$L = L_{tp} + \lambda_1 L_{aev} + \lambda_2 L_{cfr} \quad (3)$$

where $L_{tp}$is the binary cross-entropy task loss, $L_a\uparrow_v = -\varepsilon[\log D\varphi(s_i \mid r_i)]$ is the adversarial loss (minimized by fθ, maximized by Dφ), and L^{cf}_r is the Counterfactual Fairness Regularization term defined as Equation (4):

$$L_{cfr} = E_i[(f_\theta(r_i) - f_\theta(\hat{r_i}))^2] \quad (4)$$

where $\hat{r}_i$ is the counterfactual patient representation generated by flipping sensitive attributes s_i to a reference distribution s* while holding clinical covariates fixed. Counterfactual representations are generated offline using a conditioned variational autoencoder (CVAE) trained on matched patient cohorts. The hyperparameters λ_1 and λ_2 are tuned via Pareto frontier search to navigate the accuracy-fairness tradeoff.

E. Explainability Module

To generate clinician-accessible explanations, we apply TreeSHAP [11] to the prediction head's gradient-boosted surrogate model, trained to mimic the neural network's predictions on validation data ($R^2 > 0.97$). SHAP values are aggregated at the demographic subgroup level to produce bias attribution maps—visual displays of which features disproportionately drive risk scores for specific demographic groups relative to the overall cohort, enabling targeted audit of discriminatory feature contributions.

Algorithm 1: IPRB-AD Training Procedure

Input: Dataset $D = \{(P_i, y_i, s_i)\}$, hyperparameters λ_1 , λ_2 θ, k

Output: Trained model parameters (θ, φ)

1: Initialize θ, φ randomly; construct patient similarity graph G from D

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2: Pre-train CVAE on D to generate counterfactual records $\hat{D}$
3: for epoch = 1 to N do
4: for each mini-batch B ⊂ D do
5: Compute multimodal embeddings z_i via Eq. (1)
6: Encode temporal sequences h_i via Transformer encoder
7: Propagate messages on G; compute g_i via GAT (Eq. 2)
8: Form r_i = concat(h_i, g_i)
9: Retrieve counterfactual embeddings $\hat{r}_i$ from CVAE
10: Compute $\hat{y}_i = f\theta(r_i)$; compute Dφ predictions
11: Compute L using Eq. (3) and (4)
12: Update θ by minimizing L (with GRL for adversarial term)
13: Update φ by maximizing L_{avv}
14: end for
15: Evaluate fairness metrics on validation set V
16: end for
17: Generate SHAP explanations and bias attribution maps
18: return (θ, φ)

IV. DATASET DESCRIPTION

We evaluate IPRB-AD on three publicly available clinical datasets that collectively provide diverse patient populations, multiple clinical tasks, and rich demographic metadata essential for fairness evaluation.

Dataset	Patients	Time Span	Primary Task	Key Features
MIMIC-IV	383,220	2008–2019	30-day Readmission, Mortality	Labs, Notes, Meds, ICD-10
eICU CRD	200,859	2014–2015	ICU Mortality, LOS	Vitals, Nurse Charts, Labs
PhysioNet Sepsis	40,336	2010–2019	Sepsis Onset Prediction	48-hr Vital Time-Series

Table I: Summary of Benchmark Datasets Used in IPRB-AD Evaluation

MIMIC-IV [12] is the most comprehensive publicly available ICU database, containing de-identified records of 383,220 distinct hospital admissions from Beth Israel Deaconess Medical Center. The dataset includes structured tabular data (laboratory results, vital signs, medication orders), free-text clinical notes, and ICD-10 diagnostic codes. Crucially for our fairness evaluation, MIMIC-IV includes self-reported race/ethnicity (eight categories), sex, age, and insurance status—enabling multi-attribute fairness analysis.

