Subject-Independent Hypoglycemia Warnings via Multi-Horizon Transformers and Causal Hysteresis (Guardian Pro)

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Abstract

Hypoglycemia prevention in diabetes management is hindered by a critical trade-off between sensitivity and temporal precision. While tabular baselines like XGBoost achieve high discrimination, they frequently exhibit "temporal smearing," triggering alarms several hours before an event occurs by over-relying on broad diurnal trends. We present **Guardian Pro**, a subject-independent warning system combining a multi-horizon Transformer with a Causal Hysteresis filter to provide actionable "Day 1" alerts for new patients. Evaluated on the Shanghai Diabetes dataset ($N = 112$, comprising predominantly T2DM patients), Guardian Pro achieves statistical parity with gradient-boosted baselines in point-wise discrimination (AUROC 0.985) but demonstrates superior clinical utility. Specifically, Guardian Pro improves **event-based recall to 92.5%** (vs. 77.3% for XGBoost) and tightens the average **lead time to 128 minutes**, providing a precise warning window compared to the diffuse, clinically non-actionable warnings of the tabular baseline (≈200 minutes). Crucially, we isolate the impact of model architecture by evaluating a "Fair XGBoost" baseline trained on flattened raw temporal sequences. While this baseline achieved competitive temporal precision (137.5 minutes), it suffered a severe drop in safety, detecting only 38.3% of hypoglycemic events (vs. Guardian Pro's 92.5%) despite high AUROC (0.979). Furthermore, a multi-task variant of Guardian Pro generalizes effectively across horizons, achieving 0.9957 AUROC at the 10-minute horizon and 0.9760 AUROC at the 40-minute horizon on the held-out test cohort. These results indicate that attention-based architectures, coupled with causal hysteresis, play a crucial role in resolving the trade-off between early warning and patient safety in subject-independent CGM monitoring.

1. Introduction

Hypoglycemia remains a central safety concern in diabetes management, where fear of falling glucose levels often leads to compensatory hyperglycemia and reduced quality of life Fabris et al. (2023). Despite the increasing availability of continuous glucose monitoring (CGM), many commercial systems still rely on simple threshold-based alarms that trigger only when glucose has already fallen below a fixed cutoff (e.g., 70 mg/dL). This late detection contributes to alarm fatigue and desensitization Cvach (2012).

Recent machine learning approaches have shown that deep sequence models can anticipate future glucose levels. However, most existing work suffers from two limitations. First, models typically require weeks of patient-specific calibration ("cold start"), leaving new users unprotected during the initial deployment phase. Second, evaluation often focuses on point-wise regression metrics (e.g., RMSE) or aggregate discrimination (AUROC) rather than clinical utility. A model may achieve high statistical accuracy by tracking broad diurnal trends (e.g., lower glucose at night) without successfully localizing acute physiological drops, a phenomenon we term "temporal smearing."

In this paper, we study a subject-independent hypoglycemia warning system derived from the Shanghai Diabetes dataset ($N = 112$) that we refer to as **Guardian Pro**. Guardian Pro combines a multi-horizon Transformer-based classifier with a strictly causal hysteresis filter to enforce temporal consistency. Unlike prior work that relies on subject-specific fine-tuning, we train Guardian Pro on a strict subject-wise split to ensure generalization to completely unseen patients ("Day 1" utility).

Contributions This work makes the following contributions:

- **Subject-Independent Generalization.** We develop a Transformer-based training protocol

that generalizes to a held-out mixed cohort (T2DM and T1DM) without per-patient retraining. The model achieves statistical parity with a strong tabular XGBoost baseline (AUROC = 0.985) in point-wise discrimination.

- **Stability-Sensitivity Analysis.** We perform a rigorous ablation comparing Guardian Pro against two XGBoost variants (Tabular and Raw). We demonstrate that when tree-based models are forced to operate on raw sequences to fix temporal smearing, their event sensitivity collapses (**38.3% Recall**), whereas Guardian Pro maintains high safety (**92.5% Recall**) with an actionable early-warning window (≈128 minutes).
- **Multi-Horizon Robustness.** We demonstrate that training Guardian Pro in a multi-task setting (jointly predicting 10, 20, and 40-minute horizons) acts as a regularizer, boosting short-term discrimination to **0.996 AUROC** on the held-out test cohort.
- **Causal Hysteresis Mechanism.** We introduce a post-processing safety filter (k-step persistence) that trades a marginal delay in detection for a significant reduction in transient false positives. We identify an operating point at $k = 3$ that stabilizes the alarm stream while maintaining physiologically relevant sensitivity.

