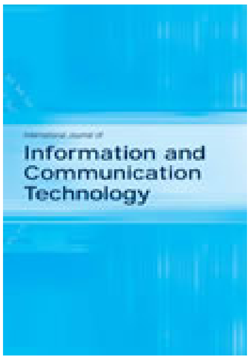

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An affective-behavioural fusion framework for proactive student mental health monitoring

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Abstract: With the increasing prominence of psychological health problems of students in colleges and universities, efficient and accurate identification of psychological states has become an urgent issue. To address this issue, this paper proposes a psychological monitoring system for college students based on affective computing and behavioural trajectory analysis (AffectPath-PM). The system firstly extracts students' multimodal characteristics by using the affective computing module, secondly obtains the characteristics of different patterns through the analysis of behavioural trajectories, and finally real-time monitoring and intervention is achieved by combining comprehensive assessment and early warning feedback. Experimental results indicate that the overall performance of this system demonstrates an average improvement of approximately 4.5% compared to the reference method. Small-scale validation experiments also demonstrate its applicability and scalability. This system offers universities a comprehensive and efficient mental health monitoring solution, possessing significant practical value.

Keywords: affective computing; behavioural trajectory analysis; psychological health monitoring; multimodal data.

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1 Introduction

In recent years, the psychological pressure on university students has increased dramatically due to rapid social and economic development and the ongoing strengthening of the competitive environment (Ahmed et al., 2023). Academic strain, employment pressure, interpersonal disputes, and difficulties in adaptation are interconnected, resulting in a significant prevalence of psychological health issues among college populations. The report on the growth of psychological health education in China's colleges and universities says that 20 to 30 percent of college students go through some kind of psychological distress while they are in school (Ali et al., 2025). Depression, anxiety, loneliness, and adjustment disorders are the most common. The same kinds of patterns have been seen all around the world. Research conducted in the USA, the UK, and Australia has indicated a persistent increase in the prevalence of psychological health issues among college students over the previous decade, characterised by youth, invisibility, and complexity. Psychological issues, if not addressed promptly and effectively, can lead to a decline in academic performance, increased dropout rates, social isolation, and even extreme behaviours, resulting in irreversible consequences for personal development, family dynamics, and societal well-being. Consequently, the timely and effective detection and intervention of psychological problems is a critical objective of psychological health education in higher education institutions.

Currently, psychological health monitoring in colleges and universities predominantly depends on conventional methods, including psychological assessment questionnaires, routine interviews, and self-reporting. While these approaches are significant for psychological health education, they also exhibit clear limits. Assessments and interviews are typically performed in phases, hindering real-time monitoring of psychological health and complicating the prompt detection of mild emotional fluctuations. Due to students' personal will and psychological defence systems, some psychological anguish may be hidden on purpose or by accident throughout the assessment, which might lead to inaccurate results (Bin et al., 2025). The psychological health centre needs a lot of people and time to do manual interviews and data analysis, which makes it hard to keep track of people's psychological health across the university on a regular basis. The traditional approach also does not work well with multi-dimensional data, which makes it hard to fully show how students' psychological states change over time. This makes it hard to notice changes and take action in practice.

As information technology keeps getting better, schools and universities have gathered a lot of digital data about students' lives and learning (Das and Singh, 2023). This makes it possible to create a psychological monitoring system that is more objective, continuous, and less intrusive. The advancement of affective computing technologies has enabled the deduction of individual emotional states from multimodal data, including voice tone, facial expression, body position, and textual semantics (Guo et al., 2022). This device can detect changes in mood without being invasive, making it useful for long-term use in everyday life and learning. It also has a lot of potential uses in areas including education, healthcare, and public safety. Behavioural trajectory analysis technology has also been very popular in the last few years (Bisogni et al., 2022). It can show students' behavioural traits, like where they spend their time, how often they socialise, and how they work and rest, by using data like Wi-Fi positioning, Bluetooth beacons, campus card swipe records, library borrowing, and classroom attendance. There is a strong link between these behavioural patterns and their psychological states (Gupta et al., 2021). For instance, smaller activity zones, less time spent with friends, and changes in work schedules are all signals that psychological health is getting worse

(Di Credico et al., 2024). The growth of these technologies gives psychologists new ways to keep an eye on people and new tools to do so.

There are pros and cons to using only one method for affective computing or behavioural analysis. Affective computing is very good at recognising short-term emotions, but things like background noise, camera angles, and lighting can easily get in the way. Behavioural trajectory analysis can show long-term habits and changes in mood, but it takes a while to pick up on changes in mood right away (Dong et al., 2023). Combining the two can give a more complete picture of psychological states across time: affective computing gives quick input on short-term mood changes, while behavioural trajectory analysis shows changes in long-term behavioural patterns. Multimodal fusion analysis can significantly enhance the precision and reliability of psychological monitoring, mitigate errors stemming from a singular data source, and offer technical assistance for the development of a comprehensive psychological health management system at universities (Elijah and Oladayo, 2024).

