SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2024, 21(4), 583.
https://doi.org/10.62617/mcb583

Article

Exploring the relationship between biometric data measured by sensors and psychological health outcomes in student management

Yangguang Chen

Guangzhou Huashang College, Guangzhou 511300, China; chenyangguang88@163.com

CITATION

Chen Y. Exploring the relationship between biometric data measured by sensors and psychological health outcomes in student management. Molecular & Cellular Biomechanics. 2024; 21(4): 583. https://doi.org/10.62617/mcb583

ARTICLE INFO

Received: 21 October 2024
Accepted: 18 November 2024
Available online: 26 December 2024

Abstract: This study focuses on analyzing the correlation between automatically collected biometric data obtained through sensors and psychological well-being in relation to student management with the purpose of identifying how physiology can inform on student's mental state. Heart rate interval, temp, and electrodermal activity (EDA) are the integral body parameters correlated with psychological state indicators, including stress, anxiety, and mood stability. Using a triangulation design of research, this study combines the quantitative academic performance data collected from the smart space biometric sensors with the qualitative data from a survey and interviews. The study adopted a stratified random sampling technique to identify two hundred students from disperse fields of study to increase the variability of the sample. Ad-hoc physiological data was captured using wearable sensors over a three months' duration and related to psychological health assessment conducted using validated self-report questionnaires. Descriptive and correlation statistics were employed to determine the extent of relationship between the biometric variables and depression. Standard procedures of ethical conduct were observed as the participants signed informed consent, and their data was protected. The presented study is focused on revealing the possibility of using biometric data as an effective nonintrusive method to evaluate and improve the efficiency of student's mental health management.

Keywords: biometric data; psychological health outcomes; student management; wearable sensors; stress and anxiety; mental well-being monitoring

1. Introduction

1.1. Background

Within the past few years, the measurement and tracking of biological parameters through tracking of biometric data has receive significant interest with the development of wearable technologies. Imagers could capture the physiological parameters anytime through wearable biometric sensors which may include heart rate variability (HRV), skin temp and electrodermal activity (EDA) [1]. The above ascertainments have been associated with stress and anxiety as well as general wellbeing state, which, in fact important determinants of mental health among student populations in academic institutions. This year mental health difficulties like anxiety and depressions have been rising among students globally. WHO estimates that 264 million people worldwide live with anxiety disorder; students are affected by anxiety owing to academic stressors and transition [2]. The requirements for objective and real time health monitoring needs are thus more acute than ever before.

The identified problems concerning features of using traditional research approaches, such as self-report surveys, to measure the intensity of psychological health issues are summarized as follows: However, such methods give only occasional indexes of the state of mental health, thus not always reflecting the existing changes. Wearable biometric sensors present one such viable solution because they are able to provide objective, longitudinal signals that parallel alterations in psychological conditions [3]. For example, research has established that heart rate variability (HRV) is a good measure of stress; low HRV implies high stress, while high HRV suggests that the individual is relaxes easier, and has more resistance to stress.

Biometric data is gradually becoming regarded as the most crucial form of data required for the prevention of the deterioration of student mental health [4]. Schools can then use these real time alerts (RTA) to get early warning signs of any student developing stress or anxiety and act accordingly. For example, monitoring such parameters as HRV may help student support teams identify that stress levels are high enough that they threaten a student's psychological well-being before that student becomes burned out or depressed. Institutions could therefore digitize student management systems to embark on biometric monitoring, in order to provide timely interventions such as stress relieve workshops or counseling services. **Figure 1** shows the flowchart of the process.

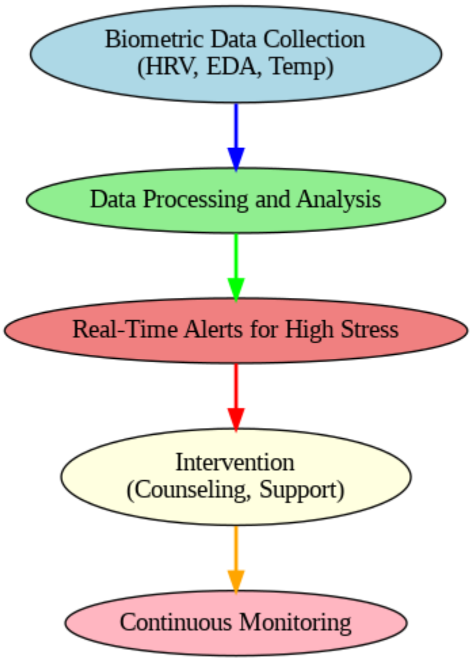

Figure 1. Flowchart of the process.

This flowchart shows the process of how biometric data of individuals will be obtained to supplying alarms or intercessions on time [5]. How data collected over wearable sensors are converted to useful structures and processed for timely student support action based on the identified physiological trends are shown.

1.2. Problem statement

One of the challenges that are being experienced in institutions of learning include mental health problems and or illnesses among learners especially given the fact that learning institutions are places that afford students the opportunity to pursue their education amidst very competitive and stressful. The World Health Organization (2021) estimates that approximately 10–20 percent of adolescents have mental health disorders; of which students in universities suffer from anxiety and stress. New opportunities created by wearable technology make it possible to track HRV, skin temperature and electrodermal activity, which are more trustworthy indicators of psychological well-being. Thus, for most of these biometric indicators, it is not quite clear how they are associated with mental health outcomes [6]. For this reason, there is a need to make sure that this relationship is well understood for purposes of ensuring that management of students aims at enhancing student well-being. To this effect, this research will seek to bridge the gap through evaluating ways in which real time biometric data could be used in the evaluation of student mental health in order to proposed a more holistic model of student care.

1.3. Aims and objectives

The purpose of this current study is to examine the correlation between biometric data and psychology well-being of students. The objectives are:

1) To investigate the practical association between certain biometric parameters indexes such as heart rate variability, skin temperature and electrodermal activity reflecting the state of psychological health, stress and anxiety levels in students.
2) To determine the relationship between change in at least 4 biometric measures and student participants' self-assessed state of psychological health at a given period.
3) In order to ascertain whether biometric data can prove useful in predicting mental health outcomes to provide insights of how student management approaches and support services can be improved.

1.4. Research questions

1) This research question aims at answering the question on how measures like heart rate variability, skin temperature and electrodermal activity closely relate with psychological well-being of students' stress and anxiety levels.
2) What is the relationship between the fluctuations in biometric data and self-identified psychological well-being trends in students over the course of one year?
3) Is it possible to rely on biometric data inputs to accurately anticipate certain results in terms of students' psychological well-being, and if it is, what should the managerial strategies in educational organizations look like?

1.5. Significance of the study

This study makes a great deal of importance especially concerning stress management among students which is a population that is more and more suffering from anxiety [7]. As a result, the contribution of this research to the field of digital mental health is established, focusing on how the use of biometric data can improve more typical tools for a psychological well-being support in educational institutions.

This involves close focus on biophysical criteria including HRV and skin conductance that provides a naturalistic means of tracking student's state of mind at that given time. These physiological indices can help diagnose psychological corrosion so that corrective measures that may enhance performance or boost the health of students may be administered on time.

