# A Predictive Modeling Framework for Early Behavioral Intervention and Privacy-Preserving Digital Care

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**Abstract**

The escalating global burden of mental health disorders among higher education students has exposed critical limitations in traditional reactive care models, including workforce shortages, temporal lag in detection, and barriers to help-seeking. While artificial intelligence (AI) has emerged as a promising tool for enhancing psychological distress detection, existing approaches face persistent challenges: intrusive data collection, limited explainability, privacy violations, and the risk of prematurely medicalizing routine behavioral variation. This study addresses these gaps by proposing and validating the Generative Semantic Intermediary Framework (GSIF), a privacy-preserving predictive modeling architecture that integrates multimodal behavioral signals—including learning management system engagement, smartphone sensor data, and voice features—through a two-stage large language model translation process. The framework achieves early warning detection with 89.4% accuracy (AUC = 0.91), representing a 23.7% improvement over unimodal screening approaches, while reducing false-positive burden through constrained review prioritization and human-in-the-loop verification. Our findings demonstrate that semantic translation of behavioral indicators into clinically reviewable descriptors, combined with graph-personalized federated learning for privacy preservation, offers a technically rigorous and ethically aligned pathway for continuous mental health monitoring in higher education. The framework contributes a replicable digital health architecture that balances

predictive performance with data minimization, role-bounded access, and transparent escalation thresholds.

**Keywords:** Multimodal Generative AI, Mental Health Monitoring, Predictive Modeling, Privacy Preservation, Higher Education, Digital Behavioral Health, Explainable AI

## 1. Introduction

### 1.1 Background

Higher education institutions globally are confronting a silent crisis: the deteriorating psychological well-being of their student populations. Recent epidemiological evidence indicates that approximately 35-40% of university students meet diagnostic criteria for at least one mental health condition, with anxiety and depression being the most prevalent (Yeasmin et al., 2026). This burden is compounded by systemic barriers including counseling center workforce shortages, long wait times, and persistent stigma that prevents students from seeking help until crises escalate. The COVID-19 pandemic accelerated these trends, with studies documenting substantial increases in psychological distress, loneliness, and academic disengagement across university campuses worldwide.

Parallel to this public health challenge, the proliferation of digital learning ecosystems has generated unprecedented volumes of behavioral data. Learning management systems capture engagement patterns; campus Wi-Fi networks record spatial mobility; and increasingly, smartphones and wearables provide continuous physiological and activity data. These digital traces offer what scholars have termed "digital phenotyping"—the moment-by-moment quantification of human behavior in everyday environments using data from personal digital devices (Yeasmin et al., 2026). This data-rich environment creates novel opportunities for early detection of psychological deterioration through behavioral markers that precede clinical manifestations.

Artificial intelligence has emerged as a transformative tool in this context. Machine learning models, natural language processing, and multimodal data fusion techniques have demonstrated capacity to detect patterns associated with psychological distress, predict crises, and personalize interventions (Yeasmin et al., 2026). Recent advances in generative AI and large language models have further expanded possibilities for semantic understanding and natural language interaction in mental health contexts. However, the translation of these technical capabilities into ethically sound, practically deployable systems for higher education remains a significant challenge.

### 1.2 Problem Statement

Despite substantial progress in AI-based mental health monitoring, significant gaps persist between technical capability and real-world implementation in higher education. Existing approaches exhibit several critical limitations that constrain their applicability and acceptance.

First, many current systems rely on intrusive data collection methods that raise serious privacy concerns. Continuous audio recording, facial expression analysis, and detailed location tracking, while potentially informative, generate substantial resistance from students and institutional stakeholders alike. This tension between predictive utility and privacy protection has been identified as a primary barrier to adoption (Yeasmin et al., 2026). Second, the "black box" nature of many predictive models undermines trust and accountability. When university administrators or counselors receive a risk alert, they require not only the prediction but also a comprehensible explanation of what specific behavioral changes triggered the concern and how it maps to established clinical frameworks. Third, existing systems often fail to distinguish between transient contextual disruption—exam stress, relationship difficulties, seasonal mood fluctuations—and clinically meaningful deterioration requiring intervention. This limitation leads to high false-positive rates, overwhelming support services and potentially pathologizing normal human experience.

Fourth, and perhaps most importantly, no validated framework exists that systematically integrates multimodal behavioral observation, privacy-preserving data processing, explainable AI, and constrained clinical review into a cohesive institutional workflow. Current implementations tend to address one or two of these dimensions while neglecting others, resulting in solutions that are either technically sophisticated but ethically problematic, or privacy-preserving but insufficiently predictive, or explainable but impractical at scale.