Based on the above background, this study aims to design AffectPath-PM, a psychological monitoring system for university students based on affective computing and behavioural trajectory analysis (Ezerceli and Dehkharghani, 2024). The conduct of this study has important scientific and practical significance. At the level of scientific research, this study introduces a multimodal fusion method of affective computing and behavioural trajectory analysis in the field of psychological health monitoring, which can theoretically explore the interactive relationship between emotions and behaviours, and provide a reference for the methodological innovation of artificial intelligence (AI) technology in the application of psychology (Farahsari et al., 2022). At the level of social and educational management, by identifying psychological risk groups in advance, it can effectively reduce the incidence of psychological crisis events and promote the healthy growth of students; at the same time, it can provide educational decision-makers with the basis for data-based interventions, and promote the transformation of the mental health management mode of colleges and universities to be proactive, precise and intelligent. At the level of engineering practice, the design and implementation of the system can provide a set of landable and sustainably operated technical solutions for psychological health management in universities, reduce the reliance on manual interviews and single assessments, and improve the coverage and efficiency of psychological health services (Hayes and Hofmann, 2021).

In conclusion, the psychological monitoring system for university students, founded on affective computing and behavioural trajectory analysis, addresses the shortcomings of traditional psychological health monitoring methods in terms of timeliness, objectivity, and comprehensiveness, while also establishing a robust data foundation for scientific and precise psychological intervention. Its implementation is crucial for improving psychological health services in colleges and universities, averting psychological crises, and refining educational management practices; it also offers a pragmatic solution for the advanced integration of AI technology in psychological health.

2 Related technologies

2.1 Affective computing

Affective computing is a significant study domain at the intersection of AI with psychology, cognitive science, neuroscience, and other multidisciplinary fields, seeking to enable computers to recognise, comprehend, express, and respond to human emotions. Picard originally came up with the idea in 1995, and the goal was to make it easier for people to engage with computers in a way that was more like how people communicate with each other (Birimoglu and Begen, 2021). Traditional computing systems are more focused on logic and data processing. With affective computing, machines can now take into account how people are feeling when they process information (Jabeen et al., 2023). This leads to big improvements in personalised services, decision support, and overall experience of interacting with technology. Affective computing has progressed from initial rule-based reasoning techniques to a multimodal intelligence processing phase, centred on machine learning (ML) and deep learning (DL) (Kong et al., 2024). It has made significant advancements in speech recognition, computer vision, and physiological signal analysis.

Four stages of emotion perception, modelling, recognition, and interaction make up the main research areas of affective computing. Emotion perception primarily entails the collection of emotion-related signals via diverse sensors and data sources, such as facial expression photos, vocal intonations, heart rate fluctuations, electrical skin reactions, gestural motions, and others. In their raw form, these signals frequently have a lot of noise and additional information, therefore they need to be processed to get rid of these things. Fourier transform (FT)-based analysis, Mel frequency cepstral coefficient (MFCC) analysis, local binary pattern (LBP) features, and convolutional neural network (CNN) automatic feature learning are all common ways to do this. After feature extraction is finished, emotion modelling is the process of putting these features into the emotion space (Kumar et al., 2025). Discrete classification models, like Ekman's six categories of emotions (happy, sad, angry, fearful, surprised, and disgusted), and continuous-space models, like the two-dimensional valence-arousal model, are two examples of common emotion representation models. In the valence-arousal model, valence stands for the pleasantness of the emotion and arousal stands for the activation of the emotion. In continuous space emotion modelling, the characteristics of various modalities can be correlated with emotion variables by the subsequent formula:

$$E = f\left(\sum_{i=1}^{n} w_i \cdot x_i\right) \tag{1}$$

where x_i is the i^{th} feature variable, w_i is its weight in predicting emotions, and $f(.)$ is a nonlinear mapping function, like softmax or sigmoid. The formula gives a single computing framework for multimodal affective computing fusion, and the accuracy of recognising emotions can be increased by optimising the weight allocation.

In the emotion recognition stage, the system must assess the user's present emotional state utilising characteristics and modelling outcomes. Support vector machine (SVM) and hidden Markov model (HMM) are two examples of classifiers that are commonly used in traditional methods. Recently, however, DL architectures like recurrent neural network (RNN), long and short-term memory network (LSTM), and transformers have done very well at time-series sentiment analysis, which is the study of how emotions change over time (Latif et al., 2023). Moreover, the measurement of sentiment intensity is a significant concern in emotional computing, which fundamentally involves executing a weighted summation according to the varying degrees of contribution of distinct elements to sentiment labels, for instance:

$$S = \frac{\sum_{i=1}^{n} \alpha_i \cdot m_i}{\sum_{i=1}^{n} \alpha_i} \tag{2}$$

where S is the intensity of the emotion, mi is the score for the i^{th} modality, and α_i is the weight coefficient for the modality. By assigning appropriate weights, the significance of various modalities in emotion identification can be equilibrated, hence enhancing the system's capacity to detect intricate emotional states.