2. Literature review

2.1. Biometric data and mental health

The use of biometric data in recording psychological health is viewed as a major step in analyzing mental state. Physiological variables, like HRV, skin temperature, and EDA are biometric measurements that give immediate and physiological data of an emotional and psychological nature.

2.1.1. Heart rate variability (HRV)

Heart Rate Variability (HRV) is an essential measure of functional capacity of the Autonomic Nervous System as well as psychological health. It is called the instability of intervals between beats, determined by the relative activity of the sympathetic and parasympathetic divisions of the nervous system [8]. In general, High-Risk HRV correlate with the relatively good cardiovascular state and stress tolerance while low-Risk HRV is linked with anxiety, depression and other pathological states. Other research has established considerable association between HRV and psychologically related outcomes. **Table 1** shows the Correlation Between HRV and Psychological States.

Table 1. Correlation between HRV and psychological states.

HRV Range (ms)	Psychological State	Stress Level
0–20	High Anxiety	High
21–40	Moderate Anxiety	Moderate
41–60	Normal Emotional Regulation	Low
>60	Calm	Very Low

HRV can be defined as the difference between subsequent intervals between two successive heartbeat and is calculated and measured mathematically by several parameters that explain different aspects of the Autonomic Nervous System.

Standard Deviation of NN intervals (SDNN):

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} \left(NN_i - \underline{NN}\right)^2}$$

where NN_i represents each normal-to-normal interval, $\underline{NN}$ is the mean of these intervals, and N is the total number of intervals. A higher SDNN indicates better adaptive capacity and resilience to stress.

Root Mean Square of Successive Differences (RMSSD) measures specifically assess parasympathetic activity and is calculated as:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} (NN_i - NN_{i+1})^2}$$

Higher RMSSD values signify healthier autonomic regulation, and this equation is sensitive to the differences between successive heartbeats.

Low Frequency/High Frequency (LF/HF) Ratio reflects the emotions and psychological conditions; distribution of the activity between sympathetic and parasympathetic divisions.

2.1.2. Skin temperature

Skin temperature is a fundamental biometric which the available literature has evidence to link to psychological states. When an individual reaches stress or anxiety phase, physiological responses can result in lowering of skin temperature due to vaso – constrictions where the blood vessels get constricted in order to pump the blood to the vital organs. This is autonomic response is stimulated by the fight or flight process, and is helpful for understanding stress in students, especially during their exams or life-altering events.

Four types of skin temperature measurements can be recorded using wearable devices with built-in thermometers or infrared cameras. There is evidence demonstrating that skin temp changes may be the feelings and stress manifestations. In a study conducted by Kettunen et al., it was established that students who displayed high levels of stress, recorded reduced skin temperature by an average 2.5 degrees Celsius below the base line. **Table 2** represents the Skin Temperature Changes Under Different Psychological States.

Table 2. Skin temperature changes under different psychological states.

Psychological State	Average Skin Temperature (°C)	Change from Baseline (°C)
Relaxed	34.5	0.0
Moderate Stress	33.0	−1.5
High Stress	31.5	−3.0

2.1.3. Electrodermal activity (EDA)

Electrodermal activity (EDA) is another term for galvanic skin response (GSR), which records electrical conductance of skin surface, and depends on skin conductivity or moisture changes because of sweat glands. EDA is an effective biomarker for the assessment of affective processing because it embodies how the ANS responded to stress and other wakeful stimuli [8]. When people get stressed, tense or excited, their skin conductance raises, and this is measurable in real time.

The results (**Figure 2**) show that EDA can offer important information about individuals' psychological conditions. Boucsein (2012) found out that anxious persons had 60% increase in EDA compared to their respective baselines. From the above column chart, it can be seen that the EDA response to stressful emotional stimuli is highest whereas that of neutral one is the lowest. This shows (**Table 3**) that EDA is sensitive in its ability to reflect the mental health conditions as a physiological parameter.

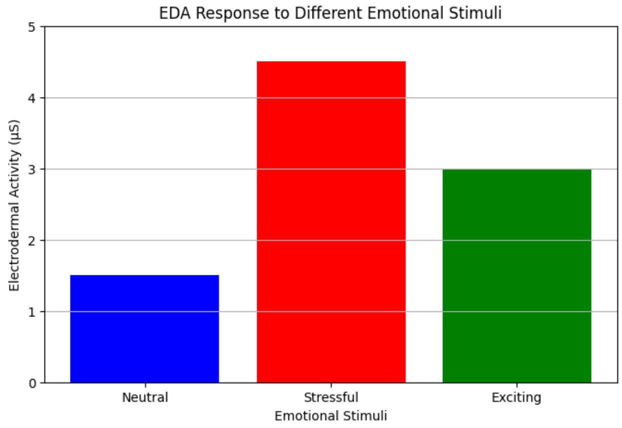

Figure 2. EDA response to different emotional stimuli.

Table 3. EDA levels across different emotional states.

Emotional State	Average EDA (µS)	Percentage Change from Baseline
Baseline	1.0	0%
Stress	4.0	+300%
Relaxation	1.2	+20%
Excitement	2.5	+150%

2.2. Use of wearable sensors in educational settings

The use of wearable sensors inside teaching-learning environments is progressively developing due to its capacity for offering almost simultaneous measurement of physiological conditions which are related to psychological emotion and well-being as well as physical fitness [9]. These sensors, introduced in smartwatches, wristbands, or even clothes, monitor parameters like heart rate, skin temperature and electrodermal activity. Within schooling spaces, these gadgets are able to identify the use of pressure, nervousness, and generally wellbeing of scholars, and institutions can aptly address this in them.

Wearable sensors that present dynamic physiological and psychological information are revolutionalising the approach to education. Education may benefit from the use of these devices in numerous ways such as; making learning personal, promoting improved mental health services. Wearable sensors' benefits for education are as follows:

2.2.1. Real-time monitoring of student well-being

The first of its strengths is that the use of wearable sensors allows the monitoring of students' physiological conditions as continuous and real-time [10]. Wearable that measures the HRV, skin temperature, and EDA allow educators and counselors to know when a student is stressed or anxious. Having assistance with matters such as stress means that appropriate action can be taken before the problem gets worse and might lead to serious mental complications.

2.2.2. Data-driven personalized learning

Smart wristbands offer physical characteristics which may be of use to adapt the learning process for each learner. For instance, students showing signs of stress in certain learning environment should be given shorter breaks or rather different workloads. Superintendents can use this information to formulate interventions that will help each teacher understand the individual learner and formulate individual teaching and learning approaches that will be helpful in learner's learning process.

2.2.3. Enhancing mental health support

By adopting wearable sensors schools should be able to put in place proper support structures for mental health. Physiological measures such as HRV and EDA can allow schools to assess levels of stress and give mental health interventions at the early stage [11]. Depending on the values obtained from the analysis of chronic stress risk indicators, students could be provided with counseling or therapeutic services, that would prevent them from constituting anxiety or depression, among other diseases.

