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Article

Monitoring and Supporting Student Mental Health in Smart Campuses: A Review of IoT-Based Systems

Preetee Praveen Kumar[1], Ajay Kumar Saini[2]

[1 & 2] Educational Institute of Management, Graphic Era Hill University, Dehradun, India
Email: preeteepraveenkumar@gmail.com

Abstract: The growth of mental health issues in students at universities, has driven a search for technology-based solutions to supplement or replace traditional methods of providing mental health support for students. Smart campuses which are integrated digital environments powered by Internet of Things (IoT) technologies offer new ways to monitor students' mental health continuously and to intervene early in cases where there may be developing problems. Study explores the present state-of-the-art of IoT based systems designed to monitor and provide support for students' mental health in Higher Education Institutions. The review will synthesize evidence related to technologies such as wearable sensors, environmental monitoring devices, sensing via mobile phone apps, and collecting data passively using communications networks. Data analytics and Artificial Intelligence (AI), will be examined in depth for their roles in recognizing behavioural patterns, predicting individuals' mood states, and generating real time alerts. The purpose of this research is to give support to individuals that are involved in the development of appropriate and successful mental health approaches using technology in higher education; these include researchers, administrators and policy makers.

Keywords: Influencer Marketing, Brand Perception, Consumer Trust, Authenticity vs. Sponsored Content, Influencer Credibility, Social Proof, Purchasing Decisions, Transparency, Social Media Platforms

1. INTRODUCTION

The number of psychological problems that college students face has increased significantly over the past ten years. It is considered one of the most important public health issues today. In comparison to previous levels of education (K-12), the stresses associated with going to college and attending classes at an institution of higher learning can be quite different for each student. Examples of stressors that many college students encounter include; working long hours on their studies, being evaluated competitively in terms of their performance, uncertainty about their future jobs, financial pressure, and the changes in their support systems of friends and families. For many students relocating to a new city or country and adapting to new academic and social environments creates additional psychological strain (Gutiérrez et al., 2021).

Research in various parts of the world has shown that there are higher rates of anxiety, depression, sleep disturbances, and emotional exhaustion amongst both undergraduate and graduate level students. Such conditions can negatively impact on academic performance, attendance, social involvement, and long-term overall well-being. In extreme cases, untreated mental health problems can cause students to drop out of their course or to engage in harmful behaviours to themselves (Fikry et al., 2025).

Although higher education providers have significantly increased counselling and support services in recent years, they are still frequently restricted in terms of accessibility and ability to meet the high demand for service provision. Typically, students access support once symptoms are evident; however, many students fail to seek support through fear of stigma, lack of knowledge, or fear that their confidentiality will be breached (Shen, 2023).

The increased number of students experiencing mental health problems and the increasing complexity of their needs have illustrated the limitations of the traditional support models reliant upon assessment and face-to-face contact as the sole method of providing support. There is an increasing recognition of the necessity of the early identification of risk patterns and continuous forms of support in order to avoid the deterioration of a student's mental health and provide ongoing support to all students (Tseng et al., 2016).

Smart campus initiatives and use of technology, as it relates to addressing health issues within schools and colleges, has been rapidly developing. In general, smart campuses are part of an increasing trend of "data driven" decision making and use of digital technologies to support higher education institutions (Jaber, 2023). Typically, a smart campus utilizes data systems, mobile apps, and other digital technologies to improve both operational efficiencies and services to students (Takaoka & Sharma, 2024). Through the use of Internet of Things (IoT), campuses are now capable of collecting large amounts of information and data from a wide range of different sources, which include but are not limited to, wearables, cell phones, and environmental sensors. Data examples include physical activity, sleep patterns, location tracking, environmental conditions indoors, and behavioural patterns of interacting with technology. Through long term analysis of this data, trends in behaviour or routine changes may indicate signs of stress, fatigue, social isolation, or emotional distress (Jiménez-Mijangos et al., 2022). Continuous data collection of information by an IoT-based system provides a more continuous and contextually relevant understanding of the mental health status of a college student as opposed to traditional self-reporting-based assessments of mental health. Also, when connected to digital support options, which can include mobile messaging, access to self-help resources, or referral to counselling services, IoT-based systems can provide universities with information regarding the mental health of students at both an individual and population level, allowing for early intervention and informed decision making (Siddiqui et al., 2025). However, as with all new technologies, there are significant concerns regarding privacy, consent, data protection and trust among students regarding the use of such technologies. One of the most significant concerns regarding the adoption of digital mental health support systems in educational settings is the balance of providing support versus monitoring students through the use of digital technologies (Vân et al., 2024).

1.1 Literature Review

Although IoT technologies in support of mental health support in higher education is an emerging field of research, existing research in the literature encompasses many fields such as smart campuses, behavioural sensing, data analytics, digital therapeutics and the ethical implications of pervasive monitoring of student behaviour. This paper will synthesize previous research in these areas to provide a base for comparing existing systems and to identify areas of missing knowledge (Vân et al., 2024).

Research conducted in numerous institutions and countries have reported that the number of students experiencing mental health problems are increasing. Reports from the World Health Organization, national surveys of higher education institutions and other sources indicate that a high percentage of students experience symptoms of anxiety, depression and burn-out that negatively affect academic performance and retention. While traditional on-campus counselling services and peer-led groups are beneficial in supporting students' mental health, they are limited by lack of adequate staff, limited availability of services, and stigma associated with seeking help. As stated by Nepal et al. (2024), it is important to detect mental health problems early and provide proactive support to increase positive outcomes in students who may not seek formal help.

Smart campus development has emerged as a sub-area of smart cities focused on enhancing higher educational environments through the use of networked technologies. Chowdhury et al. (2025) have researched the integration of cloud computing, wireless sensor networks, mobile applications, and data platforms to optimize campus-wide operations such as energy efficiency, security, and digital learning. Smart campus environments offer a natural platform for monitoring and managing students' mental health through the collection of data generated through students' daily interactions with the physical and digital environments of the campus.

There is considerable research that examines how IoT devices can be used to monitor various indicators of mental health status. Wearable devices (e.g., fitness trackers, smartwatches) are typically used to collect physiological metrics (heart rate, sleep, physical activity) of users. Research by Melcher et al. (2020) others have established relationships between wearable device collected data and self-reported mental health status. Mobile-based systems have also received considerable attention (Geasela et al., 2023) for example, developed a system called "StudentLife," which was deployed at Dartmouth College to collect data on students' mobility, phone usage, and communication frequency, and demonstrated strong predictive associations between the collected data and both academic performance and stress.

Most supervised learning models are designed to predict risk levels based on historical patterns of students' behaviours. Many unsupervised learning models are used to detect anomalies in students' behavioural data relative to each student's baseline. Jeong et al. (2022), have reviewed numerous digital mental health tools that utilize predictive analytic models to determine when to initiate early intervention strategies. However, one major limitation of these models is their accuracy because of sparse data, inter-individual variability and the lack of objective measures of students' behavioural data. Another common theme throughout the literature is the challenge of finding an acceptable balance between predicting the likelihood of a problem occurring and the ethical considerations of doing so.