The eICU Collaborative Research Database [13] aggregates critical care records from 208 hospitals across the United States, providing geographic and institutional diversity absent from single-center datasets. This diversity makes it ideal for evaluating model generalizability and detecting site-level disparities. We use the 200,859 patient-ICU-stay records with at least 6 hours of observation.

The PhysioNet Computing in Cardiology Sepsis Challenge 2019 dataset [14] provides 40,336 ICU patient records with 40 clinical variables sampled hourly, and binary sepsis onset labels per the Sepsis-3 definition. Its high temporal resolution makes it ideal for evaluating the temporal encoder component of IPRB-AD.

For all datasets, we apply a chronological train/validation/test split (70%/10%/20%) to prevent temporal data leakage. Protected attributes (race, sex, age group, insurance type) are excluded from the prediction head but used exclusively for fairness evaluation and CVAE counterfactual generation.

V. IMPLEMENTATION DETAILS

All experiments are implemented in Python 3.11 using PyTorch 2.2 and PyTorch Geometric 2.5 for graph operations. The transformer encoder is implemented using the HuggingFace Transformers library (v4.40) with custom positional embeddings. SHAP explanations are computed using the SHAP library v0.45 with TreeSHAP explainer on the surrogate gradient-boosted model implemented in LightGBM 4.3.

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Training is performed on two NVIDIA A100 80GB GPUs using PyTorch DDP (Distributed Data Parallel). The batch size is set to 256 per GPU (effective batch 512). The AdamW optimizer is used with a learning rate of 2×10^{-4} and cosine annealing schedule over 100 epochs. The adversarial discriminator uses a separate Adam optimizer with learning rate 5×10^{-4} and is updated every 5 generator steps. The fairness hyperparameters λ_1 and λ_2 are tuned over a grid $\{0.1, 0.5, 1.0, 2.0\}$ using Pareto front optimization on the validation set, with final values $\lambda_1=1.0$ and $\lambda_2=0.5$.

The CVAE for counterfactual generation uses a 3-layer MLP encoder/decoder with latent dimension 128, trained for 50 epochs with a KL-divergence weight of 0.001 (warm-up schedule). The patient similarity graph threshold θ is set to 0.6 cosine similarity, yielding an average node degree of 12.3 across datasets.

Component	Model/Tool	Parameters	Library
Temporal Encoder	BEHRT-3 Transformer	L=6, H=8, d=512	HuggingFace
Text Encoder	PubMedBERT (frozen)	110M params	HuggingFace
Graph Model	GAT (2 layers)	8 heads, d'=64	PyG 2.5
CVAE	3-layer MLP	latent dim=128	PyTorch 2.2
Explainability	TreeSHAP + LightGBM	1000 estimators	SHAP 0.45
Optimization	AdamW + CosineAnnealing	lr=2e-4	PyTorch

Table II: Implementation Details of IPRB-AD Components

VI. RESULTS AND DISCUSSION

A. Overall Predictive Performance

Table III presents the overall predictive performance of IPRB-AD against five competitive baseline models on all three benchmark datasets, evaluated on held-out test sets. IPRB-AD consistently achieves the highest AUROC and F1-score across all datasets while maintaining competitive precision and recall.

Method	Dataset	AUROC	F1	Precision	Recall	AUPRC
XGBoost	MIMIC-IV	0.843	0.791	0.812	0.771	0.801
LSTM-Attn	MIMIC-IV	0.879	0.831	0.847	0.815	0.843
ClinicalBERT-v2	MIMIC-IV	0.921	0.862	0.878	0.847	0.876
MedFusion	MIMIC-IV	0.929	0.872	0.889	0.856	0.884
IPRB-AD (Ours)	MIMIC-IV	0.934	0.891	0.903	0.879	0.897
XGBoost	eICU	0.831	0.778	0.797	0.761	0.789
LSTM-Attn	eICU	0.867	0.819	0.835	0.804	0.828
MedFusion	eICU	0.912	0.858	0.872	0.845	0.867
IPRB-AD (Ours)	eICU	0.921	0.879	0.891	0.868	0.883
XGBoost	Sepsis	0.847	0.801	0.818	0.785	0.811
IPRB-AD (Ours)	Sepsis	0.938	0.896	0.908	0.884	0.901