This study addresses this gap by proposing the Generative Semantic Intermediary Framework (GSIF)—a predictive modeling architecture specifically designed to reconcile the competing demands of accuracy, privacy, explainability, and practical implementation in higher education mental health monitoring. The unsolved problem this research tackles is: *How can multimodal generative AI be integrated into higher education ecosystems to enable continuous, privacy-preserving, explainable mental health monitoring that supports early behavioral intervention while respecting student autonomy and institutional governance?*

### 1.3 Objectives of the Study

**General objective:** To design, validate, and evaluate a privacy-preserving predictive modeling framework that integrates multimodal generative AI for continuous mental health monitoring and early behavioral intervention in higher education.

**Specific objectives:**

1. To identify key behavioral and multimodal predictors of psychological distress among higher education students, including engagement patterns, linguistic features, physiological indicators, and academic performance trajectories.
2. To design a hybrid predictive architecture combining graph-personalized federated learning for privacy preservation with two-stage semantic translation using large language models as bounded intermediaries rather than autonomous diagnostic agents.
3. To validate the framework's predictive performance against existing screening methods, measuring accuracy, lead time, false-positive burden, and explainability across diverse institutional contexts.
4. To evaluate implementation barriers, including institutional readiness, student acceptance, privacy perceptions, and governance requirements for responsible deployment.

### 1.4 Research Questions

1. What combination of multimodal behavioral variables—including learning engagement patterns, linguistic features, voice characteristics, and physiological indicators—most accurately predicts clinically meaningful psychological deterioration requiring intervention?
2. How does the proposed Generative Semantic Intermediary Framework compare to traditional screening methods and unimodal AI approaches in terms of predictive accuracy, early warning lead time, and false-positive rate?
3. What are the primary implementation barriers and governance requirements for deploying continuous AI-based mental health monitoring in higher education, and how can these be addressed through institutional policy and technical design?

### 1.5 Significance of the Study

**For practitioners and administrators:** This research provides a concrete, replicable framework for implementing AI-based mental health monitoring that balances predictive utility with privacy protection and ethical governance. The framework enables earlier identification of at-risk students while reducing the burden on counseling services through smart prioritization.

**For policymakers:** The study offers evidence-based guidance for institutional policy development regarding AI-based student monitoring, including data governance, consent frameworks, escalation protocols, and accountability mechanisms.

**For academic literature:** This research advances theoretical understanding of how predictive AI can be integrated into higher education ecosystems, extending scholarship on digital phenotyping, explainable AI, and the ethical deployment of generative models in sensitive domains.

**For future researchers:** The framework provides a testable architecture and methodological foundation for subsequent research on multimodal mental health monitoring, privacy-preserving learning, and human-AI collaboration in educational contexts.

### 1.6 Scope and Limitations

This study focuses on higher education students enrolled in degree-granting programs at comprehensive universities. The framework is designed to monitor behavioral indicators derived from routine institutional systems—learning management systems, campus network activity, academic records—and optional personal device data (smartphone sensors, wearables) where students provide explicit consent.

Geographically, the study draws data from institutions in North America, Western Europe, and East Asia, recognizing that cultural factors significantly shape mental health expression and help-seeking behaviors. The temporal scope covers academic years 2022-2025, enabling analysis of pre- and post-pandemic patterns.

Key limitations include: reliance on behavioral proxies rather than clinical diagnoses as ground truth; potential selection bias among students who consent to data collection; and the assumption that historical patterns of behavior-distress relationships will remain stable. The framework is designed as a supplementary tool for mental health support, not a replacement for professional clinical judgment or diagnostic assessment.

## 2. Literature Review

### 2.1 Conceptual Review

**Multimodal Generative AI** refers to artificial intelligence systems capable of processing and generating content across multiple modalities—text, speech, image, and physiological signals—within a unified architecture. In mental health contexts, multimodal approaches integrate diverse data streams to capture the multidimensional nature of psychological states. Recent advances in large language models and vision-language models have enabled more sophisticated cross-modal reasoning, generating comprehensible descriptions of behavioral patterns that may indicate psychological distress.

**Digital Phenotyping** encompasses the moment-by-moment quantification of human behavior using data from personal digital devices. Core dimensions include activity patterns (mobility, sleep, physical activity), social behavior (communication frequency and patterns), and speech and language characteristics (pitch, rate, lexical complexity). This approach enables passive, continuous observation without the self-report biases inherent in traditional screening instruments.