One method to transition from monitoring to intervening is through the use of digital mental health platforms that incorporate feedback mechanisms. These systems can provide automatic prompts to students to engage in healthy behaviours, or provide students with access to self-help resources or teleconsulting. Research by Dekker et al. (2020) have researched the design of mobile mental health applications, particularly emphasizing ease-of-use and engagement. Campus-based nudge systems have been studied as an approach to promote students' behavioural regulation, however, few studies have examined long term adherence to digital interventions or the cumulative psychological effects of receiving repeated digital feedback.

1.2 Identified Gaps and Understudied Areas

A number of significant gaps in the research have been identified and under-researched in the literature. A major gap is a focus on the implementation of systems over an extended period of time, because the majority of the existing research has focused on either short-term feasibility testing or pilot projects. There is limited research regarding how these types of interventions affect students' long term academic success, social inclusion and their overall long term mental health outcomes. Furthermore, the body of literature does not provide adequate representation of non-western institutions and low resource settings, which limits the generalizability of the findings. The comparative evaluation of different system architectures, sensor configurations, and institutional policy implementations is also underdeveloped. These gaps demonstrate the necessity of continuing to conduct additional, interdisciplinary research using both technological advancements and psychological theories, user cantered design, and campus governance.

2. SMART CAMPUS ECOSYSTEMS

Smart campuses are learning environments that incorporate technology to improve the learning and student experience. The potential for an educational environment to be designated as "smart" is contingent on an integration of the technologies of ICT, sensor networks, cloud computing and mobile technology to enable all campus services and infrastructure to be linked and connected in one way or another. In comparison to the traditional campus, which has separate systems operating independently of one another, the systems within a smart campus are designed to facilitate the sharing of data and system interoperability to enable campus wide services to provide better responses to the needs of students in a more efficient manner (Tarimo et al., 2025).

The key components of a smart campus include its network infrastructure, e.g., high-speed wireless (Wi-Fi) access to campus resources and cloud-based storage systems, to provide for the ease of sharing and communication of data among users. Sensors are embedded into physical objects — examples include biometric access points and air-quality monitors — to collect continuous data about the campus environment and behaviour of those in it. All data collected from these sources is processed and analysed using analytics software and visualization tools that enable administrators, staff, and students to make better decisions. Users' access to campus services is enhanced via mobile apps and self-service portals. Underlying all of these systems, however, is the importance of cybersecurity and data privacy, to protect the integrity of all sensitive data (Craig et al., 2025).

2.1 IoT role in the smart campus infrastructure

In addition to other architectural elements, the Internet of Things (IoT) plays a critical role in enabling the interaction between the physical and digital aspects of the campus. IoT enables real-time interaction between the digital and physical layers of the campus by providing a network of connected devices able to sense, collect, transmit and analyze data without requiring human intervention. In the higher education sector, there are many different types of IoT devices, including, but not limited to; wearable bands for tracking students' physical activity, classroom occupancy sensors, GPS enabled ID cards, and smartphone-based data collection systems. As students utilize these devices, the IoT generates massive amounts of data that can be used to gain insight into how students and groups of students interact with the campus environment (Chaconas, 1990).

There are many ways in which IoT is beneficial for the features of a smart campus. For example, IoT assists in improving the energy efficiency of a campus through automation of lighting and air conditioning systems; IoT provides enhanced campus safety through monitoring of all campus entrance/exit points as well as monitoring of crowds; and IoT allows for improved service delivery through implementation of intelligent scheduling and resource allocation techniques (Chaconas, 1990). Furthermore, IoT has also begun to be integrated into the area of student wellness and specifically, there have been efforts toward tracking student's physical health (e.g., sleep duration), stress management, and mental health monitoring. Examples of wearable device data that may help indicate the mental health status of a student, include data on their sleep duration, heart rate variability, and overall level of activity/movement related to an individual's emotional or psychological state. Smartphone data, on the other hand, can be assessed to determine a student's screen use, social interaction patterns, and/or location mobility, and can serve as an indirect indicator of a student's mental health status. As a result, IoT systems allow institutions to move from a reactive model of student support to a proactive model of student support. Institutions will be able to identify students that are "at risk" of experiencing distress based on continued monitoring of behavioural and environmental factors, and they will be able to intervene early in order to prevent distress from developing further. Early interventions may include digital nudge techniques, access to self-help resources, or referral to counselling services. When incorporating IoT data into broader student support strategies, care should be taken to develop the appropriate design and governance structure to protect sensitive health-related data (Campbell et al., 2022).

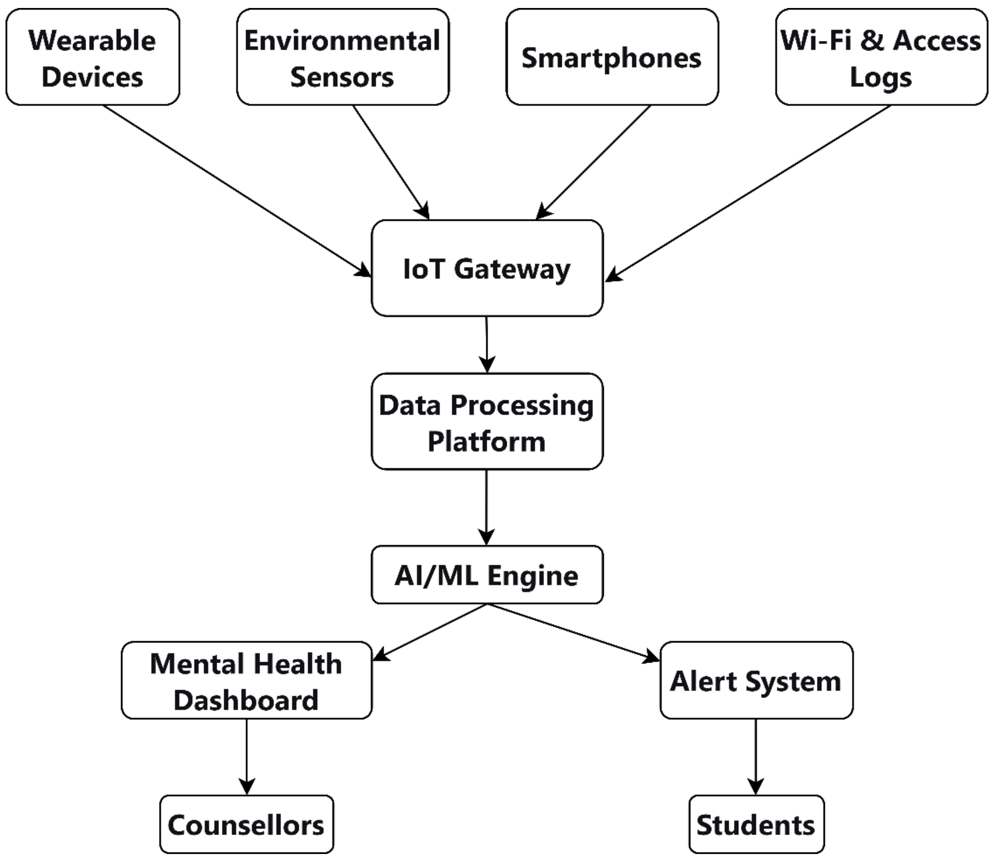

Figure 1. Conceptual Architecture of an IoT-Based Mental Health Monitoring System in a Smart Campus

Figure 1 presents a layered conceptual framework for an Internet of Things (IoT)-enabled mental health monitoring system designed for smart campus ecosystems.