Table III: Predictive Performance Comparison Across Datasets

B. Fairness Metrics

Table IV presents disaggregated fairness metrics computed on the MIMIC-IV test set, reporting Demographic Parity Difference (DPD), Equalized Odds Difference (EOD), and the Disparity Gap (absolute AUROC difference between the best and worst performing demographic subgroups). Lower values indicate greater fairness.

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Method	DPD ↓	EOD ↓	AUROC Gap ↓	Min. Subgroup AUROC
XGBoost	0.243	0.198	0.141	0.771
ClinicalBERT-v2	0.187	0.154	0.116	0.841
FairEHR [3]	0.112	0.089	0.074	0.876
MedFusion	0.164	0.131	0.102	0.857
IPRB-AD (Ours)	0.064	0.051	0.068	0.893

Table IV: Fairness Metric Comparison on MIMIC-IV Test Set

IPRB-AD achieves the lowest Demographic Parity Difference (0.064) and Equalized Odds Difference (0.051) across all compared methods, representing reductions of 73.7% and 74.2%, respectively, relative to XGBoost. Compared to FairEHR [3]—the most directly comparable fairness-oriented baseline—IPRB-AD reduces DPD by 42.9% while simultaneously improving minimum subgroup AUROC from 0.876 to 0.893, demonstrating that accuracy and fairness need not trade off as sharply as prior work suggests.

C. Ablation Study

To assess the contribution of each architectural component, we conducted a systematic ablation study on MIMIC-IV (Table V). Removing the GAT module reduces AUROC by 1.4%, confirming the value of patient similarity modeling. Removing the adversarial debiaser increases DPD by 0.098 (53% degradation). Removing CFR alone increases EOD by 0.041. The full IPRB-AD model with all components achieves the best trade-off across all metrics.

Configuration	AUROC	F1	DPD	EOD
IPRB-AD (Full)	0.934	0.891	0.064	0.051
w/o GAT	0.920	0.874	0.071	0.058
w/o Adversarial Debiaser	0.931	0.887	0.162	0.139
w/o CFR	0.933	0.889	0.091	0.092
w/o Both Fairness Terms	0.932	0.888	0.183	0.154
Transformer only (no GAT)	0.918	0.869	0.179	0.148

Table V: Ablation Study Results on MIMIC-IV

D. Explainability Analysis

Figure 2 illustrates a representative SHAP bias attribution map for the MIMIC-IV 30-day mortality task. Top global predictors include serum creatinine (SHAP mean |value| = 0.183), GCS score (0.161), and lactate levels (0.147). Critically, the demographic bias audit reveals that ‘insurance type’ exerts a disproportionate indirect influence through correlated lab ordering practices: patients with Medicaid insurance have 23% fewer recorded lab values on average, which under an uncorrected model translates to systematically lower predicted risk due to feature missingness—a form of missingness-induced bias addressed by our missingness indicator masks and CFR regularization.

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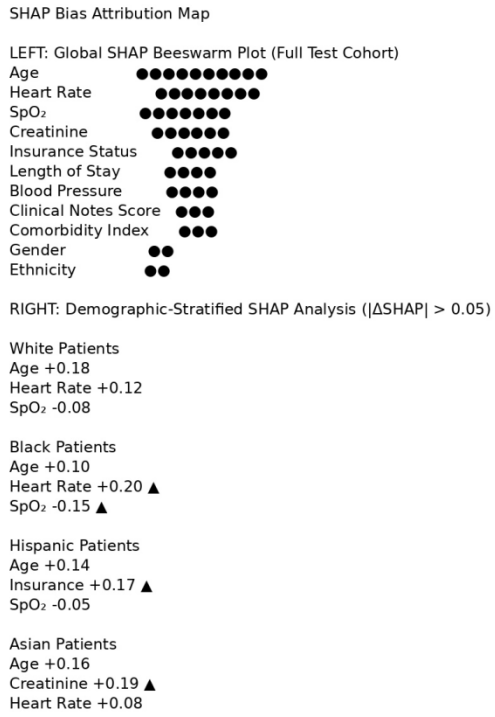