2.2.4. Improved academic performance

Stress and anxiety can be observed, and schools can work on these problems as soon as they appear to affect a student's performance. A literature review indicates that stress enhances concentration and cognitive domains as well as promote better academic performance. Hearing with the integration of wearable sensors in schools the resultants of a student's well-being outcome offer influencers that may affect performance and tackle them ahead of time. **Figure 3** visually represents the impact of stress on academic performance. From the figure, it can be seen that if the stress level increases then the academic performances become poor

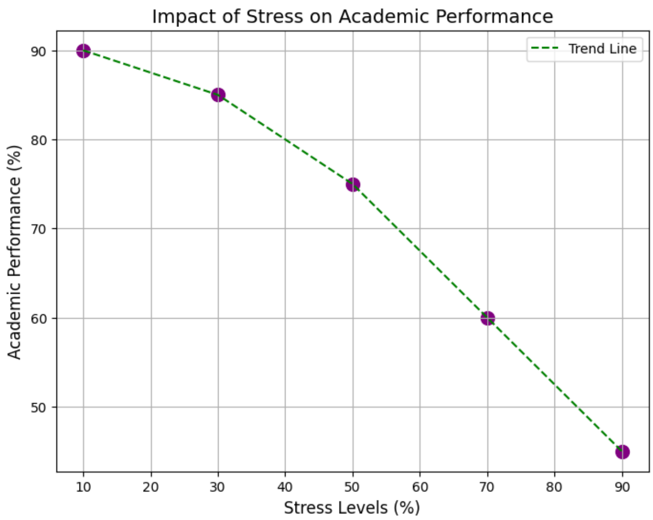

Figure 3. Impact of stress on academic performance.

2.2.5. Fostering emotional intelligence

It also helps students to develop emotional intelligence by wearing Wearable sensors. If students know how their bodies reacted to stress, then, they are able to handle their emotions better. Some interventions could be conducting stress management drills and or even organization of mindfulness strategies concerning each learner.

2.3. Use cases of wearable sensors in educational settings

Wearable sensors have brought changes to educational settings through the ability of determining the physiological and emotional status of students on a real-time basis. This technology is can be used for various purposes beginning with stress monitoring during examination period up to involvement of students in classes both physical presence and virtual classes.

2.3.1. Monitoring exam stress

Another important area of wearable sensors' application is tracking stress levels of students during stress sensitive time, for instance during examination period [12]. Using biometrics data that include HRV and EDA, educators are able to monitor stress patterns over the learners. For instance, a HRV would be lower during an exam week mean high stress.

2.3.2. Enhancing group collaboration

During group work, one is able to use wearable sensors in estimating the cardiac state's regulation, The degree of engagement, and how teamwork is being done. With the use of sensors, the teacher can know when a certain student is stressed or bored out of the activity and changes the formation of groups or provides help immediately. Further, this data may be also used after the session to identify patterns of intergroup dynamics and build recommendations as to how the group can improve cooperation.

Through the COVID-19 outbreak, online classes became more common than before, but there were difficulties to capture students' attention. One therefore can monitor attention rate while taking online classes through Wearable sensors that sense physiological signs. Temperature or EDA values, either a decrease in skin temperature or increase in skin conductance, point to disinterest or anxiety. Such data can help educators take action like providing breaks or providing extra focus to a student to avoid emotional distress.

2.3.3. Personalized learning experiences

Smart clothes can be used to establish individual learning experiences. In combination, biometric data collected during learning may help educators realize that a particular child will require more than usual or even a different approach [13].

2.4. Challenges and limitations

2.4.1. Data privacy and security

Another current problem is the need to protect information on people's biometrics extracted by wearables, which also involves privacy concerns. Schools and universities need to respect data dealing with it in compliance with data protection legislation, such as GDPR or in the case of health data in educational settings HIPAA [14]. Fraud committed using personal health information could result in severe legal an ethical penalty. Therefore, encryption procedures and adequate secure facility procedures to contain these data are essential. The **Figure 4** shows data privacy concern breakdown using a pie chart. From the pie chart, it can be seen that 30% is data breach concern, 20% is insecure storage concern, 25% is unauthorized access concern and the remaining 25% is data misuse concern.

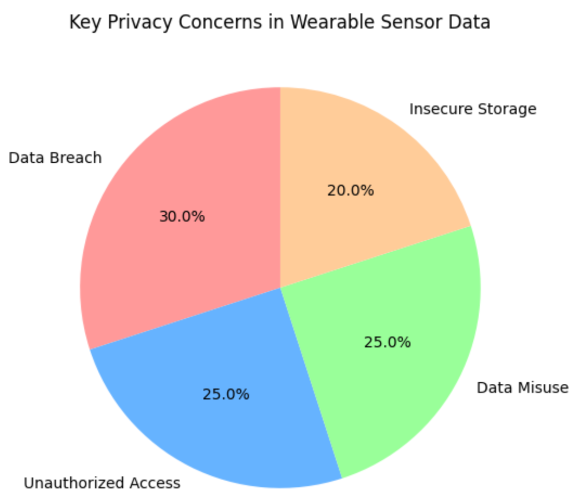

Figure 4. Data privacy concern breakdown.

2.4.2. Accuracy and reliability of data

Wearable sensors which are continuously developing are still experiencing issues with accuracy and reliability. For instance, the readings may vary from one moment to the other by alteration of movement, environmental temperature or placement of the device [15]. To rectify this problem, you need to take frequent but not too close readings of any signal; otherwise, it may result in false positives identifying stress when there is none or false negatives missing stress when it is clearly manifesting thus defeating the very purpose of using stress detection technologies to enhance student wellness. To address this, sensor calibration and validation exercise is valid, but this takes a lot of time and money.

$$Error\ Rate = \frac{False\ Positives + False\ Negatives}{Total\ Number\ of\ Measurements} \times 100$$

2.4.3. Cost and resource constraints

The affordability of wearable technology is a major challenge in technology integration in the education sector, especially due to the high prices which limits its affordability for institutions such as public-school going and colleges, universities, etc. [16]. However, as wearable sensors are still expensive, especially when incorporated in programs supported by strategic partnerships and grants, even large institutions may not be in a position to provide such technology to their students as faculties of smaller institutions. **Table 4** represents an estimated Cost of Implementing Wearable Sensors in Educational Settings.

Table 4. Estimated cost of implementing wearable sensors in educational settings.

Institution Type	Estimated Annual Cost	Funding Options
Public Schools	\$50,000–\$100,000	Government Grants, Donor Funding
Private Universities	\$100,000–\$500,000	Research Grants, Industry Funding
Community Colleges	\$30,000–\$70,000	Scholarships, Alumni Donations

2.4.4. Interpretation and actionability of data

Another challenge is to turn the data collected to be useful, that is to say to transform the data collected into usable information [17]. It is now incumbent upon educational institutions to get the interpretation of the data right, and with that, make proper decisions about interventional approaches to student mental health. Students/Teachers could get overwhelmed when they are expose to raw sensor data, few of them may not know how to use a data analysis tool to make good sense of them; therefore, the technology is only useful to an extent.

2.4.5. Student resistance

Preconceptions can work against some students to refrain from using wearable sensors because they feel that the gadgets invade their privacy, or they suppose that the devices make them nervous or stressed and thus withdraw their focus from their studies. In such cases, it is therefore important for the manufacturers to cultivate trust by informing the consumers of the usefulness of these sensors as well as their demerits.

2.5. Challenges in mental health monitoring

Supervision of mental health is one of the recent discussions since stress, anxiety and other psychological disorders are rife among students [18]. Conventional techniques including self-stakeholder administered questionnaires and one-on-one counseling interviews are effective but have their weaknesses that impact the efficiency, reliability, and time-horizons of tracking devices.