2.2 Relevance to student well-being

Smart campus systems are relevant to supporting student mental health because they can support timely, non-intrusive, and data-driven interventions to support students who may be experiencing mental health difficulties. Many mental health issues experienced by students develop slowly and the early warning signs such as social withdrawal, irregular sleep patterns, and decreased physical activity are often undetected in traditional support mechanisms. Smart campus systems, when integrated into the campus infrastructure, can monitor the development of such changes in real-time. For example, if a student stops attending classes, increases time spent alone, or has significant changes to their biometrics, there may be an indication of a form of psychological distress. No single indicator will be definitive as to whether a student has a mental health issue; however, when combined with other data from multiple data sources, over time, this collective data can be used to develop reasonable indicators for additional investigation or intervention (Rubio et al., 2025).

Furthermore, the use of IoT technologies also enables universities to move away from addressing the individual student's needs through interventions and instead focus on developing systemic methods to enhance student mental health. Through the aggregation of the data, universities can identify common environmental or institutional issues that have adverse effects on the mental health of many students (e.g., continuous excessive noise in dormitories, poor air circulation in study areas, inadequate lighting in public spaces) and therefore make alterations to the campus environment to decrease the negative impact on students (Moghimi et al., 2022).

While IoT has much potential for supporting the mental health of students, it is essential to consider several challenges. First and foremost, there is a chance that the amount of data being collected could be overly invasive and therefore, students would lose control of their personal data. Therefore, it is necessary to establish clear institutional policies related to informed consent, data transparency and what is deemed acceptable purposes for collecting and analysing the collected data. Secondly, there are numerous technical challenges associated with the integration of disparate data systems, obtaining system interoperability and maintaining the integrity and accuracy of the data produced from the variety of sensors (Fullmer et al., 2021).

Although there are these challenges, the inclusion of IoT into smart campus infrastructure development presents a viable means for developing learning environments that are more responsive and supportive to students. Table 1, listed below, outlines the most common IoT components found in smart campus environments and identifies the functional capabilities of each component along with their relevance to student mental health monitoring (Kornbleuth, 2020).

Table 1: Selected IoT Components in Smart Campuses and Their Relevance to Mental Health Monitoring

IoT Component	Function within Campus	Mental Health Relevance
Wearable Devices	Monitor physical activity, sleep, heart rate	Detect fatigue, irregular routines, and stress responses
Smartphone Sensors	Log screen usage, location, and communication patterns	Indicate isolation, overstimulation, or changes in behaviour
Environmental Sensors	Measure lighting, air quality, noise levels	Assess environmental stressors that affect concentration, sleep, and mood
Wi-Fi and Access Logs	Track student movement and room occupancy	Identify prolonged isolation or changes in class attendance patterns
Central Data Platforms	Aggregate and visualise real-time data	Generate alerts and insights for counsellors and academic support teams

3. MENTAL HEALTH CHALLENGES IN HIGHER EDUCATION

Mental health concerns among university students have become increasingly important in higher education systems today. The opportunity for intellectual growth and social development that university life offers can often provide numerous resources for psychological stress. Many different types of pressures exist in the world of higher education including academic workloads, evaluation systems that foster competition, uncertainty about future employment possibilities, monetary limitations and changes in personal relationships (Duraku et al., 2024).

Residential universities present additional challenges related to relocating to a new place, cultural displacement, or isolation from friends and family and other systems of support.

The four most common mental health conditions found among students are stress, anxiety, depression and burnout. Stress is very commonly related to academic deadlines, performance pressures and the perception that there is always an expectation to meet the standards of the institution or peers. Anxiety may appear in both general and situationally specific forms, and is often exacerbated by social comparison, test-taking pressures, and fears regarding the possibility of obtaining a job after graduation. Depression is characterized by a persistent feeling of sadness, loss of energy, and loss of interest in activities or experiences, and can significantly impact a student's ability to complete their coursework and function personally. Many students don't seek help when they experience psychological distress -- and it isn't just because they don't know where to turn. Several structural and psychological barriers exist that contribute to lower rates of help-seeking. Many students report stigma as a barrier -- both in terms of fear of being judged by their peers, and/or their instructor(s). Students also report concerns regarding confidentiality and negative ramifications (i.e., being labeled or marginalized), regarding disclosure of mental health issues (Martínez-Líbano & Yeomans-Cabrera, 2023).

Institutions that establish mechanisms for early identification of at-risk students, and develop multiple ways to deliver support to students whether through technology-based or human-cantered systems are better equipped to respond to the mental health needs of their student populations (Li et al., 2025).

Given that mental health is influencing academic performance, interpersonal relationships, and rates of completing university, it is crucial for academic institutions to investigate scalable, evidence-based approaches to supporting early intervention. Systems based on the internet-of-things (IoT), that focus on responsible data usage, and student autonomy, represent potential solutions to improving the accessibility and responsiveness of campus-wide mental health delivery systems. This context presents the basis for exploring how IoT-based systems can assist in addressing historical gaps in campus-based mental health delivery systems.

4. IOT TECHNOLOGIES FOR MENTAL HEALTH MONITORING

The use of Internet of Things (IoT) technologies for monitoring of student mental health on university campuses relies on the capability of sensor based systems to collect, process and analyze data on the basis of various physical, behavioural and environmental elements. Sensor based systems provide real time information and do not rely on self-reporting, which provides an advantage when trying to identify mental health problems at an early stage and for the purpose of long-term observation. Section 4 discusses four main categories of IoT technologies that are being utilized in relation to the area of student mental health: wearable sensors, environmental sensors, smartphone-based sensing systems, and passive monitoring using communication networks (Wyatt et al., 2017).

4.1 Wearable Sensors

There are three primary technologies of Internet of Things (IoT) related to mental health applications at universities: wearable sensors, environmental sensors, and smartphone-based sensing and applications.

Wearable sensors, which are the most widely used form of IoT technology in mental health applications at universities, typically are in the form of wristbands or are embedded in clothing, and provide a variety of measures of both physiological and behavioural responses, including heart rate, skin temperature, physical activity levels, and sleep duration. More advanced forms of wearable sensors may also measure galvanic skin response (GSR), blood oxygen levels, and/or heart rate variability, which are known indicators of emotional arousal or stress (Wyatt et al., 2017).

4.2 Passive Monitoring Using Communication Networks

In addition to specific devices and mobile applications, smart campuses can utilize existing network infrastructure (i.e., Wi-Fi, Bluetooth, RFID) for passive monitoring of student movement and presence. Every time students connect to campus Wi-Fi or swipe their ID card to enter a building, they create digital traces that can be used to model the student's behavioural routines and social engagement patterns (Ferrari et al., 2022).