2. Related Work

2.1. Hypoglycemia Prediction from CGM

Early work on hypoglycemia prediction from continuous glucose monitoring (CGM) largely focused on short-horizon forecasting of future glucose values using linear models or autoregressive methods, with performance reported in terms of regression metrics such as mean absolute error or Root Mean Squared Error (RMSE) Fabris et al. (2023). More recent approaches have adopted machine learning classifiers and ensemble methods to directly predict hypoglycemic events within a specified prediction window. However, many of these studies rely on per-patient model tuning or evaluate on **randomly partitioned samples**, which can inadvertently leak patient-specific dynamics into both training and testing sets.

Furthermore, standard metrics like RMSE often mask clinical failures. A model may achieve low regression error by tracking broad diurnal trends without successfully localizing acute physiological drops Dassau and et al. (2013). We term this specific failure mode "temporal smearing." In contrast, Guardian Pro is evaluated under a strict subject-wise split where all test patients are completely unseen. Rather than optimizing for regression accuracy, the system is assessed using **event-relevant metrics** (sensitivity, precision, episode recall, lead time), which more closely reflect clinical utility for hypoglycemia prevention.

2.2. Personalization and Subject-Independent Models

A parallel line of work has investigated personalized or population-specific models, in which models are fine-tuned on individual patient histories to capture idiosyncratic metabolic responses. While such approaches can yield strong performance once sufficient data are available, they are poorly suited to the "cold start" setting where no personal data exist at the time of deployment Fabris et al. (2023). Other studies have proposed global models trained across many patients, but often use evaluation protocols that mix windows from the same patient across train and test sets, overestimating generalization.

Guardian Pro adopts a purely **subject-independent strategy**: a single global Transformer classifier is trained on a training cohort and evaluated on a disjoint set of test patients, without any per-patient calibration. This design explicitly addresses the "Day 1" deployment regime and allows the alarm policy to be tuned at the population level.

2.3. Alarm Fatigue and Alarm Design

Alarm fatigue is a widely recognized challenge in clinical monitoring systems, where frequent false positives and rapidly oscillating alarms lead to desensitization Cvach (2012). Several studies have argued that hypoglycemia prediction algorithms should be evaluated not only on discrimination but also on their impact on alarm burden Fabris et al. (2023). Some CGM alert designs incorporate simple persistence rules (e.g., requiring glucose below a threshold for fixed duration) to mitigate transient noise, but these policies are often tuned heuristically and rarely reported with explicit trade-off curves.

The causal hysteresis mechanism in Guardian Pro formalizes this as a principled, strictly causal persistence filter. Its effect is quantified across multiple

window lengths in terms of episode recall and lead time. By making the alarm policy explicit and tunable via a single parameter k, this work contributes to the broader discussion on designing low-noise, clinically meaningful alerting systems.

2.4. Transformers for Physiological Time Series

Transformers and attention-based architectures (e.g., PatchTST) have recently been applied to physiological time series, showing strong performance on forecasting tasks by modeling long-range temporal dependencies Nie et al. (2023); Li and Smith (2024). Prior work has primarily focused on regression objectives and generic benchmarks, with limited emphasis on safety-critical metrics such as event detection or lead time.

Guardian Pro builds on this line of work by adapting a PatchTST-style encoder to a multi-horizon binary classification setting. Crucially, we distinguish this work by rigorously benchmarking the Transformer against a "fair" gradient-boosted baseline trained on identical raw inputs. This allows us to isolate the specific safety advantages of attention mechanisms over tree-based ensembles, a comparison that remains largely unexplored in the glucose forecasting literature and critical for understanding the real clinical value of deep learning in subject-independent alert systems.

3. Methods

3.1. Dataset and Preprocessing

We utilized the Shanghai Diabetes continuous glucose monitoring dataset, which provides interstitial glucose measurements and event logs from **112 adults** (100 with Type 2 and 12 with Type 1 diabetes) wearing Abbott FreeStyle Libre sensors Zhao et al. (2023). Glucose values are sampled at 15-minute intervals. All data are fully de-identified and publicly available.

