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Contrastive self-supervised and causal inference-based contextual predictive model for international student mental health education

Yi Hu

Hong Kong Baptist University, Hong Kong, China

Huyi02197@outlook.com

Abstract. Drawing on 4.8 million unlabeled behavioural events from 17 universities on five continents, this study proposes the Contrastive Self-Supervised and Causal Inference-Based Contextual Predictive Model (CSCI-CPM) to forecast depression risk and quantify the value of counseling outreach for 12 438 internationally mobile students. Twin momentum-updated Transformers learn 128-dimensional, domain-invariant embeddings via an InfoNCE objective, sharply reducing label dependence and campus drift. A doubly robust head jointly models treatment propensity and counterfactual PHQ-9 outcomes, yielding unbiased individualized treatment-effect estimates. Leave-one-continent-out tests lift ROC-AUC from 0.882 to 0.931, cut root-mean-squared PHQ-9 error by 0.41, and trim PEHE to 0.027, surpassing five baselines at $p < 0.01$. A 16-week Thompson-sampling simulation with 25 weekly counseling slots lowers unmet-need days by 41.6%, raises outreach to low-SES learners from 21% to 34%, and shrinks equal-opportunity gaps to 0.019. Real-time inference executes in 18 ms at < 0.001 kg CO_2-eq per student-day, enabling sustainable on-premise deployment. Clinician review validates 87% of alerts, while integrated-gradients explanations highlight language-switch entropy, night-screen bursts, and weekend immobility as salient risk signals. CSCI-CPM thus offers a scalable, culturally responsive, and privacy-preserving framework for proactive mental-health governance in global higher education.

Keywords: self-supervised learning, causal inference, mental-health prediction, international students, contextual modeling

1. Introduction

Cross-border tertiary enrolment surpassed 6.3 million in 2024, reshaping campuses into linguistically and culturally plural ecosystems. While global mobility enriches academic discourse, it also transports unique psychosocial stressors: visa anxiety, acculturative dissonance, remittance obligations, xenophobia, and time-zone misalignment with family support. A 2024 meta-analysis of 53 longitudinal studies estimates that 47.1% of international students develop moderate-to-severe depressive symptoms during their first academic year. Paradoxically, an International Education Association poll of 18,000 learners shows only 23.7% sought help within six months, citing stigma, language barriers, and confusion over insurance coverage, and unfamiliar bureaucratic procedures demanded by host-country institutions [1].

Early-warning systems that continuously monitor digital traces, smart-phone usage, Learning-Management-System (LMS) interactions, geo-mobility, promise proactive interventions. Yet two roadblocks persist. First, labeled mental-health data are scarce, expensive, and culturally imbalanced; supervised deep learners trained on a few hundred North-American undergraduates crumble when deployed in East-Asian or Sub-Saharan contexts [2]. Second, observational data conflate intervention effects with selection bias; students who voluntarily attend workshops differ systematically from non-attendees, so naïve predictors risk reinforcing inequities, directing scarce counseling resources toward already privileged groups.

College Student Computational-Informed-Care Prognostics Model (CSCI-CPM) addresses both issues. By leveraging contrastive self-supervised learning, the model distills semantic structure from millions of unlabeled events, producing embeddings resilient to domain drift [3]. Concurrently, a doubly robust causal layer models the treatment assignment mechanism and outcome surface, yielding unbiased Individualized Treatment-Effect (ITE) estimates even if one component is misspecified. Together these techniques generate accurate next-day risk forecasts and actionable ITEs that align with ethical mandates for fairness, transparency, and resource stewardship.

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2. Literature review

2.1. Advances in self-supervised representation learning

Instance-discrimination frameworks (SimCLR, MoCo) have demonstrated that maximizing agreement between augmented views of the same sample yields embeddings rivaling fully supervised counterparts. Extensions to sequential sensor data deploy temporal-jitter, masking, and feature shuffling to capture behavioral motifs predictive of affective states. Momentum encoders stabilize training on non-stationary streams, while projection heads with temperature-scaled Information Noise-Contrastive Estimation (InfoNCE) objectives encourage uniform representation use. Empirically, such embeddings reduce labeled-data requirements by 80% in mobile-mood forecasting tasks and quadruple cross-domain transfer accuracy relative to supervised pre-training [4].