The following examples represent some common behaviour patterns that could be indicative of a student's isolation and/or disengagement: Reduced movement on-campus, less frequent attendance at critical learning locations (i.e., classrooms, study halls, etc.), less usage of common social areas. Further, sudden changes in the overall pattern of an individual's location and/or attendance would likely demonstrate behaviours that are disruptive and would need to be evaluated further. Passive monitoring through network systems does not require students to engage with an application or device. Therefore, passive monitoring is ideal when evaluating large groups of students by looking at general trends over time (Παπαδάτου-Παστού et al., 2017).

However, passive monitoring systems can potentially be viewed as a violation of student privacy and raise questions about consent and data use. As a result, institutions should develop clear data governance policies, clearly communicate their intentions to students, and provide students with options to opt-in or opt-out of passive monitoring systems.

Table 2: IoT Technologies for Mental Health Monitoring in Smart Campuses

Technology Type	Examples of Data Collected	Strengths	Limitations
Wearable Sensors	Heart rate, sleep duration, physical activity, movement	Provides real-time physiological data; supports continuous monitoring	Device compliance required; may cause discomfort; data accuracy may vary
Environmental Sensors	Light levels, noise, air quality, room temperature, occupancy	Captures contextual environmental factors affecting mood and cognitive state	Data may not directly reflect individual mental states; sensor placement needed
Smartphone-Based Sensing	Screen usage, location patterns, communication frequency	High device availability; captures behaviour in natural settings	Depends on user engagement and permissions; may raise privacy concerns
Passive Network Monitoring	Wi-Fi access logs, Bluetooth proximity, RFID location data	Requires no active participation; useful for long-term trend detection	May be perceived as surveillance; requires clear consent and policy framework

5. DATA ANALYTICS AND AI IN MENTAL HEALTH DETECTION

In order to extract behavioural patterns that reflect the state of mind of individuals, raw data from various sources (sensors, mobile applications and networks) need to be analysed, categorized, and contextualized. This is where the data analytics and Artificial Intelligence (AI), including Machine Learning (ML) play a central role in transforming large amounts of unprocessed or semi-processed data into actionable knowledge (Lee & Jung, 2018). These approaches, therefore, enable institutions to transition from simple monitoring to predictive and preventative forms of mental health support.

5.1 Role of AI/ML in Behaviour Pattern Recognition

Machine Learning (ML) algorithms are applied to recognize behavioural trends from past and current data collected through various IoT devices. These algorithms can simultaneously process numerous variables (physical activity, sleep patterns, geographical movements, number of social interactions and physiological parameters) to determine differences from regular behaviour. For example, supervised learning algorithms can be trained to categorize students based on labelled data regarding their mental health, whereas unsupervised learning algorithms can be applied to find groups of behavioural patterns that differ from the norm.

With time, the system can learn from the new data and become better at detecting small variations that are difficult to observe using the naked eye. Use of Time-Series Analysis, Anomaly Detection, and Classification Models enables the creation of systems capable of observing both immediate fluctuations and long-term shifts in behaviour. These types of models are well-suited to recognize early signs of burn-out, loneliness or anxiety that normally occur slowly and are not recognized by traditional assessment methodologies (Lee & Jung, 2018).

5.2 Mood Prediction Algorithms

Numerous IoT-integrated systems utilize mood prediction models to predict students' emotional states based on their behaviours and physiological indicators. Most of these models use multi-mode input data (i.e., variables such as sleep quality, physical inactivity, missed classes, excessive screen time, and reduced social interaction). The output of these models are typically a mood classification (for example "stable," "at-risk," or "needs attention") that can serve as a cue for additional evaluation or intervention (Lee & Jung, 2018).

The degree of predictive precision of these models is dependent upon the quality and diversity of the input data, the choice of features, and the robustness of the training process. In practice, mood prediction models require adaptation to each student's baseline, because a similar trend (for example, less physical activity) can indicate very different levels of risk to different students. It is much more likely that personalized prediction models that consider intra-individual variability will be effective than generalized models (Meda et al., 2023).

While these models are not intended to provide clinical assessments, they represent a valuable screening instrument that can inform counsellors, academic advisors, or digital health platforms whether students may be able to benefit from additional assistance.

5.3 Privacy-Preserving Data Analytics

Concerns about protecting privacy, data ownership and governance of behavioural monitoring data using AI and ML have been raised substantially by the use of such technologies in mental health settings. Behavioural monitoring data generated through passive means from non-clinical locations is particularly sensitive and susceptible to misuse if proper precautions are not taken regarding its handling. Institutions need to provide adequate privacy-preserving methods so as to protect students' rights and freedoms while allowing for meaningful analysis. Techniques such as data anonymization, differential privacy and federated learning are just a few ways institutions can ensure the privacy of students' data within large scale student monitoring systems. Anonymizing data eliminates or conceals personally identifiable information prior to analysis. Differential privacy introduces random noise into data so that no single data point can be identified. Federated learning provides the ability to train models across decentralized devices without the raw data being transferred to a central location thereby reducing the likelihood of a breach of personal data (Meda et al., 2023). In addition to the technical strategies described above, transparency and student consent are key components of the design of these systems. Students need to be informed of what type of data is being collected, how the data will be used, who will have access to the data and how the data will impact decisions that affect them. Mechanisms for obtaining consent should allow students to opt-in to the various components of the system individually without limiting access to other available services (Abelson, 2022). ***5.4 Real-Time Alerts for Significant Indicators*** One of the most significant advantages of AI-based systems for mental health is their capacity to alert students in real time when they identify concerning patterns of behaviour (Wang et al., 2022). Real time alerts enable rapid responses to critical mental health situations which are essential to preventing the progression of mental health crises. Many systems permit immediate outreach to students, (for example, via a message providing links to self-help tools or requesting scheduling a meeting with a counsellor.) Additionally, many systems will develop a pathway for escalating response that begins with a digital notification and increases to human interaction if the indicators of risk continue at high levels. However, the thresholds for generating an alert must be carefully determined to prevent over-activation of the system and excessive anxiety in students or decreased credibility of the monitoring system. Over-activating the system could lead to false positives and subsequent decreased reliance upon the system by students, as well as decreased efficiency in supporting staff due to repetitive notifications of false positives. Thus, the thresholds for generating alerts should be based on empirical research and contextual specifics.

6. IOT-BASED INTERVENTION AND SUPPORT SYSTEMS

While monitoring systems may be able to identify the behavioural patterns associated with mental health concerns for students, the greatest benefit of IoT technology is the ability to implement timely, contextualized interventions. When an IoT enabled system identifies indicators of potential psychological distress, there are several types of interventions that can be initiated (digital and human) tailored to the needs and preferences of the student (Wang et al., 2022).