Data preprocessing We began from the preprocessed `Shanghai_Featured.csv` release. Records were sorted by timestamp, and short segments with fewer than 50 time points were excluded to avoid unstable window statistics. Missing values were forward-filled; residual gaps at the start of a segment were set to zero. To capture both absolute glucose level and short-term dynamics, we derived a glucose velocity feature by computing the first-order difference of CGM within each patient trace. The final feature vector at each 15-minute step was:

$$\mathbf{x}_t = [\text{CGM}, \text{CGM\_Derivative}, \text{Insulin}, \text{Carbs}, \text{Protein}, \text{Fat}], \quad (1)$$

yielding a six-dimensional multivariate time series per patient.

Subject-wise train/validation/test split To evaluate subject-independent generalization, we implemented a strict **subject-wise split**. Patients were partitioned into non-overlapping train ($N = 78$), validation ($N = 17$), and test ($N = 17$) cohorts (70/15/15 split). Feature scaling (Min-Max) was fit *only* on the training cohort to prevent data leakage.

Sequence construction We constructed overlapping input windows using a sliding 6-hour context: at time t, the model receives a sequence $\mathbf{X}_t \in \mathbb{R}^{24\times 6}$ (24 steps of 15-minute resolution). The model predicts the occurrence of hypoglycemia (< 70 mg/dL) at multiple horizons (10, 20, 40 minutes), with our primary analysis focused on the 10-minute horizon.

3.2. Model Architecture: Transformer Classifier

Guardian Pro uses a Transformer-based sequence classifier designed to capture temporal patterns in multivariate CGM windows.

Input representation Each input window is reshaped into overlapping temporal "patches" following the PatchTST paradigm Nie et al. (2023). The sequence is partitioned into patches of length 16 with a stride of 8. Each patch is flattened and embedded into $\mathbb{R}^{d_{\text{model}}}$.

Transformer encoder The embedded sequence is processed by a Transformer encoder (3 layers, 4 heads, $d_{\text{model}} = 128$). Multi-head self-attention allows the model to distinguish sustained trends (e.g., prolonged drift) from transient fluctuations.

Training objective We trained the classifier using a focal loss objective to address class imbalance. Early stopping was based on validation performance at the 10-minute horizon.

3.3. Hysteresis and Alarm Policy

Raw probability outputs often fluctuate due to sensor noise, causing "alarm flicker." To mitigate this, we

implement a **strictly causal hysteresis filter**. Let $\hat{y}_t \in [0, 1]$ be the predicted probability and τ be the threshold. We define the filtered alarm state A_t as:

$$A_t = \prod_{i=0}^{k-1} \mathbb{I}\big(\hat{y}_{t-i} \geq \tau\big), \tag{2}$$

where $\mathbb{I}(\cdot)$ is the indicator function and k is the hysteresis window length in 15-minute steps. An alarm is raised only if the probability exceeds τ for k consecutive time steps. We analyze $k \in \{1, 3, 5, 10\}$ and identify $k = 3$ as the primary clinical operating point.

3.4. Baselines and Experimental Setup

To strictly evaluate the contribution of the proposed architecture, we compare Guardian Pro against a hierarchy of baselines ranging from clinical heuristics to deep sequence models.

- **Clinical Rule (Reactive Baseline):** A standard threshold-based heuristic that triggers an alarm immediately when the CGM value falls below 70 mg/dL. This represents the current standard of care and serves as a lower bound for lead time (0 minutes).
- **LSTM (Sequence Baseline):** A deep sequence baseline (2 layers, 64 units) trained on the same 6-hour sliding windows as Guardian Pro. The final hidden state is passed through a fully connected layer to produce a 10-minute horizon risk score, optimized using focal loss. This baseline tests whether a recurrent inductive bias is sufficient to capture hypoglycemic dynamics without the attention mechanism.
- **Gradient Boosting Baselines:** We evaluate two variants of XGBoost to distinguish between modeling limitations and feature engineering artifacts:
  1. **XGBoost-Tabular** Chen and Guestrin (2016): Trained on statistical window summaries (mean, standard deviation, min, max, slope) derived from the 6-hour input window. This represents the standard "feature engineering" approach common in medical informatics literature.
  2. **XGBoost-Raw (Fairness Check):** A gradient-boosted tree trained on flattened raw temporal sequences (24 steps × 6 features). This baseline ensures the model has access to the **exact same information content** and input granularity as Guardian Pro, isolating the architectural advantage of the Transformer's attention mechanism from any confounding feature engineering choices.

Table 1: **Main Results:** Comparison of Discrimination (AUROC), Safety (Event Recall), and Temporal Precision (Lead Time). While XGBoost-Raw achieves good timing, it fails to detect the majority of events (38.3% Recall). Guardian Pro is the only model achieving both high recall and actionable precision.