The methodologies in emotional computing encompass multimodal perception and fusion, feature engineering and automatic feature learning, emotion modelling and classification, as well as the design of emotion interaction strategies. At the perception level, the advancement of multimodal fusion technology enables the system to concurrently leverage various information sources, including visual, auditory, and physiological data, to mitigate errors arising from reliance on a singular signal. The use of technologies like CNN, graph neural network (GNN), and temporal modelling networks at the feature engineering level greatly increases the accuracy and generalisation of emotion recognition (Ma et al., 2024). Affective computing systems must not only identify emotions but also provide natural, emotionally coherent responses, such as modulating voice synthesis, altering a virtual character's facial expression, or demonstrating empathy in conversation.

In addition to the aforementioned methods, self-supervised learning has emerged as a promising AI technique in affective computing. By leveraging unlabeled data for pre-training, self-supervised models can learn robust emotional representations without extensive manual annotations, thereby enhancing the system's adaptability to diverse emotional expressions and reducing reliance on labelled datasets. This approach is particularly beneficial in real-world scenarios where labelled emotional data is scarce or costly to obtain.

Affective computing has previously been used in a lot of different areas. In education, intelligent teaching systems can figure out how students are feeling in real time and change the way they teach; in healthcare, mental health monitoring and rehabilitation training platforms help with diagnosis and treatment by looking at how patients' emotions change; in entertainment and gaming, emotion-driven plot generation and interactive experiences make things more immersive; and in customer service and human-computer interaction, emotion recognition systems help customer service workers or robots improve communication and make customers happier. Emotion recognition systems can assist customer care workers or robots enhance communication methods and make users happier in the fields of customer service and human-computer interaction. These applications demonstrate that emotional computing is not just a prominent area of academic inquiry but also a significant avenue for the advancement of AI.

In the future, the development trend of affective computing focuses on several aspects: first, the combination with large-scale pre-training models (LLM) (Mira et al., 2024), which makes the emotion recognition and expression ability more natural and diversified; second, the introduction of explainable artificial intelligence (XAI) to solve the problem of transparency and traceability of emotion recognition results; third, the improvement of privacy protection and ethical norms, to ensure that the collection, storage and use are legally compliant; and fourth, research on cross-cultural emotion computing to improve the adaptability and accuracy of emotion recognition systems in different cultural contexts. As these areas continue to grow, emotional computing is likely to become a more important part of the future era of human-machine symbiosis.

2.2 Behavioural trajectory analysis

Behavioural trajectory analysis is a significant study avenue within data science and AI, primarily concentrating on uncovering individual behavioural patterns, preferences, and possible trends through the collection and processing of their spatial-temporal activity data. The swift advancement of smart sensors, mobile devices, and IoT technologies enables the real-time and continuous recording and analysis of the vast data produced by human behaviours (Mobini Seraji et al., 2025). This facilitates data support and decision-making for personalised services, urban management, public safety, health monitoring, and numerous other domains. Behavioural trajectory data typically encompasses an individual's location coordinates, mobility paths, duration of residence, interaction events, and other relevant metrics. Mining this data reveals behavioural patterns and trends at both macro and local levels.

The main purpose of behavioural trajectory analysis is to model and understand data that shows how things change across time and space. The trajectory points of a person on a time series often include geographic coordinates and time stamps. In trajectory analysis, some of the most important things to do are to pre-process trajectories (for example, by denoising and complementation), mine trajectory patterns (for example, by finding frequently visited places and path similarity), find behavioural anomalies, and predict trajectories. In practice, the high-dimensional spatial-temporal properties and huge scale of trajectory data make it hard to analyse (Seth and Feng, 2021). This has led academics to come up with a number of statistical, ML, and DL-based algorithms to make the process faster and more accurate. Interpolation is frequently employed during the pre-processing phase to enhance data quality by filling in missing trajectory points, eliminating aberrant data, and synchronising trajectory data temporally to guarantee the precision of subsequent analysis.

The measure of trajectory similarity is one of the fundamental problems in behavioural trajectory analysis. Commonly used methods compute the minimum cumulative distance between two trajectory sequences by nonlinearly aligning them. Such methods can effectively measure the similarity of trajectory shape and time dimensions, and are widely used in trajectory clustering, classification and anomaly detection. In addition, some improved distance-based algorithms, such as edit distance and density-based metrics, have been introduced to suit the needs of trajectory comparison in different scenarios (Straczkiewicz et al., 2021). With accurate similarity metrics, the system can better identify behavioural patterns and anomalous behaviours, improving the relevance and usefulness of the analysis.