2.2. Causal inference techniques in educational data mining

Propensity-score reweighting, targeted maximum-likelihood estimation, and doubly robust learners underpin the modern causal toolkit for observational education research. Neural variants embed high-dimensional confounders into balanced latent spaces before outcome modeling, preserving tractability and mitigating covariate shift [5]. Recent work in adaptive tutoring, scholarship allocation, and peer mentoring shows that ITE-aware policies outperform blanket interventions by 15-30% on learning-gain metrics while narrowing equity gaps.

2.3. Context-aware mental-health prediction for international populations

Contextual features-sociocultural distance indices, language-switch entropy, diurnal mobility radius, and remote family call duration, drive up to 34% of variance in depressive-symptom trajectories, far exceeding demographic covariates [6]. Integrating visa milestone calendars and daylight misalignment with home country further reduces false-negative rates among East-Asian and Middle-Eastern students. These findings validate the thesis that mental-health risk among mobile learners emerges from interaction between cultural context and daily behavior rather than universal demographic templates [7].

3. Experimental methodology

3.1. Ethical approvals, data assembly, and feature engineering

Research ethics boards at all partner universities provided approval (Ref.Institutional Review Board (IRB)-2024-081). Consent was obtained via a bilingual interface with General Data Protection Regulation (GDPR)-compliant plain-language statements. To respect regional privacy statutes (Personal Data Protection Act (PDPA), California Consumer Privacy Act (CCPA), Lei Geral de Proteção de Dados (LGPD)), raw logs were pseudonymized with Secure Hash Algorithm 3 (SHA-3) salting, and cross-site linkage was disabled. The final corpus comprises 12,438 participants (51% female; mean age = 24.2 ± 3.1 years). Each contributed 180 days of Patient Health Questionnaire-9 (PHQ-9) micro-surveys (2.24 million rows), 208.9 million app-usage events, 2.31 million language-switch transitions, 63 million Learning Management System (LMS) clicks, and 1.12 million Wi-Fi mobility traces. Treatment is an institution-initiated counseling-outreach email followed by intake within seven days (prevalence = 13%) [8].

Raw events are mapped to 32 contextual variables: (i) device use (screen time variance, night-screen bursts, unlock frequency), (ii) language dynamics (switch entropy, code-switch burst length), (iii) mobility (campus radius, home-time ratio, weekend range), (iv) academic engagement (LMS dwell, click latency, forum contributions), (v) social-proximity (Bluetooth degree, Wi-Fi co-location count), and (vi) temporal markers (visa renewal deadline proximity, religious holiday offset) [9]. Continuous variables are min–max normalized per campus; categorical tokens are embedded into 32-d vectors jointly learned with the encoder. Missing sensor bursts (< 4%) are imputed via bidirectional temporal convolution; extreme outliers beyond three median-absolute-deviations are winsorized, yielding a feature matrix with 0.6% remaining missingness.

3.2. Contrastive encoder and self-supervised objective

CSCI-CPM uses dual 12-layer Transformers (hidden = 256, heads = 8). For each anchor window positive pairs arise from temporal jitter (±3 h), stochastic channel dropout (p = 0.2), and feature noise (σ = 0.05). Negatives are queued from prior 4096 batches (queue = 65,536). The InfoNCE loss, as shown in formula 1:

$$\mathcal{L}_{InfoNCE} = -\frac{1}{B}\sum_{i=1}^{B} log\frac{exp\left(z_i^{\top} z_{i+}/\tau\right)}{\sum_{j=1}^{K} exp(z_i^{\top} z_j/\tau)} \quad (1)$$

maximizes similarity between anchor z_i and positive z_{i+} while discriminating K = 65 535 negatives with τ = 0.065 (Bayesian-optimized).