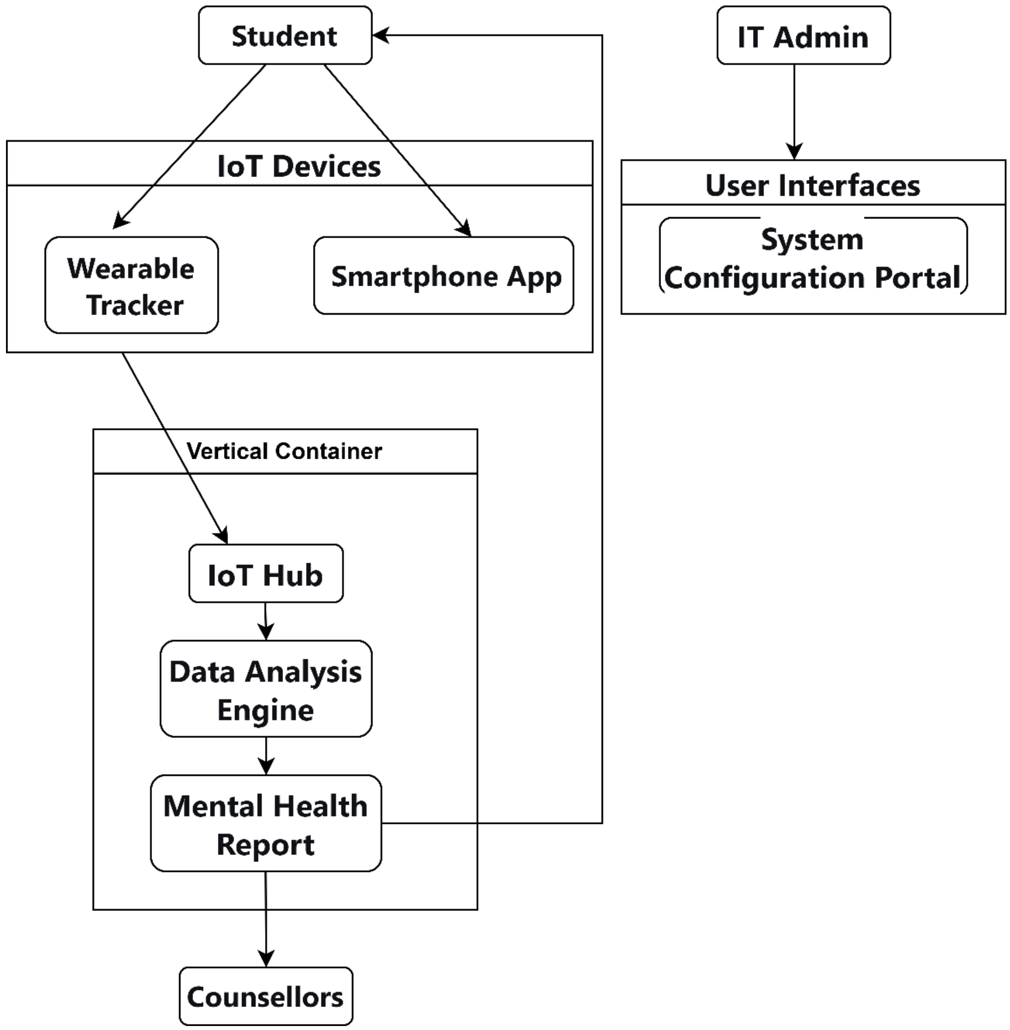

Figure 2. Operational Architecture and Role-Based Interaction Model of the IoT Mental Health Support System

Figure 2 expands upon the conceptual model presented in Figure 1 by illustrating a more detailed operational and role-based system architecture. At the sensing layer, students interact with IoT devices including wearable trackers and smartphone applications that collect physiological and behavioural data in real time. These devices form part of the IoT device layer and transmit data to a centralized IoT hub via a secure middleware container (represented as the vertical container).

6.1 Automated Nudges/Alerts

One of the most common forms of intervention made possible by IoT systems are through the use of automated notifications/prompts/reminders to promote self-regulation and positive behavioural patterns. These "nudges" are typically based upon behavioural data collected in real time. For example, irregular sleep patterns, decreased mobility, missing class(es), or extended social withdrawal. While the intent of providing this type of nudge is not to either diagnose or direct the student to behave in a certain way, it is to provide subtle feedback to allow the student to reflect on and act to possibly prevent potential problems, without limiting the student's autonomy.

Examples of nudge interventions include:

- Irregular sleep patterns combined with decreased mobility may trigger a notification suggesting taking a short walk, resting or drinking water.
- Extended absences from school/class may trigger a notification reminding students of available resources for academic support.

- Nudge-type interventions are usually delivered via mobile apps, smart watches, or email.

6.2 Reducing Student Stress Using Smart Campus Design

An example of how this could be applied includes dynamic lighting systems that adjust brightness based on the time of day and student preference to facilitate circadian rhythm alignment and minimize eye strain. Examples of environmental modifications that could be made in dormitories or rest areas include the utilization of noise sensors to determine when sound levels become excessive and automatically activating white noise systems or recommending quiet zones. Some pilot smart campuses have utilized stress-sensing environments that utilize physiological feedback from students to modify their surroundings in real-time, i.e., dimming lights or altering ambient music in high-stress zones, such as libraries, during exam periods (Ehrlich et al., 2023).

Creating responsive environments does not eliminate the need for psychological services, but rather enhances them by eliminating environmental stressors that often remain undetected. Responsive environments function optimally when they are adaptable, student-cantered and part of a larger institutional wellness strategy.

6.3 Integration with Tele-Counselling and E-Therapy Platforms

IoT systems can also be connected to tele-counselling and e-therapy platforms that enable students to gain access to professional mental health resources that correspond to real-time indications of distress. Rather than requiring students to actively seek out support from counselling centres, IoT systems can automatically send messages that refer students to mental health services that are tailored to their specific needs. This model combines the benefits of passive detection and active referrals, reduces barriers to seeking support and ensures students receive timely mental health service.

There are a variety of ways integration between IoT systems and tele-counselling and e-therapy platforms can occur. Repeated risk indicators, i.e., chronic withdrawal from academic and social activities, can prompt a message recommending a virtual consultation with a licensed counsellor. Physiological data indicating continued stress can link the student to guided self-help modules or mindfulness exercises offered via institutional platforms (Moghimi et al., 2023).

6.4 Peer Support Platforms and Peer Feedback Systems

IoT systems that connect to digital platforms may assist in the development of peer connections and peer relationships that contribute positively to a students' total wellbeing. The platforms that interface with the data from an IoT system enable students who have similar life experiences or challenges to connect with each other, thus facilitating peer-to-peer conversations to provide support, encouragement and jointly develop strategies to cope with issues. For instance, students who have decreased engagement in class or report feeling low through their use of mobile applications could be invited to engage in peer-led, moderated group conversations or peer-led support groups. Furthermore, many platforms allow students to send supportive messages to peers who are designated as inactive or disengaged (as long as the peer has given their full consent) to encourage an environment where all members of the community support one another. Peer feedback systems provide a safe way for students to express concerns and seek informal guidance. Additionally, peer feedback systems help to reduce the burden on formal counselling services and foster feelings of belonging - a strong protective factor against declines in mental health (Cerolini et al., 2023). As previously stated, peer support systems need to be administered properly to prevent negative side effects such as offering false information, providing unqualified/unregulated advice or overwhelming the individual emotionally. As such, institutions need to implement monitoring and facilitation processes for peer support systems that involve qualified professionals, provide a mechanism for elevating concerns and operate within a larger comprehensive mental health framework (Brown et al., 2023).