In terms of behavioural pattern mining, clustering analysis and sequence pattern mining are the two main techniques. Trajectory clustering aims to group trajectories with similar spatial and temporal distributions to discover common activity areas or paths, while sequence pattern mining focuses on the temporal order of behavioural events, revealing regular behaviours of individuals or groups through frequent pattern mining. In recent years, DL-based trajectory representation learning methods have emerged, using models such as RNN and GNN to automatically extract spatial-temporal features of trajectories, which significantly improves the ability of behavioural understanding. For example, trajectory data is mapped to potential space for encoding, and then the trajectory is reconstructed by decoding to achieve trajectory anomaly detection and future behaviour prediction (Barneveld et al., 2022). Meanwhile, the researchers also explore the use of self-supervised learning methods to pre-train trajectory models on unlabeled data to reduce the dependence on a large amount of labelled data and improve the generalisation ability and adaptability of the models.

Furthermore, GNNs have been increasingly applied to model complex spatial-temporal dependencies in behavioural trajectories. By representing locations and their interactions as graph structures, GNNs can capture the relational patterns between different activity nodes, such as transitions between dormitories, libraries, and cafeterias. This enables more accurate prediction of students' future behaviours and early detection of anomalous activity patterns, thereby enhancing the predictive capability of the behavioural trajectory analysis module.

In conclusion, behavioural trajectory analysis uncovers behavioural patterns and probable laws by thoroughly examining individual spatial-temporal activity data, offering significant assistance for intelligent applications across several domains. As data collecting technology and computational models keep getting better, behavioural trajectory analysis will become increasingly important for understanding how people act, making better use of resources, and improving smart services. The study focuses on integrating multi-source data while prioritising privacy protection indicates that this field will be essential in the future development of an intelligent society.

2.3 Psychological monitoring of students in higher education

As competition in society gets tougher and colleges and universities keep improving their education systems, the psychological health of students has become a major concern for academics, education administrators, and people from all walks of life. University students are at a very important time in their lives when their minds and behaviours are changing quickly. This is also a time when psychological health problems are very common. Students' psychological health is greatly affected by a number of pressures, including their academic workload, relationships with others, plans for the future, and how they see themselves. Timely and effective psychological monitoring not only facilitates the early identification and intervention of students' psychological issues but also supplies data to assist universities in developing scientifically informed psychological health management policies, thereby safeguarding students' physical and mental well-being as well as campus safety.

Early research on psychological monitoring at higher education institutions predominantly utilised psychological assessment instruments and manual interviews, encompassing structured and semi-structured questionnaires, psychological scale evaluations, and case interviews with psychological counsellors. The Minnesota Multiple Personality Inventory (MMPI), Beck Depression Inventory (BDI), and Self-Assessment Scale for Anxiety (SAS) are some of the most used psychological tests used to screen college students (Vaziri et al., 2024). These measures evaluate students' psychological states using quantitative methods, demonstrating a level of scientific validity and operational simplicity, therefore establishing themselves as fundamental instruments within the psychological community. But these methods are clearly not perfect. First, they depend on students' subjective reports, which can be biased because of their psychological defence mechanisms and social expectations. Second, the assessments are usually done on a regular basis, which makes it hard to see how students' psychological health changes over time. Third, interviews and assessments rely heavily on professionals, which makes it hard to do large-scale, all-weather monitoring.

As information technology advances, data-driven psychological monitoring techniques are progressively evolving. Colleges and universities have started to utilise various forms of behavioural data produced by campus management systems, including student attendance, grades, book borrowing, and campus card expenditures, as indirect indications of psychological health. By looking at students' daily behavioural routes, time distributions, and activity patterns, behavioural trajectory analysis finds the link between behavioural problems and psychological health risks. This information is then used to create a data-driven psychological risk prediction model. This method transcends the subjective constraints of conventional self-report assessments, facilitating a more objective, real-time evaluation of psychological status. At the same time, multimodal data fusion has been used in the field of psychological monitoring (Yoo and Kim, 2022). Multimodal data encompasses text (such as students' forum speeches and open-ended questionnaire responses), audio (telephone consultation recordings), video (facial expression monitoring), physiological signals (heart rate, galvanic skin response), and behavioural logs, among others. By integrating various data types, it provides a comprehensive representation of students' psychological status. This combination not only adds to the field of psychological monitoring and makes it more accurate, but it also gives technological support for the dynamic perception of psychological health and emotional state.

Affective computing, a key area of AI, has made a big difference in how we can keep an eye on the psychological health of college students. The system can automatically figure out students' facial expressions, speech tones, and emotional information in the text using computer vision and natural language processing. It can even recognise emotional states without the user noticing. Micro-expression detection in facial expression analysis can show possible changes in emotions, voice emotion recognition looks at the strength and type of emotions the speaker is feeling, and text emotion analysis looks at the emotional patterns in students' social media, forums, and online assignments. The combination of these technologies makes psychological monitoring far more accurate and responsive in real time. Also, because smartphones and wearable gadgets are so ubiquitous, monitoring someone's mental state based on their bodily signals is slowly becoming a reality. Physiological indicators, including heart rate variability (HRV), sleep quality, and activity level, are intricately linked to psychological health (Zhou et al., 2024). By systematically collecting and analysing these indicators over an extended duration, it is possible to detect early signs of alterations in psychological status, thereby establishing a scientific foundation for the proactive identification of psychological risks.