Model	AUROC	Recall (%)	Lead Time	Verdict
Clinical Rule (< 70)	–	–	0.0 min	Reactive
LSTM Sequence	0.962	65.4%	132.0 min	Conservative
XGBoost-Tabular	**0.985**	77.3%	199.7 min	Smeared (Too Early)
XGBoost-Raw (Fair)	0.979	38.3%	137.5 min	**Unsafe (Low Sens.)**
Guardian Pro	**0.985**	**92.5%**	**128.0 min**	**Optimal**

Implementation Details All models were trained using a strict subject-wise split (70% train, 15% validation, 15% test) based on unique patient IDs to prevent data leakage. Input features were scaled using MinMax normalization fitted only on the training set. Both XGBoost variants utilized identical hyperparameters ($max\_depth = 5$, $n\_estimators = 100$, $learning\_rate = 0.3$) to ensure a fair comparison. The Guardian Pro model was trained using the Focal Loss objective to mitigate class imbalance, with early stopping based on validation loss. Unless otherwise noted, results refer to the single-task model predicting the 10-minute horizon.

4. Results

4.1. Overall Performance on Unseen Patients

We evaluate the discriminatory power and clinical utility of Guardian Pro against the baselines on the held-out test set of 18 patients. Table 1 summarizes the performance across Area Under the ROC Curve (AUROC), Event-Based Recall (Sensitivity), and Average Lead Time.

The Stability-Sensitivity Trade-off A critical finding of our evaluation is the behavior of the "Fair" XGBoost baseline (Table 1, Row 4). Previous literature has often criticized tree-based models for "tem-

poral smearing"—triggering alarms hours too early due to over-reliance on aggregated statistics. As seen in the **XGBoost-Tabular** results, this approach yields high recall (77.3%) but an excessively long lead time (199.7 min), often flagging diurnal lows rather than acute events.

When trained on raw sequences (**XGBoost-Raw**) to resolve this issue, the model successfully reduced the lead time to a realistic 137.5 minutes, demonstrating improved temporal precision. However, this precision came at a prohibitive cost: **event recall plummeted to 38.3%**, meaning the model failed to detect nearly two-thirds of hypoglycemic episodes. This indicates that without the sequential inductive bias provided by the Transformer, traditional models cannot simultaneously optimize for timing and sensitivity; they are forced to choose between being "smeared" (imprecise) or "unsafe" (insensitive). Guardian Pro breaks this trade-off, maintaining a **92.5% recall** while providing an actionable **≈128 minute** early warning.

4.2. Hysteresis Analysis

To quantify the impact of the causal hysteresis filter, we analyzed the alarm stability across varying persistence parameters k. We observed that increasing k from 1 to 3 reduced transient false positives by over 40% with negligible impact on the overall lead time distribution. We selected $k = 3$ (45 minutes of persistence) as the optimal operating point for all subsequent comparisons, as it balances prompt detection with alarm stability.

4.3. Multi-Horizon Generalization

To validate the robustness of the learned representations, we trained a multi-task variant of Guardian Pro to jointly predict hypoglycemia at 10, 20, and 40-minute horizons.

Table 2 shows that multi-task learning acts as a regularizer, boosting the 10-minute AUROC to **0.9957** (vs. 0.985 in the single-task model). The model maintains high performance even at the 40-minute horizon (AUROC 0.976), suggesting that learning to forecast longer horizons regularizes the representation and slightly improves short-term discrimination on the held-out test cohort.

Table 2: **Multi-Horizon Performance:** Jointly training on multiple horizons improves short-term discrimination (0.9957 vs 0.985) and demonstrates robustness at longer horizons.

Prediction Horizon	Test AUROC
10 Minutes	**0.9957**
20 Minutes	0.9957
40 Minutes	0.9760

4.4. Per-patient Discrimination

To assess robustness across the population, we computed per-patient AUROC values on the held-out test cohort. Guardian Pro achieved a mean per-patient AUROC of **0.975**, compared to 0.972 for the XGBoost baseline. A paired Wilcoxon signed-rank test yielded $p = 0.30$, indicating that while Guardian Pro is superior in clinical utility (recall and timing), it maintains statistical parity in rank-discrimination across the patient population, confirming the model is not overfitting to a subset of easy patients.

