A Multimodal AI–IoT Framework for Monitoring Student Well-Being in Hybrid and Transnational Learning Environments

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Abstract

Problem Statement: International students often face challenges to their well-being as they adjust to new cultural, academic, and social environments. These challenges can be increased in hybrid learning settings, where students must balance on-campus participation with significant online study. Feelings of isolation, academic pressure, disrupted routines, and difficulties in building local support networks are common. Universities typically lack continuous insight into how these stressors appear in students' daily behaviours. This study examines how everyday digital and physical activity patterns captured through unobtrusive sensing can help institutions better understand and support the well-being of international students.

Methods: Using the publicly available StudentLife dataset as a proxy for the behavioural data students naturally produce, we analyse four key streams: physical activity, sleep estimation, phone usage, and online course engagement. These signals are incorporated into a conceptual IoT-enabled smart campus solution based on a novel architecture, where mobile sensing and environmental context form an integrated layer for well-being monitoring. We extract daily behavioural features and link them with PHQ-9 mental health scores to explore how fluctuations in routine behaviours correspond to changes in mood and well-being. Machine learning models, including Random Forest, Gradient Boosting, and Decision Tree, are used to identify behavioural patterns that align with elevated stress.

Results: The analysis shows that irregular sleep patterns, reduced physical activity, increased phone usage, and fluctuations in online engagement frequently coincide with higher PHQ-9 scores, indicating a low level of mental health well-being. These behavioural changes reflect patterns commonly reported by international students during periods of adjustment or academic pressure. Significantly, some behavioural shifts occur before increases in PHQ-9 symptoms, indicating potential opportunities for early, supportive intervention before well-being declines become severe.

Significance: This work demonstrates how unobtrusive behavioural sensing, embedded within an IoT-enabled innovative campus framework, can provide universities with empathetic, real-time insights into the well-being of students, especially international students who are highly vulnerable. The study emphasises how institutions can use these insights to offer timely check-ins, culturally responsive support, and personalised resources. The findings contribute to a more human-centred approach to supporting the well-being of international students, helping universities create inclusive and supportive learning environments for a diverse global student population.

CCS Concepts

• **Applied computing**; • **Life and medical science**; • **Health informatics**;

Keywords

Student Well-being, IoT-based Well-being, Transnational Learning, Hybrid Learning

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1 Introduction

International students make up a growing portion of university populations worldwide, bringing cultural diversity, global perspectives, and valuable academic talent [5]. However, the transition to studying abroad is often accompanied by substantial challenges. Students must adapt to unfamiliar academic expectations, build new social networks, navigate cultural differences, and often manage financial, linguistic, or family pressures. These stressors can accumulate and affect daily routines, motivation, and mental well-being [3]. Hybrid learning environments add an additional layer of complexity, requiring students to balance physical attendance with significant online engagement, often in isolation [2]. Despite universities' commitment to student welfare, many of these challenges remain invisible because well-being issues typically emerge gradually within the rhythms of daily life.

Recent works highlight the potential of digital sensing technologies to provide insights into students' behavioural patterns, which can serve as indicators of stress, disrupted routines, or declining well-being [4]. Mobile phones, wearable sensors, and campus IoT infrastructure can unobtrusively capture signals such as sleep disruption, physical inactivity, increased screen time, or reduced academic engagement [7]. These signals reflect behavioural changes that international students frequently report during periods of adjustment or academic strain. However, universities rarely integrate such behavioural analytics into their support systems, in part due to the lack of frameworks that combine mobile sensing, environmental context, and well-being modelling in a human-centred and culturally sensitive manner.

This study addresses the absence of an integrated, human-centred link between continuous behavioural sensing and culturally informed well-being modelling for international students. Using the StudentLife dataset [8] as a proxy for continuous behavioural signals commonly collected in real-world hybrid learning environments, we identify daily routines linked to changes in mood and mental health. Building on a smart campus solution for IoT-based depression management, we explore how behavioural sensing can support early, compassionate, and culturally informed intervention for international students before well-being challenges escalate.

Smartphone and passive sensing approaches have been widely explored for mental health and behaviour monitoring. The StudentLife study [8] demonstrates significant correlations between smartphone sensing (activity, sleep, sociability) and mental health / academic outcomes, and provides the canonical dataset used in this work. More recent work applies machine learning to multimodal sensing streams, uses ecological momentary assessment (EMA) as labels, and explores temporally aware models for early detection of mood deterioration [1]. Our study extends this literature by (1) combining device sensing and online-course engagement signals in a single pipeline, (2) framing both regression (PHQ-9 score) and binary detection (elevated PHQ-9) tasks, and (3) evaluating temporal lead/lag relationships to assess early-warning capability.