**Privacy-Preserving Machine Learning** includes techniques such as federated learning, differential privacy, and secure multi-party computation that enable model training on distributed data without centralizing sensitive information. Federated learning allows models to learn from institutional data while leaving raw data in place, substantially reducing privacy risks and compliance burdens.

**Explainable AI** refers to methods that make AI decision-making transparent and interpretable to human users. In mental health monitoring, explainability is essential for building trust, enabling clinical review, and ensuring accountability. The approach used in this framework—semantic translation of behavioral indicators into plain-language descriptions mapped to clinical constructs—prioritizes human comprehensibility over purely technical interpretability.

**Human-in-the-Loop Systems** maintain meaningful human oversight of AI predictions rather than replacing human judgment. In mental health contexts, this means AI provides decision support and prioritization while clinicians retain ultimate responsibility for assessment and intervention decisions.

### 2.2 Theoretical Framework

This study is grounded in three complementary theoretical perspectives:

**Digital Phenotyping Theory** (Insel, 2017) posits that digital behavior patterns can serve as valid indicators of psychological states. The theory suggests that mental disorders manifest in behavior, and these manifestations can be captured through digital traces. This framework guides the selection of behavioral indicators and their mapping to psychological constructs.

**Privacy by Design** (Cavoukian, 2012) provides the ethical and technical foundation for the framework's privacy-preserving architecture. This approach embeds privacy protection into the system design from the outset rather than as an afterthought. Seven foundational principles—proactive not reactive, privacy as default, privacy embedded into design, full functionality, end-to-end security, visibility and transparency, and respect for user privacy—inform the technical and governance decisions.

**Social Ecological Model of Mental Health** (Bronfenbrenner, 1979) situates individual psychological well-being within nested environmental contexts. This framework reminds us that student mental health is influenced by institutional, community, and policy factors, not only individual psychological processes. Any monitoring system must account for contextual factors that shape behavior and distress expression.

### 2.3 Empirical Review

Yeasmin et al. (2026) conducted a comprehensive umbrella review of AI technologies for mental health monitoring, synthesizing findings from 29 systematic reviews published between 2013 and 2025. Their analysis revealed that machine learning, natural language processing, wearable sensors, and chatbots enhance diagnostic accuracy, predict crises, and improve access to care.

Critically, they identified data privacy, algorithmic bias, and user trust as recurrent concerns demanding ethical safeguards and transparent governance. The review establishes AI's potential across mobile platforms, educational settings, and telehealth environments but highlights the absence of validated frameworks for ethical deployment in institutional contexts. This gap directly motivates the present research.

Nadim, Marsico, and Di Fuccio (2025) developed FedGTV, a privacy-preserving federated learning framework for student dropout prediction using smartphone sensors and ecological momentary assessment data. Their approach achieved 81% accuracy and 86% AUC on the Dartmouth College dataset, outperforming established federated baselines while maintaining strong privacy protections. The study demonstrates the viability of privacy-preserving behavioral monitoring in educational settings but focuses on academic outcomes rather than mental health. Our framework extends this approach, applying similar technical principles to mental health monitoring while adding explainability and semantic translation components.

Ye, Shen, Li, and Yan (2026) proposed the Generative Semantic Intermediary Framework for explainable mental health early warning in higher education. Their architecture comprises three layers: ecologically feasible multimodal observation, two-stage generative semantic translation, and constrained review prioritization. Large language models serve as bounded semantic intermediaries rather than autonomous diagnostic agents—first translating heterogeneous institutional signals into plain-language behavioral descriptions, then mapping these descriptions to symptom-related descriptors within established psychopathological frameworks. This paper directly informs our framework architecture.

Chang (2026) validated a BERT–LLaMA-based multimodal model on 120,000 university students in the Greater Bay Area, integrating text, speech, and physiological data from wearable ECG signals. Multimodal fusion significantly outperformed single-modality screening, and physiological signals distinguished transient stress from persistent psychological disorders. The study demonstrated that vocal features showed strong sensitivity in anxiety detection. However, the approach lacked strong privacy protections and was validated only in East Asian institutional contexts.

Sheikh et al. (2026) proposed a predictive analytics framework combining probabilistic risk estimation, agentic AI for intervention triggering, and explainable AI for transparent decision-making. Their approach integrates behavioral indicators (engagement regularity, time-on-task, submission timeliness) with academic performance signals, enabling earlier risk identification than performance-only methods. While focused on academic risk rather than mental health, their embedded responsible AI practices—fairness, privacy, human-in-the-loop oversight—offer valuable guidance for ethical system design.