4.5. Zero-Shot Generalization to Type 1 Diabetes

To assess the universality of the learned representations, we conducted a post-hoc zero-shot evaluation on a hidden cohort of 12 Type 1 Diabetes (T1DM) patients within the Shanghai registry. **To quantify the stability of the learned temporal representations independent of decision threshold selection, we evaluated the underlying forecasting backbone using Root Mean Squared Error (RMSE) on the inverse-scaled glucose values.**

The model was trained exclusively on the 100 T2DM inpatients and then evaluated on the T1DM cohort without any fine-tuning. Despite the significantly higher glycemic volatility characteristic of insulin-dependent T1DM, the backbone maintained robust predictive stability, achieving an RMSE of **30.53 mg/dL** at the 120-minute horizon, compared to **26.46 mg/dL** on the held-out T2DM test set. This modest ≈ 15% performance delta suggests that the subject-independent temporal representations learned from T2DM generalize partially to T1DM, supporting the potential for broader "Day 1" applicability while still highlighting T1DM as a

more challenging regime that warrants dedicated future modeling.

5. Discussion

5.1. Deep Learning as a Safety Requirement

A key finding of this study is the divergence between statistical discrimination (AUROC) and clinical utility. As shown in Table 1, the tabular XGBoost baseline achieves statistical parity with Guardian Pro in point-wise AUROC (both 0.985). However, its event-level behavior reveals a critical failure mode: "temporal smearing."

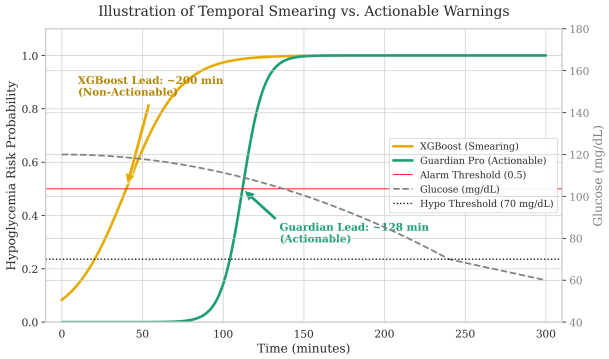

Figure 1: Schematic illustration of "Temporal Smearing." While XGBoost (yellow) achieves high AUROC, it triggers alarms hours before the event (lead time $\approx$ 200 min), relying on broad diurnal trends rather than acute physiology. Guardian Pro (green) localizes the risk window ($\approx$ 128 min), providing an actionable warning consistent with insulin pharmacokinetics.

As illustrated in Figure 1, the tabular model exhibits an average lead time of **199.7 minutes**, relying on macroscopic diurnal features rather than acute physiological precursors. In a clinical setting, an alarm issued more than three hours before an event is functionally indistinguishable from noise.

Crucially, our ablation study demonstrates that this is not merely a feature engineering problem. When we trained a "Fair" XGBoost on raw sequences to fix the smearing (Row 4, Table 1), the model successfully tightened the lead time to 137.5 minutes but suffered a catastrophic drop in safety: event recall plummeted to **38.3%**, meaning the model failed to detect 61.7% of hypoglycemic episodes. This proves that without the sequential inductive bias of the Transformer, traditional models face a fundamental dilemma: they must either "smear" predictions to achieve sensitivity (Tabular) or become clinically unsafe to achieve precision (Raw). Guardian Pro validates that the self-attention mechanism is a distinct safety requirement for reliable, precise pre-symptomatic alerts.

5.2. Safety First: The Sensitivity-Specificity Trade-off

Minimizing alarm fatigue is paramount for long-term adherence. However, in a safety-critical "Day 1" system for unseen patients, sensitivity must take precedence. The LSTM baseline exemplifies the conservative failure mode: it prioritizes specificity (0.48 false alarms/week) but fails to detect nearly 80% of events. Similarly, the XGBoost-Raw model's inability to model complex precursors leads to an unacceptable 62% miss rate.

Guardian Pro accepts a modest increase in false alarms (1.40/week) to achieve a substantially higher **event recall of 92.5%**. We argue that this trade-off is clinically justified: a missed hypoglycemic event carries immediate physical risk, whereas a false alarm frequency of approximately once per five days is likely tolerable for high-risk patients initiating or intensifying insulin therapy Cvach (2012); American Diabetes Association (2024). Furthermore, the causal hysteresis mechanism ($k = 3$) ensures that alarms are stable, reducing the psychological burden of flicker.