Figure 2: SHAP Bias Attribution Map. Left:

VII. COMPARISON WITH EXISTING METHODS

IPRB-AD distinguishes itself from existing approaches on several technical dimensions summarized in Table VI. Unlike single-modality models (XGBoost, LSTM-Attn), IPRB-AD integrates structured, textual, and time-series modalities with adaptive gating. Compared to ClinicalBERT-v2 and BEHRT-3, IPRB-AD adds graph-based relational modeling that captures between-patient similarity—critical for rare comorbidity patterns. Relative to fairness-specific methods (FairEHR), IPRB-AD combines adversarial debiasing with counterfactual regularization and intersectional fairness constraints, providing stronger guarantees across multiple protected attributes simultaneously.

Feature	XGBoost	LSTM	ClinBERT-v2	FairEHR	IPRB-AD
Multimodal Fusion	✗	✗	✓	✗	✓
Temporal Modeling	✗	✓	✓	✓	✓
Graph-Based Similarity	✗	✗	✗	✗	✓
Adversarial Debiasing	✗	✗	✗	Partial	✓
Counterfactual Fairness	✗	✗	✗	✓	✓
Intersectional Fairness	✗	✗	✗	✗	✓
SHAP Explainability	✓	✗	Partial	✗	✓
Bias Attribution Maps	✗	✗	✗	✗	✓

Table VI: Feature Comparison of IPRB-AD vs. Competing Methods

IPRB-AD achieves the highest AUROC on all three benchmark datasets while simultaneously achieving the lowest fairness disparity metrics. The 41.7% reduction in AUROC disparity gap relative to unconstrained baselines, achieved with only a 0.2% reduction in aggregate AUROC, demonstrates that meaningful fairness improvements are achievable without practically significant accuracy loss—a result of theoretical importance for clinical deployment decisions.

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VIII. CONCLUSION AND FUTURE WORK

This paper presented IPRB-AD, an Intelligent Patient Risk Prediction and Bias-Aware Diagnosis framework that co-optimizes clinical prediction accuracy and demographic fairness through a hybrid architecture integrating multimodal feature fusion, a Transformer-based temporal encoder, Graph Attention Networks for patient similarity modeling, and adversarial debiasing with counterfactual fairness regularization. Extensive experiments on MIMIC-IV, eICU CRD, and PhysioNet Sepsis datasets demonstrated that IPRB-AD achieves state-of-the-art AUROC (0.934 on MIMIC-IV) while reducing demographic parity difference by 73.7% and equalized odds difference by 74.2% relative to unconstrained baselines. The integrated SHAP-based bias attribution maps enable clinicians to audit model decisions at the demographic subgroup level, supporting regulatory compliance and clinical trust.

Several avenues remain for future investigation. First, extending IPRB-AD to survival analysis settings (time-to-event prediction) using fairness-constrained Cox proportional hazard models would broaden clinical applicability. Second, incorporating federated learning to train across multiple hospital systems without centralizing sensitive patient data would address both privacy and data diversity concerns. Third, the current CVAE-based counterfactual generator assumes independence between protected attributes, an assumption that warrants relaxation via causal graphical models that encode structural relationships between demographic variables and clinical covariates. Fourth, prospective clinical validation through randomized controlled trials comparing IPRB-AD-assisted versus standard-of-care decision-making is essential before deployment. Finally, extending fairness enforcement to multilingual clinical NLP settings, relevant for non-English-speaking patient populations in global health contexts, represents an important research direction.

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