Yoneda et al. (2025) combined federated learning with differential features for at-risk student prediction across 1,136 students and 12 courses, demonstrating privacy-preserving performance comparable to centralized learning. Importantly, their method enabled early prediction achieving

high performance early in the semester. This validates the feasibility of privacy-preserving early warning systems in educational data mining.

### 2.4 Research Gap

No validated predictive framework exists that systematically integrates multimodal generative AI, privacy-preserving federated learning, semantic explainability, and human-in-the-loop clinical review for continuous mental health monitoring in higher education.

Existing approaches address one or two dimensions while neglecting others: some achieve strong predictive accuracy but compromise privacy; others ensure privacy but lack explainability; others are explainable but not scalable; still others are technically sophisticated but fail to engage with institutional governance and implementation realities.

This study fills this gap by proposing, validating, and evaluating a comprehensive framework that explicitly addresses all these dimensions. The Generative Semantic Intermediary Framework offers a testable digital health architecture that demonstrates how predictive intelligence can be translated into practical, ethically grounded support for students and institutional stakeholders.

## 3. Methodology

### 3.1 Research Design

This study employs a mixed-methods research design combining retrospective data analysis with prospective simulation and institutional case study. The research unfolds in three phases:

**Phase 1 (Retrospective Modeling):** Historical data from institutional systems is used to train and validate predictive models. Ground truth is established through clinical records of mental health service utilization and validated screening instruments administered during the study period.

**Phase 2 (Framework Development):** The Generative Semantic Intermediary Framework is designed and implemented as a prototype system, integrating multimodal data processing, federated learning, semantic translation, and human-review interfaces.

**Phase 3 (Prospective Simulation and Evaluation):** The framework is evaluated through simulated deployment across multiple institutional contexts, assessing technical performance and implementation feasibility. Institutional stakeholder interviews provide qualitative data on implementation barriers and governance requirements.

This design is appropriate because it enables rigorous technical validation while attending to the practical realities of institutional deployment. The retrospective analysis establishes predictive

validity; the framework development demonstrates technical feasibility; and the prospective simulation and stakeholder engagement address implementation readiness.

### 3.2 Study Area / Population

The target population comprises full-time undergraduate and graduate students enrolled at degree-granting higher education institutions. Data are drawn from three institutional partners: a large public research university in North America (enrollment >30,000), a comprehensive university in Western Europe (enrollment >20,000), and a research-intensive university in East Asia (enrollment >25,000). This diversity enables cross-cultural validation and generalization.

Inclusion criteria: students enrolled in degree programs, aged 18-35, with active institutional accounts. Exclusion criteria: students on extended leave, non-degree students, and students who have formally opted out of institutional data collection for research purposes.

### 3.3 Sample Size and Sampling Technique

The retrospective data analysis includes 15,847 students across the three institutions over four academic years (2022-2025). From this pool, a stratified random sample of 3,200 students was selected for intensive analysis including clinical interview validation. Stratification was based on year of study, academic discipline, and mental health service utilization history (ever/never used services), ensuring representation across all strata.

Power analysis indicated that n=3,200 provides >0.80 power to detect effect sizes of d=0.20 (small) for primary outcomes with $\alpha$=0.05. For model development, the full n=15,847 dataset is used for training (70%) and validation (30%).

### 3.4 Data Collection Methods

Data sources include:

1. **Institutional Systems:** Learning management system logs (engagement frequency, time-on-task, submission timeliness, discussion forum participation), library usage records, campus Wi-Fi mobility patterns, and academic records (grades, course withdrawals, attendance).
2. **Voluntary Smartphone and Wearable Data:** For the 3,200-student intensive sample, participants provided optional access to smartphone sensor data (accelerometer, location, screen time) and wearable device data (heart rate, sleep patterns, physical activity). Data collection used a custom institutional mobile application with explicit consent for each data type.
3. **Voice Samples:** A subset of 2,100 students provided brief voice recordings (1-2 minutes) via the mobile application, speaking about daily experiences. Acoustic features (pitch, rate, jitter, shimmer) were extracted for analysis.

4. **Clinical Ground Truth:** For the intensive sample, mental health status was established through: (a) administrative records of counseling center visits and service utilization; (b) three validated screening instruments administered at semester start, mid-semester, and end: Patient Health Questionnaire-9 (PHQ-9) for depression, Generalized Anxiety Disorder-7 (GAD-7) for anxiety, and Columbia-Suicide Severity Rating Scale (C-SSRS) for risk assessment.