Using ML and DL algorithms has made it much easier to identify psychological risks. Many people have utilised traditional ML algorithms like SVM, decision tree (DT), and random forest (RT) to classify psychological health. DL techniques, particularly RNN, LSTM, and attention mechanism models, are adept at analysing time-series behavioural and emotional data, effectively capturing intricate nonlinear correlations and temporal dynamics. Multimodal models provide for a thorough evaluation of students' psychological health by concurrently integrating facial expressions, speech, text, and behavioural data. These models not only make predictions more accurate, but they also let counsellors do in-depth studies of the origins of risk and the most important emotional elements. In the last few years, new technologies like self-supervised learning and reinforcement learning have been added to the model to make it even better at understanding and adapting to changes in psychological states that are hard to grasp.

Some universities have created comprehensive psychological health monitoring platforms that include four parts: data collecting, psychological assessment, danger alert, and intervention assistance. The software uses AI algorithms and data fusion from several sources to keep an eye on kids' psychological health and manage risk categorisation. Once the monitoring system finds those who are at high risk, it can automatically send out early warning messages and suggest personalised intervention strategies to help psychological counsellors do targeted counselling. Online psychological counselling services are also linked with psychological health education to make a complete system of psychological health assistance. Students' psychological health awareness and ability to control their own behaviour improve through psychological health education classes, the spread of psychological knowledge, and self-help assessments. This lowers the number of psychological issues.

Even if technology is always becoming better, keeping an eye on the psychological health of college students is still quite hard. First, protecting people's privacy and dealing with ethical issues are becoming more and more important. Psychological data contains very private information about people. The key to system design and promotion is to preserve students' right to know and keep their data safe while still using it. Second, data gathering is sometimes interrupted, partial, or affected by noise, which makes the monitoring system less accurate and reliable. Third, the model's ability to generalise is restricted, and the algorithms that are already in use do not adapt well to varied cultural backgrounds, genders, and individual variances. This makes it hard to make sure that the model works for everyone. Fourth, the technologies for standardising, synchronising, and combining multimodal data are still in their early stages, which makes it harder to combine information from different sources. Fifth, multidisciplinary collaboration is still not enough, and the deep integration of psychological theories and computer technologies is still not enough. This limits the system's ability to innovate and use it in new ways.

In the future, the advancement of psychological monitoring for university students will exhibit the following trends: Using wearable devices, environmental sensors, and mobile terminals together to collect data in all weather, in many different places, and without any sensory input. This data covers many different aspects of psychological health and makes sure that the data is both accurate and complete. Use cutting-edge technology like federated learning and differential privacy to make it safe to share and work together on data across different platforms and organisations while still safeguarding people's privacy. To make the model more generalisable and clearer, combine self-supervised learning, multi-task learning, and interpretable AI technologies. This will help the system adapt to changes in diverse people and circumstances, enhance monitoring accuracy, and build user trust. Adapt the monitoring strategy in real time based on each student's unique traits, the environment, and their mental state. Combine this with psychological intervention techniques to provide personalised and accurate psychological health care. At the same time, it strengthens the close cooperation among multiple disciplines, such as psychology, education, computer science, ethics, etc., promotes the deep integration of theory and technology, and promotes the development of the psychological monitoring system in the direction of scientific, standardised and humanistic care at the same time.

In general, the field of psychological monitoring of college students has changed and improved from traditional manual assessment to multimodal data fusion and intelligent technology driven. In the future, technological advancements and institutional protections will enhance psychological monitoring in colleges and universities, facilitating improved management of students' psychological health, enabling early detection, precise early warning, and tailored intervention, while assisting in fostering a positive and healthy environment that promotes students' physical and mental well-being and comprehensive development.

3 Methodology

AffectPath-PM is a psychological monitoring system for college students that uses affective computing and behavioural trajectory analysis to keep track of students' psychological health in a dynamic, thorough, and accurate way. See Figure 1. The system collects data from many different places and uses it to construct a multi-dimensional psychological profile of pupils by looking closely at their emotional expressions and behavioural patterns. This lets them warn and intervene early if there is a risk. Below is a detailed description of how these four main components were designed and put into use.