2.5.1. Subjectivity and recall bias in self-reported data

A major problem with regard to mental health check-up is that the assessment is normally done by the patient and thus, it is very subjective. Sometimes students may give biased or even unreal information because of social desirability, and sometimes people can simply recall things inaccurately.

2.5.2. Lack of continuous monitoring

Previous mental health screen tests are often on a discretized basis implying that only once in a while is the student's or patient's status checked as contrasted with a consistent basis [19]. This can result into lack of information regarding their mental health equilibrium and as on when they are shifting from one phase to the other because of issues such as pressure arising from school work, or personal problems.

2.5.3. Data privacy and ethical concerns

One of the biggest hurdles is privacy and confidentiality of individuals from which we collect the data especially if it entails mental illness [20]. Smart clothing and other biometric wearables can monitor vital personal health parameters and some people may start to worry about how this data is saved, who might view it and how it may be used. Isolation of these concerns rises from the need to develop ethics in the process while ensuring that anonymization is done correctly. Ethical Considerations in Mental Health Monitoring are visually shown in **Figure 5**. From the figure, it can be seen that there are mainly two ways of collecting biometric data collection and those are anonymization & encryption and consent & transparency.

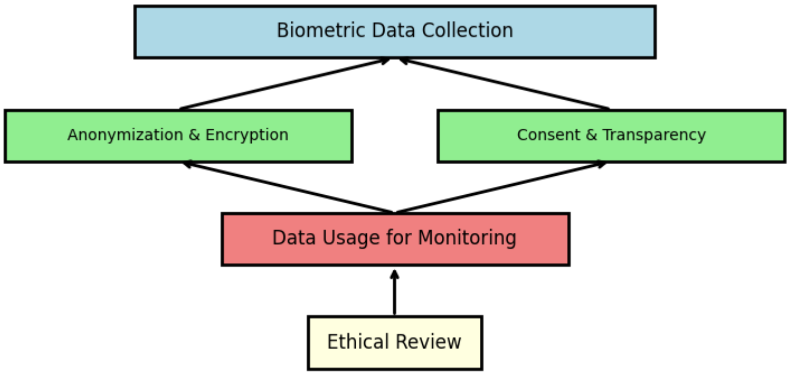

Figure 5. Ethical considerations in mental health monitoring.

2.5.4. Interpreting biometric data

Biometric data can give an investigator objective information about physiological effects, however, using this data to reach conclusions about mental health is not straight forward. There are many confounding variables that can exist with it including physical health of the rider, environmental circumstance, and even the reliability of the sensor. This creates the problem of lacking concrete biometric readings from which conclusions can be easily drawn.

2.5.5. Technical limitations of wearable devices

Wearable devices have their own limitations Worn devices, despite their potential, have to face a number of problems. The quality of the sensor, battery power or even position on the body, can all cause variability in data readings. Furthermore, these devices are sometimes expensive and thus they cannot be afforded by so many schools, colleges and universities.

To address the difficulties in identifying the patients with mental issues, it is becoming essential to have continuous and preferably physical objective patient monitoring while respecting patients' individual rights and ethical standards [21]. Wearable devices when associated with artificial models for predictive analysis are useful for early diagnosis and timely intervention; however, there is the need for the development of better models and greater accessibility. The availability and interpretation of accurate real-time data and enhanced Technologies that can be utilized by the users will definitely make mental health checkup smoother in the future.

2.6. The role of technology in student management

2.6.1. Student information systems (SIS)

Student Information System also known as SIS refers to systems that accept, process, store, retrieve and distribute information all about students as well as duties on their behalf. With their help, institutions can keep proper records of enrollment of students, their attendance, grades and demographic characteristics. Proper implementation of a SIS helps in the improved flow of information between students, faculty and other administrators.

2.6.2. Learning management systems (LMS)

Learning management systems (LMS) support online learning delivering course content, promoting class discussion, and providing opportunities for submitting assignments from remote locations. LMS platforms are designed for facilitating a hybrid learning model that has emerged as crucial in response to the COVID-19 situation [22]. They also facilitate control and determination of student participation and achievement by the instructors.

2.6.3. Biometric monitoring technologies

Digital surveillance tools like smart clothing and wearable gadgets are utilised in tracking subjects' biometrics, like HRV, skin temperature, or EDA including students. These devices offer the current data that can be useful for the interventions of the mental health [23].

3. Methodology

3.1. Research design

This study employs the quantitative and qualitative research methods in designing the research to investigate the correlation between the biometric data captured through sensors and students' psychological health.

3.1.1. Study framework and workflow

It is crucial to present a general outlook of the research procedure so as to appreciate the steps used in data collection and analysis. The following flowchart (**Figure 6**) illustrates the workflow of the study from biometric sensor data, the psychological health assessment of students, data analysis of information gathered.

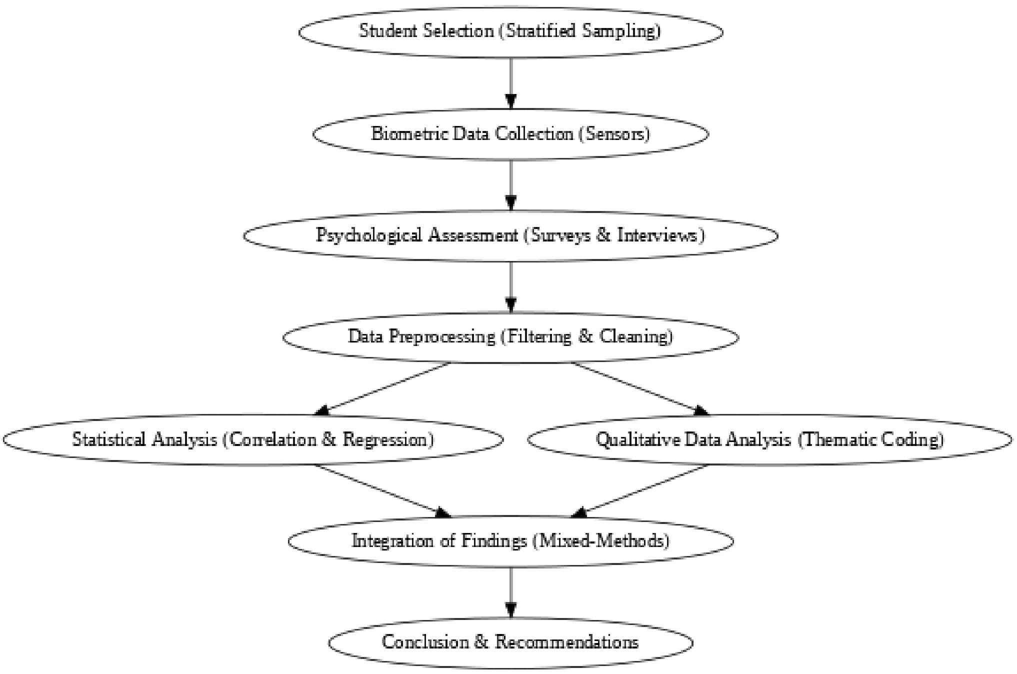

Figure 6. Visual representation of study framework and workflow.