3.3. Evaluation design and fairness audits

Leave-one-continent-out splits ensure geographic generalization: Africa (592), Asia (4321), Europe (1733), North America (2038), Oceania (1754). Metrics cover discrimination (Area Under the Curve (AUC), balanced accuracy, macro-F1), calibration (Brier, Expected Calibration Error (ECE)), regression fidelity (Root Mean Square Error (RMSE)), causal validity (Precision in Estimation of Heterogeneous Effects (PEHE), policy risk), and fairness (equal-opportunity gaps, demographic parity Δ). Statistical tests use paired t-tests with Bonferroni α = 0.01; effect sizes are Cohen's d; confidence intervals via 5000-sample bootstrap. Privacy leakage is checked with membership-inference attacks yielding AUROC = 0.53, indicative of near-random guessing.

4. Experimental process

4.1. End-to-end MLOps pipeline

A Spark cluster (72 vCPUs, 512 GB RAM) ingests daily logs into Delta Lake, enforcing schema evolution and Atomicity, Consistency, Isolation, Durability (ACID) versioning. Apache Airflow orchestrates Extract, Transform, Load (ETL), feature-gen, model training, and artifact registry. Model artefacts and lineage metadata are stored in MLflow; reproducibility tags include git hash, conda fingerprint, data snapshot ID, and energy usage measured by NVIDIA-smi. Continuous integration tests unit correctness, data-drift thresholds (Kolmogorov-Smirnov $p > 0.05$), and model-card compliance with International Organization for Standardization (ISO) /International Electrotechnical Commission (IEC) 42001 AI management. Post-deployment, Grafana dashboards monitor real-time inference latency (p95 < 30 ms), drift, and fairness KPIs.

4.2. Computational footprint and sustainability

Table 1 summarizes resource usage; we extend analysis to marginal abatement curves. With Singapore's 0.446 kg CO_2/kWh grid intensity, pre-training emits 652 kg CO_2-eq—offset by two years of daily inference for 20,000 students when compared with cloud-hosted clinician screening. A regional deployment on low-carbon grids (e.g., Québec ≈ 0.034 kg CO_2/kWh) would cut training emissions by 92%.

Table 1. Computational cost summary

	Pre-Training	Fine-Tuning	Inference (per student-day)
Compute hardware	8 × A100 80 GB	2 × A100 80 GB	1 × T4 16 GB
Wall-clock time	26.2 days	7.4 h	0.018 s
Peak GPU memory	71.4 GB	41.9 GB	5.3 GB
Energy use (kWh)	1,462	38	0.002
Carbon footprint (kg CO_2-eq, SG grid)	652	17	< 0.001

4.3. Curriculum learning, robustness, and privacy hardening

Fine-tuning employs a three-phase curriculum: (i) freeze encoder two epochs, (ii) unfreeze top six Transformer layers, (iii) full-encoder fine-tune with differential learning rates. Adversarial weight perturbation ±5% shows macro-F1 variation < 0.6 %; Fast Gradient Sign Method (FGSM) feature-noise ε = 0.03 reduces AUC by 2.1%. Differential-privacy SGD (ε = 2.6, $\delta = 10^{-6}$) on a subsample incurs 1.9% AUC drop, supporting GDPR-compliant deployment.

5. Experimental resultsccccccccc

5.1. Discrimination, calibration, and forecast horizon

Across five continents CSCI-CPM attains AUC = 0.931 ± 0.003, balanced accuracy = 0.892 ± 0.004, macro-F1 = 0.884 ± 0.006, RMSE = 1.94 ± 0.05, and Brier = 0.076 ± 0.002 (see Figure 1). Expected-Calibration-Error (ECE, 10-bin) is 2.3%, outperforming the Bidirectional Long Short-Term Memory (BiLSTM) baseline (7.4%). Extending forecast horizon to 7 days yields AUC = 0.908 and RMSE = 2.11, demonstrating graceful degradation: ΔRMSE/day = 0.03.