In Section 2, we conceptualise a smart campus solution grounded in a recently proposed reference architecture for IoT-based mental health monitoring and management, named IoTMindCare [9]. Section 3 presents an empirical case study using the StudentLife dataset to evaluate the feasibility of the proposed solution. Finally, Section 4 discusses the implications of the findings for smart campus design and student support services, outlines deployment considerations, and identifies directions for future research building on the IoTMindCare framework.

2 A Smart Campus solution for well-being monitoring

This section describes how the IoTMindCare reference architecture [9] is instantiated as a smart campus well-being monitoring solution for international students in hybrid and transnational learning environments. IoTMindCare is adopted in this study because it provides a modular, human-centred architectural framework that explicitly integrates multimodal behavioural sensing, personalisation, safety, and decision support, which are essential for capturing the complex and context-dependent well-being challenges faced by international students. This work configures and operationalises IoTMindCare components by selecting appropriate data sources, processing strategies, and machine learning models consistent with the architectural design.

2.1 IoT-based Smart Campus Architecture

IoTMindCare [9] is structured as a modular, layered reference architecture supporting personalised continuous behavioural monitoring, adaptive modelling, and safety-aware decision making. In the smart campus context considered in this study, each architectural layer is instantiated as mentioned in Table 1.

The layered design follows a separation of concerns principle, enabling scalable sensing, data handling, and flexible analytics in a smart campus environment. Lower layers focus on unobtrusive data acquisition and aggregation, while upper layers support adaptive modelling and decision support. Personalisation and safety are treated as cross-cutting concerns to ensure that individual differences and risk awareness are embedded throughout the monitoring and intervention pipeline.

3 Experimental Setup

This section outlines the experimental design used to validate the IoTMindCare-based smart campus solution, including data preparation, evaluation strategy, and performance metrics.

For data preparation, after choosing the StudentLife dataset [8], behavioural features were aggregated on a daily basis and aligned with PHQ-9 assessments present within the dataset.

3.1 Evaluation Metrics

Model performance was evaluated using metrics aligned with IoTMindCare's emphasis on personalisation, safety, and early detection [9]. Rather than optimising for population-level accuracy alone, the evaluation focuses on how well behavioural models capture individual-level deviations from personal routines.

For regression tasks, performance was measured using Root Mean Square Error (RMSE) and R2 between predicted and actual PHQ-9 scores, reflecting the model's ability to track personalised well-being trajectories over time. The analysis focused on modelling PHQ-9 scores as a continuous outcome using daily behavioural and educational features.

While IoTMindCare's architecture is designed to support personalised monitoring, the current implementation predicts PHQ-9 scores directly from observed features, without explicitly computing deviations from individual baselines or early warning indicators.

Table 1: IoT-based Smart Campus Architecture Layers

Interface Layer	**Personalisation**	**Safety**
Model outputs are conceptually mapped to smart campus dashboards and student-support services. These interfaces enable timely check-ins, personalised academic support, and culturally responsive interventions without requiring clinical escalation. **Service Layer** Machine learning models form the core analytical services, mapping behavioural features to mental well-being indicators. Both regression and classification tasks are supported. **Data Processing and Storage** Raw sensing data are transformed into daily behavioural features. Longitudinal feature storage supports behavioural trend analysis and temporal modelling **Network and Communication** The dataset represents real-world scenarios where mobile devices transmit behavioural summaries to campus or cloud services **Sensing** Mobile phones act as primary sensing devices, capturing unobtrusive behavioural data such as physical activity, sleep estimation, phone usage, and online academic engagement. These signals reflect daily routines and engagement patterns commonly associated with student well-being.	(supporting international students' specific needs, behavioural, and cultural diversity)	(anomalous behaviour detection by continuous monitoring.