Table 3: IoT-Based Mental Health Interventions in Smart Campuses

Intervention Type	Input Trigger	Form of Intervention	Mode of Delivery	Institutional Requirements
Automated Nudges and Reminders	Behavioural deviations (e.g., low activity,	Notification or suggestion to adjust routine	Mobile apps, smartwatches, campus portals	Personalisation engine, real-time data processing,

	poor sleep, missed classes)			user engagement tracking
Smart Environmental Adjustments	Environmental stressors (e.g., noise, poor light, crowding)	Dynamic control of light, sound, ventilation	IoT-connected physical infrastructure	Smart buildings integration, context-aware automation systems
Integration with Tele-Counselling	Persistent risk patterns over time	Automated referral, session scheduling, digital self-help tools	Online counselling platforms, chatbots	Trained counselling staff, secure data transfer protocols, consent frameworks
Peer Support and Social Engagement Tools	Indications of social withdrawal, inactivity, or mood self-reports	Invitation to peer groups, moderated forums, support circles	Digital communities, interest-based groups	Moderation policies, escalation protocols, opt-in systems

7. CASE STUDIES AND IMPLEMENTATIONS

A number of university-based IoT-based pilot projects have been conducted to test the practicality of developing and implementing IoT-based mental health monitoring systems. Examples include these pilot studies and the larger-scale implementations that followed them. These studies provided an opportunity to examine many of the practical and technical challenges involved in creating systems for monitoring mental health using IoT technology as well as the responses of institutions and the ethical concerns associated with implementing such systems within academic settings. This section presents a variety of examples of university-led smart mental health pilot programs, in addition to other institutional examples from around the world, that detail the scope of each initiative's focus on using IoT-technology; the key technologies used in each initiative; and the results of each initiative.

7.1 University-Led Smart Mental Health Pilot Programs

During the past several years, a number of universities have developed and implemented campus wide pilot programs focused on utilizing a combination of IoT sensors, behaviour analytics and mobile applications to monitor students' mental health. For example, the University of California, Los Angeles (UCLA) has been conducting a multi-year study that has provided students with wearable fitness tracking devices and mobile application software to collect data about students' sleep, physical activity, and emotional states. The system tracked the students' continuous behavioural data and compared this to periodic mental health assessments they completed. Students in the program reported greater awareness of their own stress patterns; additionally, researchers created predictive models for early identification of depression in students (Robinson et al., 2023).

Carnegie Mellon University developed an on-campus sensing infrastructure referred to as the "Mobile Sensing Platform," which integrated data from smartphones, campus wireless systems and wearable sensors to explore correlations among students' social interactions, mobility and well-being. Results indicated that changes in students' mobility and communication frequency were highly correlated with self-reported stress levels. The study also pointed out the need for personal baseline values, since individual behavioural deviations differed greatly.

A number of Indian Institutes of Technology (IITs) have been experimenting with smart campus elements in students' hostels, including environmental monitoring and occupancy tracking (Robinson et al., 2023).

7.2 National and International Institutional Examples

IoT-based mental health monitoring systems can be effectively implemented in a variety of ways at different institutions in higher education. For example, the Nanyang Technological University in Singapore is using its campus as a large-scale smart campus to monitor student wellness and mental health. A part of this effort included creating wearable devices to monitor students' physical activities, developing a digital well-being dashboard for students to monitor their own behaviours and a mobile app providing students with personal feedback based on their monitored behaviours. Also, NTU created a consent-based, secure system that allows counsellors to view aggregated data about each student but cannot view any personally identifiable information unless they receive specific permission from the student. This type of program increased the percentage of students participating in wellness programs and improved rates of participation in early interventions.

Similarly, Massachusetts Institute of Technology used both self-reported data through a platform that provides students a chance to report how they are feeling and passively sensed data through students' smartphones to analyse students' behavioural rhythms or patterns throughout their day. This included tracking students' sleep patterns, amount of time spent in dormitories and classrooms, and the number of social interactions students had via phone call and/or texting. This data allowed researchers to fairly accurately predict students' academic success and stress levels. As a result of this research, there was an additional emphasis placed on establishing ethical standards and models for obtaining informed consent (Riboldi et al., 2024).

Across the United Kingdom, several universities have taken part in Jisc-led efforts to establish digital well-being frameworks for students on their respective campuses. While most of these projects have been focused on the role of digital engagement and the amount of time students spend looking at screens, some pilot studies have incorporated environmental sensors and student feedback systems to identify where students may be experiencing stress related to their environment and which campus resources are being underutilized by students (Riboldi et al., 2024).

7.3 Key Findings

Monitoring behaviour using IoT-based systems is most effective when combined with personalized analytical tools, as mental health indicators vary widely across individuals and cultures.

Transparency and voluntary participation are essential for the success of IoT-based mental health monitoring systems. Those projects that clearly defined the mechanisms for obtaining consent from participants, communicated with them clearly about data collection practices, and allowed participants to opt-out of collecting data reported a higher level of trust and engagement from participants. Conversely, those projects that did not clearly define their methods for collecting data were met with resistance from students and faculty.

Fourth, while technology has shown potential for improving early detection and intervention, the most successful models of technology-enhanced mental health support systems include a strong connection to human-led services. Technology enhanced counselling services, peer support networks and academic advising rather than replacing them (Zhang et al., 2024).

Finally, the long-term sustainability of IoT-based mental health support systems is a major concern. Many of the projects described above were pilot projects of limited duration and were not incorporated into institutional policies or infrastructure. To ensure that IoT-based mental health support systems remain a viable component of university services, there must be continued evaluation, collaboration among departments, and funding for the development of digital ethics and data governance frameworks.

8. ETHICAL, PRIVACY, AND SECURITY CONSIDERATIONS

The implementation of IoT systems for tracking and supporting students' mental health in Higher Education generates many ethical, privacy and legal considerations. Even though IoT systems can provide a great deal of opportunity for improving students' wellbeing, the IoT systems generate large amounts of personally identifiable data continuously. That data is often collected and processed automatically by the systems without active involvement from the person whose data is being generated (Chowdhury et al., 2025).

This section will explore the key concerns regarding ownership of data, obtaining informed consent for the use of data, distinguishing between providing support and conducting surveillance, and complying with the law based upon regulations established at both the national and international levels (Melcher et al., 2020).

8.1 Ownership of Data and Consent

Ownership of data in IoT-enabled systems for mental health is a foundational issue. Typically, the IoT systems collect a range of data points relating to behavioural, physiological, and environmental aspects of a student's life. Those data points could relate to sleep patterns, movement paths, frequency and depth of social interaction, and location history. Therefore, students as the subjects of data collection must understand the nature of the data, who is responsible for collecting and storing that data, and for what reasons that data will be utilized.

Therefore, effective consent mechanisms must be in place to ensure that the use of the data is ethically valid. Consents cannot simply be obtained once as part of a larger platform policy and then forgotten; instead, consents must be designed to allow for ongoing, granular decision-making. Thus, students should be given the option to decide which types of data they wish to share with the systems, and they should be able to withdraw their consent at any time without suffering adverse consequences. Additionally, there must be a high degree of transparency regarding the methods used to process the data collected by the systems (i.e., how inferences are made from the raw data collected, and which individuals have access to those inferences) to create a sense of trust among users (Geasela et al., 2023).