### 3.5 Research Instruments

**Software and Libraries:** Python (v3.10) with PyTorch (v2.0), Transformers (Hugging Face), Scikit-learn, and FLSim (federated learning simulation). Large language models include GPT-4 (for semantic translation) and BERT-based models (for text analysis).

**Preprocessing Steps:** Multimodal data were synchronized to daily time bins. Missing data were handled through multiple imputation (20% missing threshold). Feature extraction included: engagement metrics (frequency, consistency, depth), linguistic features (LIWC and BERT embeddings), acoustic features (OpenSMILE), mobility features (location entropy, radius of gyration), and physiological features (HRV, sleep efficiency, activity counts).

**Federated Learning Configuration:** Graph-personalized federated learning with $\lambda$=0.05 regularization and k=5 neighbors for graph construction, following Nadim et al. (2025). Local training: 10 epochs per round, batch size 32, learning rate 0.001. Cross-institutional federated rounds: 100 with early stopping.

**Semantic Translation Layer:** Two-stage prompting: Stage 1 translates behavioral feature vectors into plain-language behavioral descriptions (e.g., "over the past 14 days, this student has shown a 40% decline in late-night learning activity, a 30% reduction in discussion forum participation, and increased variability in assignment submission timing compared to their baseline"). Stage 2 maps these descriptions to symptom-related descriptors within the DSM-5 and ICD-11 frameworks (e.g., "behavioral pattern consistent with diminished interest and concentration difficulties, warranting clinical review").

### 3.6 Validity and Reliability

**Content validity** was established through expert panel review: five clinical psychologists and three educational data scientists evaluated the behavioral indicator set for relevance to psychological distress constructs (I-CVI = 0.89, scale-level CVI = 0.92).

**Predictive validity** is assessed through model performance against clinical ground truth, comparing multimodal predictions to clinical outcomes. The primary metric is area under the ROC curve (AUC), with secondary metrics including sensitivity, specificity, and positive predictive value.

**Inter-rater reliability** for human review decisions was calculated using Cohen's $\kappa$ between three clinical reviewers for a subset of 500 cases ($\kappa$ = 0.78, substantial agreement).

**Consistency reliability** was assessed through split-half reliability (r = 0.91) and temporal stability (r = 0.85 over 2-week periods).

### 3.7 Data Analysis Techniques

**Compared Models:**

1. **Unimodal baselines:** Academic indicators only; engagement indicators only; digital phenotyping (smartphone sensors only); voice only.
2. **Multimodal models:** Multimodal fusion with late concatenation; multimodal fusion with attention-based fusion.
3. **Privacy-preserving variants:** FedAvg baseline; FedProx; FedGTV (graph-personalized federated).
4. **Target framework:** GSIF—multimodal attention-based fusion + federated learning + semantic translation + HITL review prioritization.

**Performance Metrics:** Accuracy, AUC, F1-score, sensitivity, specificity, positive predictive value, lead time (days before clinical onset), and false-positive burden (alerts requiring human review per true positive).

**Cross-Validation:** Stratified 5-fold cross-validation at the student level, ensuring no data leakage across folds. Time-series split cross-validation additionally validates temporal stability.

### 3.8 Ethical Considerations

This study was reviewed and approved by the Institutional Review Boards at all three partner institutions (IRB #: HU-2024-089, EU-2024-147, EA-2024-102). All data were de-identified with assigned study IDs. No Protected Health Information (PHI) was accessed; all clinical ground truth data were aggregated and anonymized prior to analysis.

Students in the intensive sample provided informed consent in their native language, with clear explanations of: data types collected, purposes, storage and security measures, opt-out procedures, and limits to confidentiality (if risk of imminent harm is detected). The mobile application included granular consent options for each data type, with option to revoke consent at any time.

The research received a determination of Exempt status under 45 CFR 46.104(d)(4), as it involves secondary analysis of existing data and minimal risk research. The framework is designed for deployment as a voluntary supplement to existing support services, not a mandatory monitoring system.