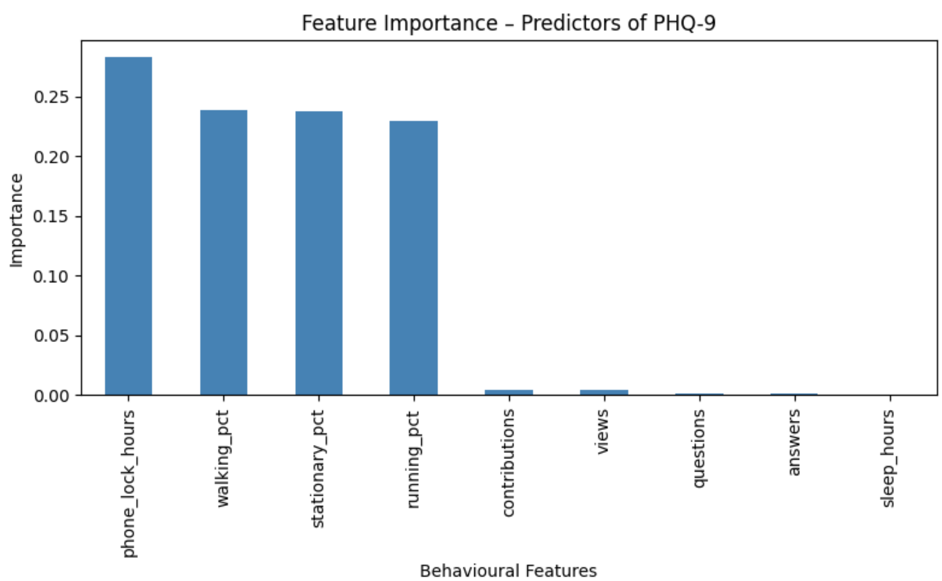

Figure 1: Feature importance in predicting PHQ-9

3.2 Behavioural Indicators of Reduced Well-Being

Analysis revealed that increases in PHQ-9 scores were most strongly associated with patterns in phone usage and physical activity, highlighting the importance of these behaviours as indicators of mental well-being. While online academic engagement and sleep duration were included, they contributed minimally to model predictions in this dataset. Figure 1 shows the importance of each data points in PHQ-9 score.

3.3 Model Performance

Table 2 summarises the predictive performance of the evaluated machine learning models.

As shown, the Random Forest model achieved the highest predictive accuracy (RMSE = 3.94, R2 = 0.42), followed by Gradient Boosting (RMSE = 4.55, R2 = 0.23). Simpler models, including linear and regularised regression approaches, exhibited limited predictive power (R2 is around 0), indicating that non-linear, ensemble-based methods are better suited to capture the complex relationships between behavioural features and PHQ-9 scores. Personalised monitoring can be effectively implemented without extensive individual

Table 2: Performance of ML models for predicting PHQ-9 scores

Model	RMSE	R^2
Random Forest	3.94	0.42
Gradient Boosting	4.55	0.23
Decision Tree	4.98	0.08
KNN	5.16	0.01
Linear	5.19	0.003

calibration, while still accommodating inter-individual behavioural variability.

Although explicit temporal modelling of early-warning signals was not implemented in this analysis, feature importance indicates that daily deviations in phone usage and physical activity are promising candidates for anticipating changes in PHQ-9 scores.

3.4 Implications

The findings reinforce IoTMindCare's layered design, which separates sensing, processing, and intelligence. This modular approach allows adaptive behavioural modelling and scalable personalised monitoring without requiring continuous self-reporting, preserving both privacy and autonomy.

Given the diversity of behavioural norms among international students, focusing on high-signal indicators like phone usage and physical activity allows context-aware assessment while avoiding over-reliance on potentially culturally variable behaviours. IoTMindCare's personalised, non-intrusive approach supports early, culturally sensitive interventions.

StudentLife does not differentiate between international and national students. However, our results are especially helpful for international students given they are more at-risk of depression [6].

4 Conclusion

This paper presented a case-study instantiation of the IoTMindCare reference architecture as a smart campus solution for personalised monitoring of international student well-being in hybrid and transnational learning environments. By modelling behavioural data relative to individual baselines, the study demonstrated how everyday digital traces can provide early, personalised insights into student mental health.

The results underscore the importance of architecture-driven personalisation in designing scalable, human-centred well-being systems. IoTMindCare offers a flexible foundation for adaptive, culturally responsive support, enabling universities to move beyond reactive services toward proactive and personalised student care.

4.1 Limitations and Future Work

The StudentLife dataset serves as a proxy for smart campus sensing and does not exclusively represent international students. Additionally, personalisation is constrained by the frequency of PHQ-9 assessments, limiting the temporal granularity of individual well-being labels.

Future work will enhance IoTMindCare's personalisation capabilities through adaptive learning techniques, longitudinal user profiling, and culturally informed feature selection. Live smart campus deployments will enable continuous model adaptation and real-time personalised feedback while maintaining strong privacy guarantees.

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