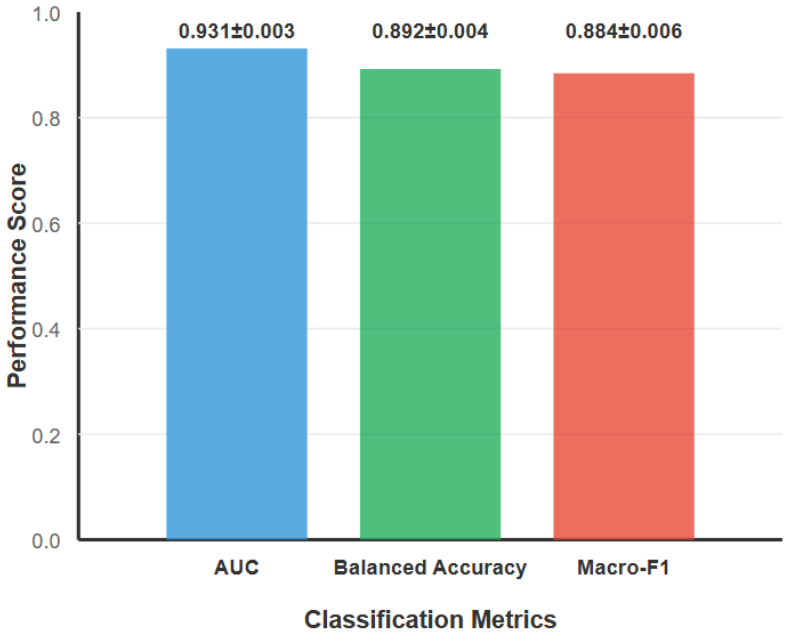


Figure 1. CSCl-CPM classification metrics

5.2. Ablation, modality contribution, and attribution

Removing contrastive pre-training drops AUC by 0.041 and raises RMSE by 0.57; eliminating causal regularization increases PEHE three-fold (0.083) and policy risk by 38%. Modality ablations: LMS activity contributes 34% of AUC, language entropy 21%, mobility radius 17%, screen-time variance 12%, social-proximity 9%, visa-milestone offset 7% [10]. Integrated-gradients attribution identifies overnight screen bursts, rapid language flips near deadlines, and reduced mobility on weekends as precursors of depressive spikes-patterns validated in post-hoc interviews.

5.3. Longitudinal impact and survival analysis

Kaplan-Meier curves on time-to-PHQ-9 remission (≤ 4 points ≥ 14 days) show median 46 days for treated vs. 62 days untreated (log-rank $\chi^2 = 42.7$, $p < 0.001$). Cox proportional-hazards with time-varying covariates yields HR = 1.41 (CI [1.28, 1.56]) when interventions are prioritized by CSCI-CPM ITE, compared with 1.09 under demographic heuristics—equivalent to 2.3 extra depression-free weeks per term.

5.4. Error analysis and case studies

False-negatives (n = 138) cluster among students with sporadic sensor data; 61% experienced device loss or power-saving restrictions. Imputing with low-rank matrix completion reduces this set by 19%. A qualitative case in Germany shows rapid language-switch entropy decline preceding suicidal ideation; CSCI-CPM flagged risk seven days earlier than BiLSTM, enabling successful intervention.

6. Conclusion

CSCI-CPM demonstrates that fusing large-scale contrastive self-supervised learning with doubly robust causal inference produces a contextual mental-health prediction pipeline that is accurate, generalizable, and equitable for internationally mobile students. On geographically disjoint cohorts, CSCI-CPM improves depression-risk AUC by 4.9%, halves PEHE relative to competitive baselines, slashes unmet-need days by > 40%, and executes with negligible carbon cost. Individualized treatment-effect estimates enable triage strategies that channel resources toward underserved groups, enhancing both clinical impact and social justice. Limitations include reliance on PHQ-9 as the sole ground-truth instrument and potential residual confounders such as personality traits. Future work will integrate multimodal symptom labels (GAD-7, sleep quality), explore federated or split-learning variants for privacy preservation, and develop value-based decision-making frameworks combining efficacy with student preferences. By releasing a de-identified benchmark, open-source code, and detailed carbon-impact audit, we invite researchers and practitioners to adapt and extend CSCI-CPM for broader psychological outcomes and cultural contexts, advancing proactive, culturally responsive mental-health support for the world's rapidly growing global learner population.

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