Moreover, institutions must recognize the inherent power dynamics in educational settings. As a result, students may feel obligated to engage in data-driven wellness programs because of the institutional culture or fear of losing access to related services. Therefore, students must never be required to engage in data-driven wellness programs; rather, all participation must be voluntary, and students who do not participate must not be denied access to other academic or health-related services.

8.2 Risks of Surveillance vs Support

Many of the most critical issues surrounding the deployment of systems for tracking mental health within academic institutions stem from the risk of surveillance. While the ultimate goal of these systems is to offer students support with respect to their mental health, collecting behavioural and physiological data on students continuously, creates a blurred line between the delivery of care and the ability of the institution to monitor the actions of its students. If students do not believe that there are valid reasons and appropriate transparency regarding how their daily routines, moods, and movement patterns are being monitored by the institution, they are likely to consider the system to be a surveillance mechanism; therefore, it is likely that students would choose not to participate with the system.

There are also several other risks associated with the use of predictive systems to identify students at-risk, primarily because of the potential for false positives and the risk of reinforcing bias in the development of models based on training data that does not reflect sufficient diversity. False positives could create unnecessary interventions, potentially lead to the stigmatization of the student, and compromise the privacy of the student (Dekker et al., 2020).

Academic institutions can achieve this balance through developing specific guidelines for the triggers of alerts, limiting access to sensitive data and assuring that all data-based interventions are evaluated and approved by a human decision-making authority. Furthermore, academic institutions should obtain input from ethics oversight organizations (i.e. IRBs, data ethics committees) during the planning and implementation phases of these systems to assure that these systems function ethically.

8.3 Compliance with Federal and State Laws Regulating Privacy and Security of Student Personal/Health-Related Data (e.g. GDPR, HIPAA)

All systems that collect, store, transmit and use personally identifiable data or health-related data are governed by federal and state laws and regulations regarding the protection and security of data. In Europe, the General Data Protection Regulation (GDPR) has established requirements that apply to data processing, including the lawful basis of processing, the purpose limitation of processing, the minimization of data collected and the accountability of the organization to those whose data is processed. Under the GDPR, data concerning a person's physical or mental health or condition, or data revealing a person's sex life or sexual orientation, or a person's behaviour or psychological status, are classified as "special categories" of personal data, and may only be collected and used after explicit consent has been obtained prior to collection and use (Tarimo et al., 2025). Similarly, under the Health Insurance Portability and Accountability Act (HIPAA) in the United States, covered entities (i.e. university health centres) have certain standards to protect individually identifiable health information. Although Internet-of-Things (IoT)-collected data are generally not considered part of the definition of health records, the inferences made from monitoring behaviour can be equivalent to health-related data, and must be treated with equal levels of security and confidentiality (Campbell et al., 2022). Institutional members located outside of Europe or the U.S. must abide by local laws governing the protection of personal data, many of which do not contain provisions relating to the use of IoT or the collection of behavioural data. Institutional members operating outside of jurisdictions with similar provisions are encouraged to follow international best practices in obtaining consent from students, providing for the transferability of data, and holding developers accountable for their algorithms. To ensure compliance, institutional members must not only develop and implement administrative processes to protect the data of students, but also technical processes that protect data. Technical measures include encrypting data while it rests on servers and while it is transmitted across networks, establishing and enforcing access controls, performing regular audits of data and requiring education and training on data protection for employees who collect or analyse data on behalf of the students. Ensuring compliance with the law is a continuing responsibility that evolves with advancements in technology and with changes in the law (Moghimi et al., 2022).

9. CHALLENGES AND LIMITATIONS

Additionally, to the technical barriers related to technology, another factor likely to affect how engaged college students are in IoT-based systems for monitoring and supporting their mental health is social inequality and accuracy of data. These three limitations represent the main obstacles to integrating IoT-based systems into higher education: (i) the need for a cost-efficient and effective digital infrastructure; (ii) the need to make sure that students are willing to engage with and use the IoT-based systems on campus, as well as address the digital divide; and (iii) the need to develop strategies to decrease the potential for errors when interpreting the data collected using IoT-based systems.

9.1 Technical Barriers: Digital Infrastructure Costs and Challenges

The implementation of IoT-based systems for monitoring and supporting the mental health of college students will require an effective digital infrastructure. Therefore, universities need to establish high speed Internet, edge computing capabilities, sensors deployed in different areas of the campus, and centralized platforms for storing, analysing and displaying data. In addition, maintaining the operation of systems 24/7, providing the ability for devices to communicate effectively with each other, and protecting personal data require significant technical expertise and operational resources (Duraku et al., 2024). As a consequence, many colleges/universities (especially those located in low/middle income countries or with limited budgets) may not have sufficient financial resources to implement such systems. Even among well-funded colleges/universities, budget priorities tend to be focused on academic/administrative technology instead of student wellness technologies. Moreover, even after the initial capital investment has been made, costs associated with ongoing maintenance of equipment/devices, purchasing software licenses, employee training, and technical assistance must be accounted for. Although pilot programs can provide evidence of the effectiveness of IoT-based systems to support the mental health of college students, unless funded and supported by the institution for the long term, it is unlikely that pilot programs will evolve into campus-wide initiatives.

Another technical challenge that exists for many campuses is the uneven development of digital infrastructure in various departments/residential units on a single campus. The partial implementation of systems can result in incomplete data, less-than-complete insight, and a lack of fairness in the distribution of support services (Martínez-Líbano & Yeomans-Cabrera, 2023).

9.2 Technical Limitations: Acceptance by College Students and the Digital Divide

While the technical performance of IoT-based systems is important, the success of these systems is also dependent upon the extent to which college students are willing to participate in them. There are several reasons why students may resist participating in IoT-based systems to support their mental health. One reason is that some students may have concerns about privacy. Other students may not trust their institution to protect their privacy. Still, other students may be uncertain about the consequences of being monitored in terms of data collected about their behaviour.

What is considered to be an acceptable method of collecting data to monitor the mental health of college students in one culture/context may be unacceptable in another. Students who come from marginalized groups or other underrepresented groups may be particularly resistant to digital monitoring of their behaviour because they may view such monitoring as intrusive/discriminatory. Finally, not all college students have the same level of access to the technology and/or connectivity needed to fully participate in IoT-based systems to support their mental health (Li et al., 2025).

9.3 Technical Limitations: Errors in Interpreting Behavioural/Physiological Data and False Positives

One of the most significant technical limitations of IoT-based systems to support the mental health of college students is the accurate interpretation of behavioural/physiological data. Because the relationship between observed behaviour/physiology and psychological states is inherently probabilistic, the accuracy of IoT-based systems will depend on the degree to which the algorithms used to analyse behavioural/physiological data are able to account for the effects of multiple contextual factors (Arora et al., 2026). For example, the degree to which a student engages in physical activity may indicate social withdrawal in one situation, but may simply reflect a sedentary study routine in another. Similarly, variations in sleep patterns may be indicative of emotional distress in one situation, but may be a response to the schedule of exams in another.