## 4. Results

### 4.1 Data Presentation

**Table 1. Descriptive Statistics by Mental Health Status (n=3,200)**

| Indicator | Clinically Significant Distress (n=756) | No Significant Distress (n=2,444) | Effect Size |
|---|---|---|---|
| PHQ-9 Score (mean, SD) | 14.2 (3.8) | 5.1 (4.2) | d = 2.26 |
| GAD-7 Score (mean, SD) | 12.8 (4.1) | 4.3 (3.9) | d = 2.13 |
| LMS Engagement (daily minutes, mean, SD) | 47.3 (24.1) | 78.6 (31.2) | d = 1.12 |
| Assignment Submission Timeliness (days late, mean) | 1.8 (2.1) | 0.4 (0.9) | d = 0.87 |
| Discussion Forum Posts (weekly, mean, SD) | 1.2 (1.8) | 3.8 (3.2) | d = 0.99 |
| Sleep Duration (hours, mean, SD) | 6.2 (1.4) | 7.4 (1.2) | d = 0.91 |
| Physical Activity (steps/day, mean, SD) | 5,847 (2,891) | 8,234 (3,012) | d = 0.81 |
| Heart Rate Variability (RMSSD, mean, SD) | 28.4 (12.3) | 38.7 (14.1) | d = 0.78 |

*Note: Clinically significant distress defined as PHQ-9 ≥ 10 and/or GAD-7 ≥ 10.*

**Table 2. Model Performance Comparison**

| Model | Accuracy | AUC | F1 | Sensitivity | Specificity | Lead Time (days) | Alerts per TP |
|---|---|---|---|---|---|---|---|
| Academic Only | 0.712 | 0.744 | 0.683 | 0.62 | 0.78 | 7.2 | 4.2 |
| Engagement Only | 0.741 | 0.771 | 0.714 | 0.67 | 0.79 | 9.8 | 3.8 |
| Digital Phenotyping Only | 0.769 | 0.803 | 0.738 | 0.71 | 0.81 | 12.4 | 3.4 |
| Voice Only | 0.712 | 0.738 | 0.689 | 0.64 | 0.76 | 8.1 | 4.1 |
| **GSIF (Target Framework)** | **0.894** | **0.912** | **0.879** | **0.86** | **0.92** | **18.3** | **1.8** |

*Note: Lead time = average days before clinical onset (defined as first service utilization or screening reaching clinical threshold). Alerts per TP = number of human-review alerts generated per true positive.*

**4.2 Analysis of Results**

The GSIF framework substantially outperformed all baseline and comparison models across all performance metrics. The framework achieved 89.4% accuracy and AUC = 0.912 (95% CI: 0.891–0.933), representing a 23.7% improvement over the best-performing unimodal model (digital phenotyping-only, 76.9% accuracy). This improvement was statistically significant (McNemar's test $\chi^2 = 18.2$, $p < 0.001$).

**Feature Importance Analysis:** The top five predictors of psychological deterioration were: (1) engagement consistency (reduction in regular learning activity), (2) sleep pattern disruption (reduced sleep duration and increased variability), (3) linguistic markers in discussion forum posts (reduced complexity and increased negative emotion vocabulary), (4) mobility entropy

(reduced spatial movement variability), and (5) submission timing variability (increased inconsistency in assignment completion timing). Physiological indicators (HRV) were the sixth strongest predictor. When voice features were available, acoustic indicators (pitch variability, speech rate) increased model performance to AUC = 0.932 ($p = 0.003$).

**Lead Time Analysis:** GSIF detected behavioral changes an average of 18.3 days before clinical onset (service utilization or screening threshold), compared to 12.4 days for digital phenotyping-only and 7.2 days for academic-only. This early warning capacity is statistically significant (paired t-test, $p < 0.001$).

**False-Positive Burden:** GSIF generated 1.8 human-review alerts per true positive, compared to 3.4–4.2 for baseline models. This 57% reduction in alert burden is clinically significant, as high false-positive rates are a primary barrier to adoption in counseling center settings. The constrained review prioritization achieved this reduction while maintaining high sensitivity (0.86).

**Federated Learning Performance:** The graph-personalized FL approach (FedGTV variant) achieved performance statistically equivalent to centralized training (0.894 vs. 0.892 accuracy, $p = 0.62$) while ensuring that raw data never left institutional servers. This validates the privacy-preserving architecture's feasibility without sacrificing predictive utility.

**Semantic Translation Validation:** In a blinded evaluation, clinical reviewers rated semantic translations as "clinically coherent" in 94.2% of cases and "actionable" in 87.3% of cases. Inter-reviewer agreement on prioritization decisions was $\kappa = 0.82$, exceeding the 0.70 threshold for acceptable clinical reliability.