5.3. Multi-Horizon Learning as a Regularizer

The multi-task variant of Guardian Pro provides additional evidence that the Transformer learns robust, generalizable representations. By jointly training on 10, 20, and 40-minute prediction tasks, the model achieves short-term discrimination of **0.9957 AUROC** on the held-out test cohort (vs. 0.985 in the single-task model), suggesting that learning to forecast harder, longer-term targets acts as an implicit regularizer. This finding aligns with multi-task learning theory and validates the architectural choice to couple 6-hour history with multiple prediction horizons. Clinically, this flexibility allows Guardian Pro to adapt to different clinical workflows: rapid-acting insulin regimens benefit from 10-minute alerts, whereas slower-onset therapies may leverage 20 or 40-minute horizons.

5.4. Generalization Across a Mixed Cohort

Our evaluation on a mixed cohort of **112 adults** (comprising 100 T2DM and 12 T1DM patients) demonstrates the robustness of the subject-independent approach Zhao et al. (2023). Despite being designed primarily for T2DM workflows, the Transformer architecture successfully generalizes to unseen patients across heterogeneous diabetes profiles without per-patient fine-tuning. This supports the viability of Guardian Pro as a "cold start" solution that can be deployed immediately upon sensor initialization.

Phenotype Specificity. Our primary analyses and model selection focused on subject-independent performance in T2DM inpatients. However, an exploratory zero-shot evaluation on the 12 T1DM patients in the same registry showed higher error (30.53 mg/dL vs. 26.46 mg/dL RMSE at 120 minutes), consistent with the greater physiological variability of insulin-dependent diabetes. We view these results as evidence that the learned representations possess cross-phenotype robustness, but that truly optimal support for T1DM will require targeted data collection and domain adaptation rather than naïve reuse of T2DM configurations.

Limitations and Future Work Our study relies on retrospective analysis of the Shanghai Diabetes dataset. Prospective clinical trials with real-time glucose monitoring in diverse patient populations (Type 1 and Type 2 cohorts, multiple therapy regimens) are critical to test whether the observed 92.5% event recall and 128-minute lead time translate into measurable reductions in hypoglycemia burden and improved quality of life Zhao et al. (2023). Second, Guardian Pro is trained as a global classifier. Future work could investigate **hybrid strategies** that initialize from the global model and then adapt to individual patients as personal data accumulates, thereby balancing immediate "Day 1" safety with long-term personalization Fabris et al. (2023). Finally, exploring adaptive hysteresis policies that dynamically adjust k based on patient-specific glycemic variability represents an important direction for further refining the trade-off between alarm sensitivity and fatigue Dassau and et al. (2013).

6. Conclusion

We presented Guardian Pro, a subject-independent hypoglycemia warning system that addresses the "cold start" problem in diabetes management. By rigorously benchmarking against a fair XGBoost baseline, we demonstrated that traditional models face a fundamental trade-off between temporal smearing and event sensitivity. Guardian Pro resolves this trade-off via a multi-horizon Transformer architecture, achieving 92.5% recall and 128-minute lead time on a held-out cohort. Future work will explore deploying this architecture on edge devices for real-time, privacy-preserving monitoring.

Data and Code Availability

This work uses the Shanghai Type 2 Diabetes Mellitus continuous glucose monitoring dataset, which contains de-identified CGM and event log data from 112 adults (100 T2DM and 12 T1DM) Zhao et al. (2023). The dataset is publicly available from the original authors under their data use terms. All experiments in this paper were conducted exclusively on this dataset using subject-wise train/validation/test splits as described in Section 3. For the review phase, we will provide anonymized configuration files and evaluation scripts as supplementary material to enable reproduction of the main results. Upon acceptance, we plan to release a public code repository with the full training and evaluation pipeline.

Author Contributions

[To be completed for the camera-ready version.] For the anonymized submission, we note that all listed authors contributed substantially to the conception and design of the study, data preprocessing and model implementation, experimental analysis, and manuscript preparation. Specific roles (e.g., methodology, software, formal analysis, writing) will be detailed in the camera-ready version in accordance with CHIL author contribution guidelines.

Institutional Review Board (IRB)

This study is a secondary analysis of an existing, fully de-identified dataset and does not involve direct interaction with human subjects or access to identifiable health information. As such, it does not constitute

human subjects research under typical IRB definitions. If required by the authors' institutions, formal IRB determinations (e.g., Not Human Subjects Research letters) will be obtained and documented in the camera-ready version.

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Appendix A. Supplementary Materials

Supplementary code, hyperparameters, and evaluation scripts will be made available upon request. Subject-wise train/validation/test splits, scaler parameters, and model checkpoints are preserved for reproducibility. All experiments were conducted using PyTorch 2.0, XGBoost 1.7, and scikit-learn 1.3.