3.1.2. Experimental design

The quantitative part is based on the information received from the built-in sensors that capture biomarkers, including recipients' RHR, skin temperature, and EDA, which are known to be related to stress and affective response. Hear rate variability will be applied to reflect the level of emotional control and stress, as stress and lack of resilience to it is present in people with lower HRV. Skin temperature will be used as an estimate of emotional and physical responsiveness to changes in the environment since skin temperature reflects the activity of the autonomic nervous system. Skin conductance will be recorded to indicate EDA since higher skin conductance is associated with increase in stress or anxiety, for example.

For the quantitative analysis Pearson's correlation and regression tests will be used to determine the relationship between these biometric indicators and other psychological variables such as stress and anxiety. Statistical methods are used to examine the data; computer print-outs will be used to make all the calculations, trends, correlations, and projection to be presented with the help of graphs where appropriate so that any relational as well as aberrant data can be easily detected. Besides the biometric data, qualitative data is collected through semi structured interviews only from a number of participants. From these interviews, the students will be able to present their own stress stories and ways they use in managing stress, which will complement the biometric data. To categorize the collected interview data, thematic analysis will be used to label emerging patterns issues in the present study, for example, perceived stress, coping and mental health among students.

3.2. Sample selection

The target population was university students, and the sample was 200 students chosen by means of a stratified randomized quota sampling technique. This helped to achieve representation of other related demographic variables like gender, academic discipline, and year of study. Separation was done on the basis of the understanding that varying sub-populations of students may handle and develop stress in various ways. For gender, equal gender-H/M was used implication that both male and female students were included. Consequently, both male and female participants from STEM, Arts, and Humanities was employed in order to capture every type of academic pressure common among students that can lead to high stress levels. Furthermore, participants were chosen based on their year of study ranging from first-year, middle-year, to final year students with the aim of get a wider view on progression through a level of tertiary education and how stress is handled. Besides giving the study a better coverage and a more refined randomly selected sample, this technique also avoided or greatly reduced biases in such a way that the results could be appropriately generalized to different subgroups of the students. Participants were contacted through social media platforms at the participating universities and upon explaining the purpose of the study and the volunteers' rights, there consent was sought.

3.3. Biometric data collection

Sensors and Metrics:

Heart Rate Variability (HRV) is used for measuring stress and emotional regulation. Skin Temperature is the indicator of emotional and physical responses to environmental changes. Electrodermal Activity (EDA) helps to measures the skin's conductance, associated with emotional arousal (**Table 5**).

Table 5. Biometric data collection timeline.

Weeks	Activity
1–2	Sensor Setup and Student Orientation
3–6	Continuous Biometric Data Collection
7–9	Midpoint Data Review and Adjustments
10–12	Final Data Collection and Student Feedback

3.4. Data analysis and integration

Quantitative and qualitative methods of data analysis were employed in the course of this study with the aim of delivering an all-round assessment of biometric data and psychological health among students [24]. For quantitative study, we used statistical software to elect correlation and regression tests. Pearson correlation coefficient was used to analysis the strength and the direction of the relationship between biometrics and psychological constructs (stress and anxiety). Projections are made to show these relationships, with trends and values outside from the data presented through graphics.

For the qualitative data, the responses from the semi-structured interviews were taken and transcribed and then, the thematic analysis was taken on these responses. In this process, data was read, coded, and analyzed with a focus on creating major categories of themes regarding stress as seen from the student's perspective, the ways in which these students managed stress, and finally, emotional wellness. Qualitative results were merged with the quantitative data in order to obtain an all-encompassing perspective of the interaction between biometric data and psychological well-being results.

4. Findings and analysis

4.1. Biometric data and psychological health outcomes

The analysis focuses on three primary biometric indicators: systolic and diastolic blood pressure, HRV, skin temperature, and EDA. These indicators are associated with psychological well-being data collected with the Perceived Stress Scale (PSS) and the Generalized Anxiety Disorder 7-item scale (GAD-7).

4.1.1. Heart rate variability (HRV)

Information summarised above in the **Table 6** gives a summary of the heart rate variability (HRV) and the Perceived Stress Scale (PSS) results of the student's population. An analysis of the average HRV value of 55.6 ms means moderate value of HF, which is characteristic for healthy people and those, who have a lower risk of cardiovascular diseases and stress impact [25]. The proportionate small value of 12.4 ms shows that the majority of participants possess HRV values near the average values indicating a more or less same physiological state among them. Here, the mean of

HRV at 54.2 ms is essentially the same as the median, which points to great variability without extreme shifts.

Table 6. Results of HRV and psychological stress levels.

Indicator	Mean (ms)	Median (ms)	Minimum (ms)	Maximum (ms)	Standard Deviation (ms)	Interquartile Range (ms)	Correlation with PSS	*p*-value
HRV	55.6	54.2	40.0	75.0	12.4	10.5	−0.45	< 0.01
PSS	22	23	15	30	4.5	5.0	-	-

The psychological stress was established by finding the mean of the total PSS which was 22; a higher figure denotes more stress levels in a group of students. That is why standard deviation of 4.5 is quite appropriate when describing variability of the sorts of stress experiences in terms of respondents' replies. Lowest and highest obtained scores of fifteen to thirty capture the variation of stress across the sample group. The strong negative correlation coefficient of −0.45 between HRV and PSS, with a statistically significant *p*-value of <0.01, underscores an important relationship: in turn it may be stated that the lower the score in HRV, the higher is the degree of perceived stress. This postulation means that there is a significant relationship between lower HRV and higher stress; in arguing this, the authors underscore HRV as a useful biomarker to analyze psychological well-being consequences among students.

4.1.2. Electrodermal activity (EDA)

Table 7 shows the quantitative findings in EDA and the GAD-7 scores validated anxiety levels. According to this EDA mean value, 2.34 µS, it is concluded that the subject had moderate level of physiological activity related to emotions. The hourly median of the EDA was 2.25 µS, this means that 50% of the participants EDA was less than this mean. The other parameter values of EDA varied from 1.0 µS as the lowest value and extended up to 3.5 µS with the standard deviation of 0.76 µS. This variability underscores the variability in students' physiological makeup, stress levels and coping mechanisms to stress.

Table 7. Statistical results of eda and anxiety levels.

Indicator	Mean (µS)	Median (µS)	Minimum (µS)	Maximum (µS)	Standard Deviation (µS)	Interquartile Range (µS)	Correlation with GAD-7	*p*-value
EDA	2.34	2.25	1.0	3.5	0.76	0.9	0.38	<0.05
Anxiety Level (GAD-7)	12	12	7	20	3.2	4.0	-	-

Concerning self-report anxiety, the overall mean GAD-7 score of 12 positioned each participant at the mild to moderate level of anxiety [26]. The group mean and median for the GAD-7 was 12, which corresponded to the central tendency of anxiety within the studied cohort. The anxiety scores were obtained from 7–20 with a standard deviation of 3.2 that implies moderate variation of anxiety symptoms experienced by the students.

There is a positive moderate correlation between EDA and the level of anxiety The obtained coefficient was $r = 0.38$. This means that high levels of EDA, indicating high level of physiological activation, correlate with higher scores in anxiety. Statistically, the value is equal to $p < 0.05$, that allows to strengthen the notion that the correlation between the given indexes is statistically significant, and therefore physiological responses identified through EDA can be used as a biomarker for anxiety level evaluation in students.