3.1 Affective computing module

The affective computing module is the most important aspect of the AffectPath-PM system. It is responsible for capturing and precisely analysing the emotional state of university students in real time. The module is meant to mix visual and textual modal information to accomplish multi-dimensional and multi-angle emotion perception. This is necessary because the campus has a lot of different situations and changes in the environment. The module first uses cameras setup in important parts of the campus to record video of students' facial expressions in real time. It then uses CNN to extract features from the image data. CNN can automatically learn the relationship between changes in facial muscles and different emotional states. It does this by using the activation function $f(.)$ to create a feature map F from the input image data X after the convolution kernel W and bias term b have been applied. The module is also made to use cameras setup in important parts of the campus to see and analyse students' facial expressions in real time:

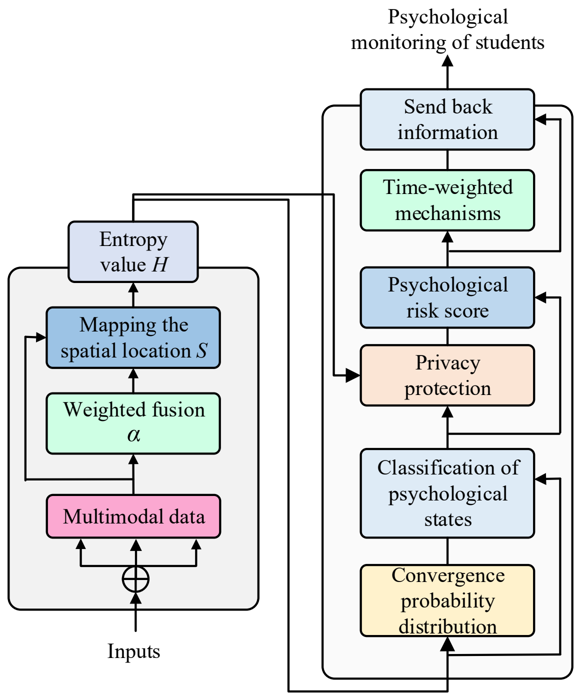
$$F = f(W * X + b) \tag{3}$$

This method accurately pulls out the main emotional aspects of the student's face, which is a good starting point for further classification. After going through multi-layer convolution and pooling, the model slowly concentrates on small changes in facial expressions and micro-expressions to better recognise complex emotions. The softmax function turns the model's final output into the probability distribution of each emotion category. It does this by:

$$P_{face}(c) = \frac{e^{z_c}}{\sum_k e^{z_k}} \tag{4}$$

where z_c is the score corresponding to mood category c. The probability value intuitively reflects the confidence level of the student's current mood.

Figure 1 Framework of psychological monitoring system for university students (see online version for colours)



Meanwhile, the textual sentiment recognition analyses students' online textual data, covering a variety of sources such as social media statements, psychological questionnaires and emails. To get the text sentiment likelihood, the linear layer and softmax classify the text variable $H_{[CLS]}$:

$$P_{text}(c) = \text{softmax}\left(W_{cls} H_{[CLS]} + b_{cls}\right) \tag{5}$$

where W_{cls} and b_{cls} are the parameters that define the categorisation. This method can accurately detect changes in pupils' emotions using written words, which is a useful addition to visual recognition that does not always work well. It works best when emotional expressions are not clear.

To enhance the precision and resilience of the overall emotion assessment, the affective computing module employs a weighted fusion technique to integrate the emotion probability distributions from facial expression and text:

$$P_{final}(c) = \alpha \cdot P_{face}(c) + (1-\alpha) \cdot P_{text}(c) \tag{6}$$

Historical data training automatically changes the weighting coefficient α so that the system can adapt to changing acquisition conditions and data quality to get the optimal fusion effect. The fusion method not only makes emotion recognition more stable, but it also lets the system keep working well even when one of the modes is missing or is interfering with it.

The affective computing module also has a full data pre-treatment and quality control system. Facial photos are de-noised and normalised to lessen the effects of changes in lighting and posture. Text data is pre-processed with word segmentation, de-duplication, and spelling correction to make text analysis more accurate. The module also allows for real-time data updates and the analysis of historical emotion trajectories, giving dynamic and multi-level emotion information for the next full assessment of psychological state and danger warning module.

The module's design not only answers the need for quick and accurate emotion recognition for monitoring the psychological health of college students, but it also makes the system more flexible and able to resist interference by combining different types of data. The AffectPath-PM system can show how students' moods change in real time, find possible psychological problems, give a scientific basis for psychological health intervention, and effectively promote psychological health management and risk prevention and control of university students through the affective computing module.

3.2 Behavioural trajectory analysis module

Behavioural trajectory analysis module is an important part of AffectPath-PM system, aiming at revealing the correlation between the behavioural patterns and psychological state of university students through in-depth excavation of their daily behavioural trajectories, so as to achieve the auxiliary monitoring and early warning of psychological health. The module collects data from multiple sources on campus, including Wi-Fi positioning systems, Bluetooth beacons, campus card swipe records, and mobile phone apps. It then uses this data to create a database of each student's behavioural trajectories, including their location and activity time sequences. Behavioural trajectory data not only shows how pupils walk, but also how they interact with others and how they live their lives. This is a crucial part of the dynamic analysis of psychological state.