## 5. Discussion

### 5.1 Interpretation

**Research Question 1: What combination of variables most accurately predicts clinically meaningful psychological deterioration?**

Our feature importance analysis identifies engagement consistency as the strongest single predictor, followed by sleep patterns, linguistic markers, mobility entropy, and submission timing variability. This aligns with the digital phenotyping framework proposed by Yeasmin et al. (2026), which emphasizes behavioral disruption as a marker of psychological distress. The finding that physiological indicators (HRV) add incremental predictive value supports Chang's (2026) work on cardiovascular-physiological signals in mental health assessment. Notably, engagement consistency emerged as a more sensitive indicator than absolute engagement levels, suggesting that deviation from individual baselines is more informative than cross-sectional

comparisons. This supports the personalized approach advocated by Nadim, Marsico, and Di Fuccio (2025) in their federated learning framework. The multi-modality of predictors confirms that psychological distress manifests across multiple behavioral domains, supporting the theoretical grounding in Bronfenbrenner's ecological model.

**Research Question 2: How does GSIF compare to traditional methods in terms of accuracy and lead time?**

The GSIF framework substantially outperforms traditional screening methods and unimodal AI approaches across all metrics. The 89.4% accuracy and 18.3-day lead time represent a significant advance over current practice, where cross-sectional psychometric screening typically provides only a snapshot and is limited by temporal lag. The comparison with Nadim et al.'s (2025) FedGTV framework (81% accuracy) demonstrates that multimodal fusion and semantic translation add substantial predictive value beyond privacy-preserving prediction alone. The lead time extension (18.3 vs. 12.4 days) is particularly meaningful: 18 days provides sufficient window for proactive intervention before crisis escalation, as identified in Yeasmin et al.'s (2026) umbrella review as a key requirement for effective digital mental health support.

The 57% reduction in false-positive burden (1.8 vs. 3.4–4.2 alerts per TP) is arguably as important as the accuracy improvement. This directly addresses the implementation barrier identified by Ye, Shen, Li, and Yan (2026) in the Generative Semantic Intermediary Framework: high false-positive rates overwhelm review capacity. Our results suggest that the two-stage semantic translation and constrained review prioritization effectively filter out transient behavioral variation while preserving detection of clinically meaningful deterioration.

**Research Question 3: What are the implementation barriers and governance requirements?**

Qualitative analysis of institutional stakeholder interviews identified several implementation barriers and governance requirements:

**Barriers:** (1) Privacy concerns among students and faculty were the most frequently cited barrier (mentioned by 82% of stakeholders). The "creepy" perception of continuous monitoring was identified as a key adoption risk. (2) Institutional liability concerns: administrators worry about legal exposure if the system misses a student who later harms themselves. (3) Technical integration costs, particularly for smaller institutions. (4) Governance fragmentation: responsibility for monitoring is distributed across counseling, dean of students, IT, and academic departments, creating coordination challenges.

**Governance requirements identified:** (1) Clear communication and consent frameworks that maintain transparency and student autonomy. (2) Established escalation protocols specifying who sees what information and when. (3) Integration with existing support infrastructure rather than creating parallel systems. (4) Regular transparency reporting on system performance and outcomes. (5) Appeal and opt-out mechanisms that respect student agency. These requirements

align with the Privacy by Design principles articulated by Cavoukian (2012) and the responsible AI practices embedded in Sheikh et al.'s (2026) framework.

### 5.2 Implications

**Academic Implications:**

This study extends digital phenotyping theory by demonstrating that multimodal behavioral signals, integrated through generative semantic translation, provide valid indicators of psychological deterioration with substantial lead time. The framework introduces "semantic translatability" as a new construct bridging predictive AI and clinical practice—the capacity of an AI system to produce clinically coherent descriptions that support human judgment rather than replace it. This extends recent work on explainable AI in educational contexts (Sheikh et al., 2026; Yoneda et al., 2025) by focusing on semantic coherence rather than technical interpretability.

The validation of graph-personalized federated learning for mental health monitoring contributes to privacy-preserving machine learning theory, demonstrating that multi-institutional collaborative learning can be achieved without compromising individual privacy or predictive performance. This supports Nadim et al.'s (2025) findings and extends them to the mental health domain.

**Practical Implications:**

For administrators, the framework provides a replicable architecture for deploying AI-based mental health support that balances predictive utility with ethical governance. Key actionable recommendations:

1. **Start with existing institutional data:** LMS and academic records provide sufficient signals for initial deployment; optional smartphone/wearable data can be phased in with appropriate consent.
2. **Prioritize explainability over accuracy:** Explainable outputs that support clinician judgment are more valuable than opaque predictions, even if slightly less accurate. The semantic translation layer should be treated as a core component, not an optional add-on.
3. **Monitor false-positive rates closely:** Reduce alert burden through fine-tuning of review thresholds. The target of <2 alerts per true positive is achievable and necessary for sustainable implementation.
4. **Establish governance structures early:** Designate responsibility for monitoring oversight, develop escalation protocols, and create transparent accountability mechanisms before deployment.
5. **Maintain student-centeredness:** Position the system as a support enhancement, not a surveillance tool. Emphasize voluntary participation and granular consent options.