4.1.3. Skin temperature

Table 8 shows the statistical analysis quantitative data of skin temperature and the correlation with psychological well-being and psychological stressful level assessed with PSS. Mean skin temperature was established at 36.5 °C while median skin temperature was 36.4 °C, illustrating that most of the students' skin temperatures were fairly uniform. Skin temperature varied from its minimum of 35.5 and maximum of 37.5 degrees Celsius and is supported by a standard deviation of 0.6 Celsius degrees. This has averaged standard deviation to show that that majority of the participants' skin temperatures were not very much different from the overall average.

Table 8. Statistical results of skin temperature and psychological health outcomes.

Indicator	Mean (°C)	Median (°C)	Minimum (°C)	Maximum (°C)	Standard Deviation (°C)	Interquartile Range (°C)	Correlation with PSS	*p*-value
Skin Temperature	36.5	36.4	35.5	37.5	0.6	0.8	0.42	< 0.05
PSS	22	23	15	30	4.5	5.0	-	-

Interquartile Range (IQR) is 0.8 °C, confirming that 50% skin temperature was within the central range and confirming the measurements had standard deviation. The present study, in fact, revealed that $r = 0.42$, which displays a positive correlation of the middle order in terms of the skin temperature and psychological stress. This suggests that, with respect to skin temperature, levels of psychological stress are likewise likely to rise. Since the p-value is less than 0.05, these findings support the assumption that physiological markers, for instance skin temperature may be useful in determining the psychological health consequences in students.

4.2. Qualitative insights

To get the broad perspective of the relationship between biometric data and psychological health outcomes, we conducted one on one semi-structured interviews with 30 students [27]. Five dominant themes emerged from the data during the thematic analysis and these highlighted students' understanding and experience concerning stress and biometric monitoring. One of this was highlighted as the identification of several stressors. As much as students surveyed pointed out that academic workload, financial pressure, and social anxiety as the leading causes of stress. Sixty per cent of participants suggested that academic load was the primary cause of stress, followed by 30% that pointed to stress caused by part-time work finances, and 50% that identified stress associated with peer interactions. In the case of the current paper, these sources of stress have been depicted visually to balance and compare them based on their effect this to the psychological well-being of students. The students showed a generally positive tone with the idea of monitoring awareness and stressing through biometrics. According to the above study, stakeholders 80%

reported that they will be able to effectively manage stress levels once biometric data like heart rates or stress levels, are made available. The interviews observed the students' great interest in support mechanisms originating from the biometric data analysis. Regarding specific features, several students showed enthusiasm in features regarding alert for stress level and access to mental health services according to biometrics [28]. About an equal number of respondents, 70% and 60%, respectively, expected real-time alerts and immediate support for mental health issues.

5. Discussion

5.1. Interpreting the relationship between biometric indicators and psychological health outcomes

Heart Rate Variability (HRV): An inverse correlation between low HRV and high perceived stress conforms to basic positive science literature. Specifically, HRV has been proposed to reflect the functioning of the ANS, and especially the parasympathetic branch of the nervous system. An underlying HRV evidences a poor capacity to restore after stress and reflects higher sympathetic influence (SNS), associated with states of concern and stress. The moderate negative relationship of using correlation coefficient of −0.45 ($p < 0.01$) projects that the level of perceived stress, causing less capacity to regulate the stress autonomously by means of HRV. It is handy when discussing the overview of HRV, now it is continued during the studying discussion, as it may act as the stress indicator and facilitate quicker return to the normal functioning when working with burnt out students or learners with the first signs of anxiety disorders.

Correlation Coefficient (r) = −0.45, $p < 0.01$.

Electrodermal Activity (EDA): The analysis of data revealed that there was a positive linear relationship ($r = 0.38$, $n = 30$, $p < 0.05$) between EDA and the scores of the questionnaires designed to reflect the level of anxiety that is, the higher the level of anxiety the students experienced, the higher skin conductance which indicates the level of physiological arousal. In EDA, skin's conductance of electrical current is evaluated, depending on the performance of the sweat glands, which are usually triggered by feelings of stress or apprehension. This discovery can help explain the physical process of how anxiety plays out in the student population and the importance of EDA to track anxiety in real time. In student management, this may feed into the creation of preventive solutions that could help to minimize anxiety in students at high risk e.g. elaborate stress busting sessions or counselling.

Correlation Coefficient (r) = 0.38, $p < 0.05$.

The correlation matrix is visually represented in **Figure 7**. It clearly shows the correlation values between the variables. A heatmap or color matrix is also used to visually represent the correlation levels.

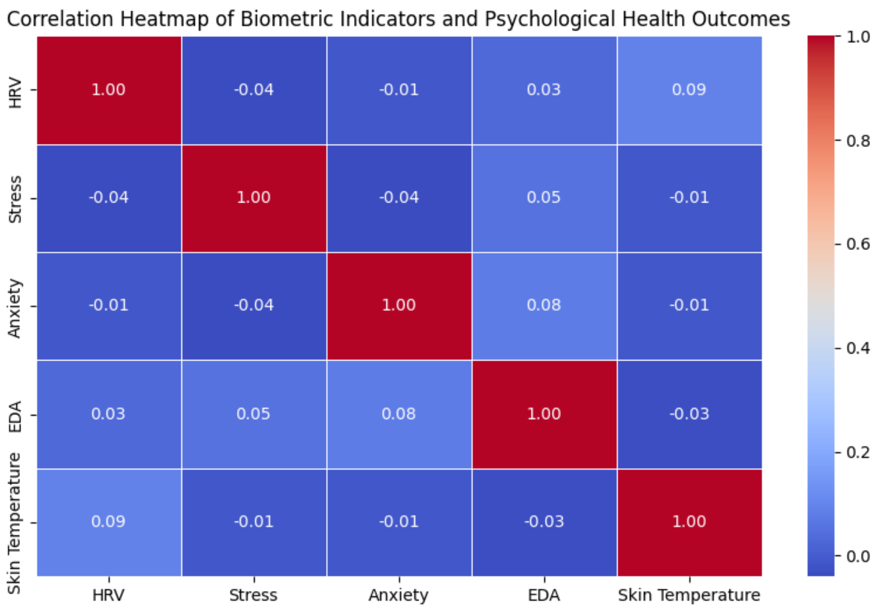

Figure 7. Correlation heatmap of biometric indicators and psychological health outcomes.

Skin Temperature Fluctuations: It is interesting to explore some connection between skin temperature changes and emotional response to stimuli. Cools relate to stress or anxiety while warm relate to relaxation or sexual arousal among other things. This opens great potential for skin temperature changes to reflect different emotions which is highly useful in educational contexts as guidance about students' ability to regulate their emotions over time is crucial to their success and well-being. For instance, subjects showing conspicuous daily oscillations may be candidates for practices intended for modulation of affective volatility by ways of, for instance, mindfulness or biofeedback techniques.

5.2. Implications for student management

Real-Time Monitoring: Biometric monitoring is unintermittent; this means that stress and anxiety levels are detected as early as possible [29]. This way, student support services can identify incidents, immediately deliver helpful information or assist in counselling if necessary.