In terms of data processing, the behavioural trajectory analysis module first cleans and pre-processes the gathered raw location information to remove noise points and anomalous data to ensure the continuity and correctness of the trajectory. Next, the continuous spatial location points S are linked to different parts of the campus map that serve a specific purpose, including teaching buildings, dormitory spaces, cafeterias, libraries, and so on. This is how the trajectories get their semantic meaning. Mining the spatial-temporal aspects of these data is the basis of this module, specifically, density-based spatial clustering of applications with noise (DBSCAN) is used to identify the students' stopover sites and activity hotspots, and the clustering results are expressed as:

$$C = \left\{ c_j \middle| c_j = \left\{ p_k \in S \middle| dist\left(p_k, \mu_j\right) \leq \grave{o} \right\} \right\} \tag{7}$$

where C is the set of clusters, μ_j is the centre of the j^{th} cluster, ϵ is the spatial distance threshold, and *dist*(.) is the distance function. The method successfully identifies students' high-frequency activity zones and transient stopping locations, facilitating the comprehension of their daily habits and behavioural patterns.

The temporal distribution of behavioural trajectories is significant; the module develops a time series model to examine students' routines and behavioural diversity by quantifying their activity density across various time intervals. The entropy value H is used to figure out how complicated and stable the behaviour patterns are:

$$H = -\sum_{i=1}^{m} p_i \log p_i \tag{8}$$

where p_i is the chance that pupils will show up in the i^{th} activity area or behaviour pattern, and m is the number of areas or behaviour categories that are separated. A high entropy value means that the students' activities are interesting and varied, and that life is going at a normal pace.

The behavioural trajectory analysis module and the affective computing module work together to create a multi-dimensional psychological portrait by combining behavioural patterns and emotional states. By combining geographical behavioural aspects with emotional data, the system can find unusual psychological patterns that are hard to find with just one type of data. This makes for a more complete and scientific mental health assessment.

At the same time, the module design strictly adheres to the principle of data privacy protection, adopting data anonymisation and encryption technologies to safeguard the security of students' personal information. The system accomplishes real-time behavioural monitoring and analysis of extensive student groups while ensuring privacy protection, effectively addressing the essential requirements of psychological health management in higher education institutions.

To sum up, the behavioural trajectory analysis module shows how students' daily behaviour can be linked to their psychological health. It also provides strong data support for psychological health intervention in universities, encourages the psychological monitoring system to move from just identifying emotions to doing a full behavioural analysis, and makes campus psychological health management smarter and more accurate.

3.3 Comprehensive psychological state assessment module

The module is an important part of the AffectPath-PM system. It combines the multidimensional data from the affective computing module and the behavioural trajectory analysis module to create a complete, dynamic, and scientific evaluation of the psychological health of college students. The module's goal is to go beyond the limits of a single source of information and combine visual emotion, textual emotion, and behavioural trajectory features to create a more accurate and timely way to monitor psychological health.

The integrated assessment module first gets the fusion probability distribution $P_{final}(c)$ of facial expression and textual emotion from the affective computing module. This shows how the student is feeling right now. At the same time, it gets multidimensional behavioural features from the behavioural trajectory analysis module, such as behavioural entropy value H, activity clustering result C, and abnormal behavioural indicators. To achieve effective data fusion, the module utilises feature-level fusion technology, which uniformly translates modal features into a high-dimensional feature space and creates comprehensive feature variables.

$$F = \left[P_{final}(c), H, \phi(C), \psi(A) \right] \tag{9}$$

where $\phi(C)$ is the numerical representation of the trajectory clustering features and $\psi(A)$ is the quantitative value of the abnormal behaviour indicator. The composite feature variable holds important information on feelings and actions that can give a full picture of how children are feeling mentally.

The module creates an ML-based psychological state classifier so that it can intelligently analyse the composite features. The classifier learns how to tell if pupils are in danger of having psychological health problems by applying a number of different algorithms. During training, the model parameters are optimised using labelled historical data to improve the accuracy and recall of the classification, which is necessary for the risk warning to work. The classifier's method of making decisions can be written down as:

$$y = f(F; \theta) \tag{10}$$

where y is the label for the mental state category (for example, normal, slightly abnormal, or severely abnormal), f is the classification function, and θ is the model parameter. This gives campus psychological health management strong technical support and a basis for making decisions, and it pushes the development of university psychological services toward intelligence and personalisation.

The module design also takes into account the data's noise and uncertainty. It uses probabilistic methods like Bayesian inference to give confidence indications to the assessment results. This makes the system's decision-making clearer and more reliable. The assessment results not only serve as the basis for mental health warning but also enable counsellors and mental health centres to create tailored intervention plans and obtain correct psychological services.

To further improve the interpretability and performance of the psychological state classifier, an attention mechanism is incorporated into the model. This AI technique allows the system to dynamically weigh the importance of different features, such as emotional intensity, behavioural entropy, and activity clusters, during the classification process. By focusing on the most relevant indicators for each student, the attention mechanism enhances both the accuracy and transparency of psychological risk assessment, facilitating more targeted and understandable intervention recommendations.