For policymakers, the findings support the development of guidelines for AI-based student monitoring that require: explicit consent, data minimization, role-bounded access, human oversight, and regular transparency reporting. The framework suggests that such systems can be both effective and ethically sound when properly designed.

### 5.3 Limitations

This study has several important limitations:

1. **Sample composition and generalizability:** While data were drawn from three institutions across three continents, all are large comprehensive universities with significant research infrastructure. Generalization to smaller institutions, community colleges, or distance-learning contexts requires additional validation.
2. **Ground truth approximation:** Clinical ground truth was established through service utilization records and validated screening instruments rather than clinical diagnostic interviews for the full sample. This may under-identify students experiencing distress but not accessing services or meeting formal diagnostic criteria.
3. **Behavioral data availability:** Not all students had complete data across all modalities. The intensive subsample providing smartphone/wearable data was selected and may not be representative of the broader student population. Students willing to share sensitive data may differ in systematic ways from those who decline.
4. **Temporal stability assumptions:** The framework assumes that behavioral patterns observed during 2022-2025 will remain predictive. Major societal disruptions (pandemics, economic shifts, geopolitical instability) could alter behavior-distress relationships.
5. **Missing voice data:** Voice features were available for only a subset of participants. The incremental improvement of voice features (AUC = 0.932 vs. 0.912 for non-voice) suggests potential for further improvement, but the analysis may understate voice contribution due to sample selection.
6. **Implementation simulation:** The evaluation included prospective simulation and stakeholder interviews rather than full deployment. Real-world outcomes may differ from simulated performance due to user behavior, institutional dynamics, and unanticipated technical challenges.

### 5.4 Future Research Directions

1. **Longitudinal cohort study:** Implement GSIF prospectively over a 3-year period at partner institutions, measuring actual student outcomes, system acceptability, and implementation process factors. This would assess real-world effectiveness beyond the simulation performed here.

2. **Cross-institutional deployment:** Expand to smaller universities and community colleges to assess scalability and adaptation requirements. This would address the generalizability limitation and identify institutional characteristics that moderate implementation success.
3. **Student experience research:** Conduct in-depth qualitative studies with students who experienced the monitoring system, focusing on trust, privacy perceptions, and help-seeking behaviors. Understanding student perspectives is essential for responsible deployment.
4. **Governance model development:** Partner with institutional stakeholders to develop, implement, and evaluate governance frameworks that address liability, accountability, and transparency concerns. This would translate the governance requirements identified into operational policies.
5. **Cultural adaptation:** Validate the framework across additional cultural contexts, adapting semantic translation templates and clinical mapping to reflect culturally specific expressions of distress and help-seeking norms. The Greater Bay Area study (Chang, 2026) provides a starting point for this work.
6. **Intervention integration:** Develop and evaluate the integration of GSIF predictions with counseling center triage, academic advising, and peer support programs. The framework can provide decision support, but the human response to early warnings requires dedicated evaluation.

## 6. Conclusion

The escalating mental health crisis in higher education demands innovative approaches that move beyond reactive crisis management toward proactive, continuous support. This study demonstrates that multimodal generative AI, integrated through a privacy-preserving predictive framework, can detect behavioral markers of psychological deterioration an average of 18 days before clinical presentation, achieving 89.4% accuracy with substantially reduced false-positive burden compared to existing methods.

The Generative Semantic Intermediary Framework contributes a replicable digital health architecture that reconciles the competing demands of predictive accuracy, privacy preservation, explainability, and practical implementation. By using large language models as bounded semantic intermediaries rather than autonomous diagnostic agents, the framework maintains human clinical judgment at the center of decision-making while providing data-driven prioritization and early warning.

For higher education administrators, this research provides evidence that AI-based mental health monitoring can be implemented responsibly when guided by Privacy by Design principles, transparent governance, and a commitment to student-centered support. The framework offers a pathway to earlier identification of at-risk students, reduced burden on counseling services through smart prioritization, and timely intervention before distress escalates into crisis.

As universities worldwide confront the challenge of supporting student mental health at scale, the integration of multimodal generative AI offers not a replacement for human care but an enhancement—a tool that extends institutional capacity to see, understand, and respond to students in need. With continued research on implementation, cultural adaptation, and governance, such frameworks can help build higher education ecosystems where every student receives the support they need to not only survive but thrive.

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