Personalized Interventions: Mental health in learners can be categorized based on biometric data to ensure appropriate targeted health interventions for each learner. For instance, learners experiencing early markers of stress may need to be enrolled in mindful practice sessions or stress coping mechanisms programs.

Informed Decision-Making: There is always an opportunity for university policy makers and administrators to gain general knowledge on the trends of student positive and negative health with the use of data.

5.3. Qualitative insights from interviews

Academic Pressure: From the questionnaires, it was revealed that most of the students felt that high academic pressure was a major cause of pressure. Some of them specifically requested for the need for adequate support that they can turn to so as to deal with the overwhelming amount of work.

Social Dynamics: Students' peer relations also stood as a major concern as some of the students noted that social relationship(ship) orgainsation helped in reducing depressive symptomatology.

Awareness of Biometric Monitoring: most subjects agreed to the usefulness of biometric feedback to enhance their understanding of mental health more specifically it was mentioned that it would make one get proactive to stress.

6. Conclusion and recommendations

6.1. Conclusion

It aimed at investigating the complex interaction between the measurements obtained by means of wearable sensors and self-identified psychological well-being of students and thus discuss the potential of biometric markers as enriching predictors of mental status among the referred population [30]. The outcomes identified that level of metabolism including heart rate variability (HRV) and electrodermal activity (EDA) have measurable relationship with stress and anxiety level of students. Particularly, the data revealed that lower HRV coincided with higher stress, thus suggesting that student with a poor cardiac variability may be under more psychological pressure. On the other hand, higher rates of EDA were discovered to be correlated with levels of anxiety, which indicates that psychological reactions to stressors are mirrored in students' emotions.

The research paradigm was quantitative and survey in nature and the biometric data was gathered through sensors from students in various fields. This approach enabled the collection of continuous physiological data which were correlated with the self-reported pathological indexes of psychological well-being. The sampling technique used was purposive to cover a diverse group of students so as to generalize the finding to other students. Descriptive statistics, probability correlation coefficients, coefficients of determination, and multiple regression models yielded accurate and effective predictions of biometric measures and related psychological variables.

The repercussion of these study findings is paradigm shifting calling for implementation of biometric scrutinization in the student health and positive deserved well-being planned programs of educational institutions. Through biometric data therefore, universities can create ways of protecting learners who are at risk of developing certain mental health issues or who require certain protective measures based on information gathered from their biometric data. Furthermore, the findings of this study support the use of a biosocial model for understanding and managing students in which physiological parameters are effective additional to conventional psychological markers.

Besides, this work enriches the knowledge about the impact of biometric data and their absence on mental health and open new avenues for further research in this field. Altruistic perspective requires further investigation into the link between physiological mechanisms and psychological well-being in order to improve comprehensiveness of student support services as a positive academic organizational culture [31]. As mental health is slowly becoming a vital factor in education systems all over the world, the integration of biometric data into the system offers a way forward for enhancing on student's achievements and wellbeing.

6.2. Recommendations

Integration of Biometric Sensors into Student Management Systems: Universities should therefore think about installing wearable biometric sensors in their health facilities to track the psychological health of students for prolonged durations while they are learning. This could help in giving feedback in real-time to see the students that could be in distress, the early intervention could be made.

Development of Support Programs: Develop mental health services that act based on the biometrics obtained from the client and offer treatment that meets the aspects of the body's physiological reaction [32]. For instance, students who have had high stress indicators throughout their time in school can be taken through counseling or stress reducing exercises.

Further Research: Further investigations should be done to replicate these results among other populations of students and in other learning environments. In turn, longitudinal research could be useful for getting more understanding about the efficacy of the biometric control in the context of the patient's mental health.

6.3. Limitations of the study

Sample Size and Generalizability: A major deficiency of the study is that it used purposive sampling method only. While this would ensure that students of diverse group would be targeted, it may lower the validity of the studies among all students. The 'control' variables, such as age, gender, race, and time since testing – to list but a few – would be defined by the individual survey responses of a more representative sample of Roosevelt students, and thus this research could analyze the correlation between the specific biometric indicators and particular psychological health outcomes for different student subpopulations.

Cross-Sectional Nature: In the study conducted, cross-sectional survey was applied which implies that data was collected at one time only. Such an approach can be useful to identify the relationships between two pieces of data though doesn't help in identifying the cause-and-effect results. Further research about what happens to biometrics over time, in relation to students' mental health, as well as systematic experiments grounded on such findings to identify whether their early intervention helps to stave off later years of subjects' psychological deterioration is one of the method's deficiencies.

Biometric Data Accuracy and Calibration: Despite the constant advancements in and wide application of wearable sensors, the data collected fails to be one hundred percent accurate because of various factors such as the calibration of the sensors, environmental conditions, and variability among persons. In the case in question, if the sensors were not calibrated or positioned correctly, then it is possible to have some mistiming of the data which is meaningful for the study. Also, the quality of the data can be low due to the inter individual variability which could originate facts like body type, activity and health state influencing biometrics.

Subjectivity in Psychological Health Measures: While biometric data gives physiological facts, the study employed self-assessed wellbeing indices including pressure and anxiety. Self-report may have method biases such as desirability bias and variations within the level of literacy or understanding of the mental health issue by participants. This could lead to differences between the physiological signals recorded and the participant self-assessment, which could restrain the generality of conclusions made.

External Factors Influencing Data: There was no interference with extrinsic influences that could affect the changes in biometrics and the overall psychological well-being of persons. For instance, students' sleep, caffeine or physical activity are known to impact the HRV, EDA, or skin thermal conductivity respectively. These variables could with the censoring of incidents cause distorting noise in to the data, which makes it hard to detect the first order consequences of academic pressure and social processes on psychological fitness.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

References

1. Y. Amanvermez et al., "Feasibility and acceptability of a guided internet-based stress management intervention for university students with high levels of stress: Protocol for an open trial," Internet Interventions, vol. 24, 2021, doi: 10.1016/j.invent.2021.100369.
2. J. Galante, J. Stochl, G. Dufour, M. Vainre, A. P. Wagner, and P. B. Jones, "Effectiveness of providing university students with a mindfulness-based intervention to increase resilience to stress: 1-year follow-up of a pragmatic randomised controlled trial," Journal of Epidemiology and Community Health, vol. 75, no. 2, 2021, doi: 10.1136/jech-2020-214390.
3. R. A. M. Darkhawaja et al., "Exploring the role of social capital, self-efficacy and social contagion in shaping lifestyle and mental health among students representing the future healthcare workforce in Palestine: Social cohort study protocol," BMJ Open, vol. 12, no. 1, 2022, doi: 10.1136/bmjopen-2021-049033.
4. F. Khademian, A. Aslani, R. Ravangard, P. Bastani, M. Nami, and P. Jafari, "Efficacy of a web application for stress management among Iranian college students during COVID-19 outbreak: a study protocol for randomized controlled trials," Trials, vol. 21, no. 1, 2020, doi: 10.1186/s13063-020-04949-0.
5. N. Imran, A. Rahman, N. Chaudhry, and A. Asif, "Effectiveness of a school-based mental health intervention for school teachers in urban Pakistan: a randomized controlled trial," Child and Adolescent Psychiatry and Mental Health, vol. 16, no. 1, 2022, doi: 10.1186/s13034-022-00470-1.
6. C. C. G. da Silva, C. V. Bolognani, F. F. Amorim, and A. M. Imoto, "Effectiveness of training programs based on mindfulness in reducing psychological distress and promoting well-being in medical students: a systematic review and meta-analysis," Systematic Reviews, vol. 12, no. 1, 2023, doi: 10.1186/s13643-023-02244-y.
7. K. Ligus, E. Fritzson, E. A. Hennessy, R. L. Acabchuk, and K. Bellizzi, "Disruptions in the management and care of university students with preexisting mental health conditions during the COVID-19 pandemic," Translational Behavioral Medicine, vol. 11, no. 3, 2021, doi: 10.1093/tbm/ibab020.
8. M. Flaucher et al., "Evaluating the Effectiveness of Mobile Health in Breast Cancer Care: A Systematic Review," Oncologist, vol. 28, no. 10. 2023. doi: 10.1093/oncolo/oyad217.
9. J. Y. Choi et al., "Health-Related Indicators Measured Using Earable Devices: Systematic Review," JMIR mHealth and uHealth, vol. 10, no. 11. 2022. doi: 10.2196/36696.
10. G. L. Bate et al., "The Role of Wearable Sensors to Monitor Physical Activity and Sleep Patterns in Older Adult Inpatients: A Structured Review," Sensors, vol. 23, no. 10. 2023. doi: 10.3390/s23104881.