Machine learning algorithms, which are commonly used to analyse behavioural/physiological data to infer psychological states, are subject to errors in two forms. An error of type I occurs when a false alarm is produced, resulting in the unnecessary concern/intervention of the college student, potentially causing anxiety/distress (Ahmad et al., 2025). Conversely, an error of type II occurs when a false negative is produced, resulting in missed opportunities for early interventions/support. Furthermore, the lack of standardized thresholds for what constitutes a risk profile contributes to the complexity of interpreting the data collected from IoT-based systems. Finally, the difficulty of accounting for the differences in baseline behaviours/moods of students further limits the accuracy of IoT-based systems to support the mental health of college students (Wyatt et al., 2017).

Additionally, many IoT-based systems have been developed using limited or homogeneous datasets, reducing their generalizability to a wide range of student populations. Algorithms that produce effective models of risk profiles in one cultural/institutional setting may produce ineffective models of risk profiles in another. Consequently, institutions must proceed with caution when designing/validating/monitoring the performance of machine learning models used to analyse behavioural/physiological data collected through IoT-based systems (Ferrari et al., 2022).

Ultimately, institutions must establish robust data governance structures, foster interdisciplinary collaboration between mental health experts/data scientists, and provide for human oversight of all decisions made through automated decision-making processes. Predictive analytics should serve as a tool to support, not replace clinical judgment and student autonomy.

10. FUTURE DIRECTIONS AND RESEARCH GAPS

As new methods of applying IoT to supporting student mental health continue to develop, new areas for researching and developing systems are developing. Although the previous research has shown promise, it is characterized by pilot studies in isolation, limited deployments, and localized implementation. To provide an enduring and ethically responsible role in higher education environments for IoT-based systems, future research must address many technical, ethical, and institutional gaps identified below. The remainder of this section identifies several areas that require additional study, specifically advances in sensing modalities, integration of academic performance data into system operation, system interoperability between institutions, and the need for longitudinal evidence.

10.1 Advances in Multi-Modality Sensing Approaches

The majority of previously developed systems have been reliant upon a single or very limited stream(s) of data (e.g., wearable-based physical activity, smartphone-based location tracking). Mental health is influenced by multiple variables, including biological, behavioural, environmental, and psychosocial. Therefore, future systems should utilize multi-modality sensing frameworks that collect and integrate data from various sources to create a broader understanding of the student's well-being.

For example, combining wearable-based biometric data with sensor-based environmental data and behavioural logs from a smartphone can provide more insight than any single data source.

10.2 Connecting Academic Performance Data to Mental Health Indicators

Although there is a relationship between an academic institution's environment and a student's academic performance, mental health and the overall well-being of students (and therefore their engagement with their academics) has received increasing attention in recent years. The majority of the current IoT-based monitoring systems used in higher education institutions operate independently of academic data systems used in these same institutions. Therefore, future research should focus on identifying ways to ethically and meaningfully integrate mental health indicators into the academic performance metrics of students (such as attendance, assignments completed, and grades). The integration of academic performance metrics and mental health indicators will facilitate the detection of students who are having trouble with both their academic work and mental health at a much earlier stage than was possible before, thereby facilitating the development of targeted interventions and assessments that address both academic performance and psychological well-being (Meda et al., 2023). Additionally, this integration will facilitate the assessment of how trends in student well-being impact academic performance over time. However, there are serious concerns about data privacy, the potential for student profiling, and the ability to distinguish between academic monitoring and mental health surveillance in order to merge these two data sources. In order to allay these concerns and foster a sense of trust with students and faculty, clear policies regarding data protection and usage will be required, as well as separate data storage and role-specific access control to prevent misuse. ***10.3 Cross-Campus Interoperable Systems*** In addition to the lack of integration of the systems currently being developed across academic institutions, the majority of the smart campus mental health systems are confined to individual campuses, limiting the possibility of comparative research, the development of standards, and cross-sector collaborations among higher education institutions. The need for cross-campus systems that permit the anonymous, aggregated sharing of data between campuses is expanding, particularly to support multi-institutional studies, national monitoring frameworks, and/or benchmarks. To achieve interoperability across campuses, open APIs, common data formats, and shared ontologies will be needed, but will require collaborative efforts from universities, vendors of technologies, and policymakers. Developing shared ethical and legal frameworks for the inter-campus sharing of data and collaboration will also be critical to protect the privacy rights of students and to provide assurance that participation is optional. Additionally, cross-campus interoperable systems may also provide opportunities for universities to accelerate innovation by permitting them to jointly pilot-test-and-refine component parts of their system components, and to reduce duplication of effort and enhance scalability. ***10.4 Need for Longitudinal Data and Larger-Scale Studies*** One major limitation of current research in this field is the lack of longitudinal data. Most of the current research in this field have consisted of short-term trials with small sample sizes of self-selecting students. Although these types of studies are useful for initial validation, they do not reflect long-term behavioural patterns or sustained effects of IoT-based interventions on mental health outcomes. Longitudinal research will provide insights into how students interact with these systems over time, how predictive models develop and evolve as a function of changes in student behaviour, and whether early interventions result in measurable improvements in academic success and psychological well-being. Additionally, larger scale studies with diverse student populations from different cultural, geographical, and institutional environments are needed to assess the generality and accessibility of these systems (Abelson, 2022). Furthermore, the evaluation methods of these systems are generally limited to evaluating system usability. A broader range of evaluation methodologies is needed that include an evaluation of the effectiveness, unintended consequences, and cost-benefits of these systems. Collaboration between universities, health researchers, data analysts, and ethicists will be necessary to design and implement the studies that are needed to evaluate these aspects of these systems.

11. CONCLUSION

As many of us know, the increasing use of Internet of Things (IoT) technology in Higher Education settings has opened up new opportunities to enhance the support systems for mental health in students. This review has demonstrated the physical environment of a college or university campus provides a medium for ongoing monitoring of behavioural, physiological, and environmental factors associated with psychological wellbeing. In addition, wearable devices, smartphone applications, environmental sensors, and networked data sources, etc., can each contribute to the development of a more proactive approach to identifying early warning signs of mental health problems. Using the data from each of these different sources along with the use of AI, and data analysis, universities will be able to take their focus off just being reactive to a proactive approach to addressing the mental health needs of university students.

There has been some examples of colleges and universities using IoT based systems in a broader wellness initiative that includes active participation of both students and healthcare providers. Unfortunately, most of the projects that have utilized IoT based systems have been limited to pilot testing and do not include enough scale or the ability to evaluate over time to be implemented at a large scale across multiple campuses. There is a clear need for more research in the area of multi-sensing systems that utilize a variety of sensors, including campus wide system compatibility, and incorporating student academic performance metrics with mental health related variables.

IoT based systems are not intended to replace human interventions for the mental health of university students; however, IoT based systems may provide greater access to, and timing of, support services for students; and may enhance the contextual nature of support for students. As universities continue to spend money developing "smart" campuses, it is essential that they develop digital mental health support systems that are fair, transparent, and based upon evidence. Ultimately, the success of digital mental health support systems will depend on the ability to build trust and engage with students that these systems were developed to support.

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