11. S. Buchman et al., “Different combinations of mobility metrics derived from a wearable sensor are associated with distinct health outcomes in older adults,” Journals of Gerontology - Series A Biological Sciences and Medical Sciences, vol. 75, no. 6, 2020, doi: 10.1093/GERONA/GLZ160.
12. H. Gerlach, S. R. Chaudoir, and P. M. Zebrowski, “Relationships between stigma-identity constructs and psychological health outcomes among adults who stutter,” Journal of Fluency Disorders, vol. 70, 2021, doi: 10.1016/j.jfludis.2021.105842.
13. M. Hybholt, “Psychological and social health outcomes of physical activity around menopause: A scoping review of research,” Maturitas, vol. 164. 2022. doi: 10.1016/j.maturitas.2022.07.014.
14. M. Buultjens, A. Farouque, L. Karimi, L. Whitby, J. Milgrom, and B. Erbas, “The contribution of group prenatal care to maternal psychological health outcomes: A systematic review,” Women and Birth, vol. 34, no. 6. 2021. doi: 10.1016/j.wombi.2020.12.004.
15. P. M. Bamonti, S. A. Robinson, E. S. Wan, and M. L. Moy, “Improving Physiological, Physical, and Psychological Health Outcomes: A Narrative Review in US Veterans with COPD,” International Journal of COPD, vol. 17. 2022. doi: 10.2147/COPD.S339323.
16. L. yin Liang and H. bo Che, “Fear of COVID-19 and Adverse Psychological Health Outcomes Among Chinese Elderly: a Serial Mediation Model of Social Participation and Loneliness,” Applied Research in Quality of Life, vol. 18, no. 5, 2023, doi: 10.1007/s11482-023-10182-z.
17. N. Mostafa and S. D. Smith, “Improving Psychological Health Outcomes in Children with Atopic Dermatitis,” Clinical, Cosmetic and Investigational Dermatology, vol. 16. 2023. doi: 10.2147/CCID.S393254.
18. Adedeji, T. Y. Akintunde, F. Metzner, and E. Idemudia, “Psychological health outcome of Sub-Saharan African migrants in Germany,” Electronic Journal of General Medicine, vol. 20, no. 1, 2023, doi: 10.29333/ejgm/12602.
19. D. M. Hilty, C. M. Armstrong, D. D. Luxton, M. T. Gentry, and E. A. Krupinski, “A Scoping Review of Sensors, Wearables, and Remote Monitoring For Behavioral Health: Uses, Outcomes, Clinical Competencies, and Research Directions,” Journal of Technology in Behavioral Science, vol. 6, no. 2. 2021. doi: 10.1007/s41347-021-00199-2.
20. H. Saner et al., “Potential of Ambient Sensor Systems for Early Detection of Health Problems in Older Adults,” Frontiers in Cardiovascular Medicine, vol. 7, 2020, doi: 10.3389/fcvm.2020.00110.
21. S. Munasinghe et al., “The Impact of Physical Distancing Policies During the COVID-19 Pandemic on Health and Well-Being Among Australian Adolescents,” Journal of Adolescent Health, vol. 67, no. 5, 2020, doi: 10.1016/j.jadohealth.2020.08.008.
22. Poudyal et al., “Wearable digital sensors to identify risks of postpartum depression and personalize psychological treatment for adolescent mothers: Protocol for a mixed methods exploratory study in rural Nepal,” JMIR Research Protocols, vol. 8, no. 9, 2019, doi: 10.2196/14734.
23. K. A. Kercher et al., “Association Between Head Impact Exposure, Psychological Needs, and Indicators of Mental Health Among U.S. High School Tackle Football Players,” Journal of Adolescent Health, vol. 72, no. 4, 2023, doi: 10.1016/j.jadohealth.2022.11.247.
24. M. Alneyadi, N. Drissi, M. Almeqbaali, and S. Ouhbi, “Biofeedback-based connected mental health interventions for anxiety: Systematic literature review,” JMIR mHealth and uHealth, vol. 9, no. 4. 2021. doi: 10.2196/26038.
25. G. Liyanaarachchi, G. Viglia, and F. Kurtaliqi, “Privacy in hospitality: managing biometric and biographic data with immersive technology,” International Journal of Contemporary Hospitality Management, 2023, doi: 10.1108/IJCHM-06-2023-0861.
26. K. L. Jacobsen, “Biometric data flows and unintended consequences of counterterrorism,” International Review of the Red Cross, vol. 103, no. 916–917, 2021, doi: 10.1017/S1816383121000928.
27. M. Griniuk, “Performance Art Using Biometric Data,” Art History and Criticism, vol. 17, no. 1, 2021, doi: 10.2478/mik-2021-0009.
28. Ross, S. Banerjee, and A. Chowdhury, “Deducing health cues from biometric data,” Computer Vision and Image Understanding, vol. 221, 2022, doi: 10.1016/j.cviu.2022.103438.
29. F. Rosique, P. J. Navarro, L. Miller, and E. Salas, “Autonomous Vehicle Dataset with Real Multi-Driver Scenes and Biometric Data,” Sensors, vol. 23, no. 4, 2023, doi: 10.3390/s23042009.
30. S. G. L. Persiani, B. Kobas, S. C. Koth, and T. Auer, “Biometric data as real-time measure of physiological reactions to environmental stimuli in the built environment,” Energies, vol. 14, no. 1, 2021, doi: 10.3390/en14010232.

31. Ross, S. Banerjee, and A. Chowdhury, “Security in smart cities: A brief review of digital forensic schemes for biometric data,” Pattern Recognition Letters, vol. 138, 2020, doi: 10.1016/j.patrec.2020.07.009.
32. S. F. Jacoby, A. J. Robinson, J. L. Webster, C. N. Morrison, and T. S. Richmond, “The feasibility and acceptability of mobile health monitoring for real-time assessment of traumatic injury outcomes,” mHealth, vol. 7, 2021, doi: 10.21037/mhealth-19-200.