3.4 Early warning and feedback module

The early warning and feedback module is the last part of the AffectPath-PM system that can dynamically check on university students' psychological health. Its job is to find psychological risks based on the results of a full assessment and give feedback to the right management staff or the students themselves as soon as possible. By creating a scientific early warning system and a multi-level feedback system, the module makes it possible to actively monitor and intervene in abnormal psychological states. This improves the intelligence and accuracy of psychological health services in colleges and universities.

More specifically, the early warning module gets the psychological risk score S from the complete psychological state assessment module first. This number shows how abnormal the student's current psychological condition is in a general way. The system creates a multi-level warning model based on thresholds to make sure that the early warning is both scientific and tailored to each person. The warning threshold is set as τ, when the psychological risk score meets the condition:

$$S \geq \tau \tag{11}$$

The device initiates the early warning signal and delivers the warning message to the counsellor, the student or the psychological health centre. The threshold value τ can be dynamically modified based on the previous data of each student to facilitate personalised risk assessment and improve the accuracy and responsiveness of the warning.

The early warning module also uses a time-weighted technique to keep track of and tally up the trend of changes in pupils' psychological risk levels. The exact formula is as follows:

$$S_t = \beta \cdot S_{t-1} + (1-\beta) \cdot S_{current} \tag{12}$$

where S_t is the composite risk score at time t, S_{t-1} is the risk score at the last time, $S_{current}$ is the immediate score at the current time, and β is the time weighting factor. The process works well to smooth out changes in risk and stop false alarms from happening when there are infrequent abnormalities. It also gives higher weights to states that are consistently high-risk to make sure that potential crises are found quickly.

In short, the early warning and feedback module uses scientific threshold setting and time-weighted dynamic adjustment to monitor university students' psychological risks in real time and respond quickly. It also has a multi-channel feedback mechanism that provides strong technical support and service guarantee for campus psychological health management. This helps change psychological intervention from a passive response to active prevention.

4 System testing and results analysis

4.1 Data collection and pre-processing

To validate the efficacy of the AffectPath-PM system, two publicly accessible and representative datasets were selected for this study. Both datasets contain extensive emotional information and behavioural trajectory data, effectively reflecting the psychological state and behavioural characteristics of university students, thereby facilitating the overall functional validation and performance evaluation of the system. The initial dataset is Dataset for Affective States in E-Environments (DAiSEE), which records diverse emotional states via numerous videos of students' facial expressions in online learning contexts, featuring high-quality visual emotion annotations, and facilitates the evaluation of the affective computing module. This dataset also has some text comments, which add to the multimodal emotion information. The second dataset is called the StudentLife dataset. It gathers data from students' mobile phone sensors, such as GPS tracking, communication records, and activity monitoring. Along with the psychological health questionnaire, it shows how students' behaviour changes over time and how it affects their psychological health. It is also a key testing tool for the system's behavioural trajectory analysis and complete evaluation module. Both datasets include multimodal data, which helps to check how well the system works for recognising emotions, analysing behaviour, and getting a full picture of someone's psychological health. Tables 1 and 2 show the specific data.

For the DAiSEE dataset, the video data were first pre-processed by extracting frames and detecting faces. This removed frames that were not genuine or were too blurry to ensure that the facial expression recognition was correct. After that, the photos go through processes like normalising and enhancing, which include changing the lighting, rotating, and cropping them to make the model more stable. Then, the textual emotion data is cleaned and encoded by separating words, removing duplicates, and changing word vectors. For the StudentLife dataset, the raw sensor data is first synchronised in time and filled in for missing values. Then, interpolation and sliding-window smoothing methods are employed to make sure that the trajectory data is complete and continuous. Then, the location data is mapped to the campus' functional regions and paired with timestamps to find the halting points and activity pathways of students. Cluster analysis and entropy computation are used to further quantify behavioural traits, which provide high-quality input data for a more thorough examination later.

The system may successfully combine emotional and behavioural data through the above data collecting and pre-processing method. This creates a strong data foundation for accurately identifying and dynamically monitoring psychological states.

Table 1 DAiSEE dataset overview

Attribute	*Description*
Data type	Facial expression videos and associated text comments
Emotional labels	Attention, confusion, disgust, excitement, neutral
Sample size	Over 9,000 video clips
Environment	Online learning settings
Data format	RGB video frames, frame-level annotations, text comments

Table 2 StudentLife dataset overview

Attribute	*Description*
Data type	Mobile sensor data and psychological surveys
Sensor modalities	GPS, call logs, SMS, accelerometer, activity recognition
Sample size	Data collected from ~48 students over 10 weeks
Psychological data	Weekly psychological health surveys including stress and depression scales
Environment	University campus

To thoroughly assess the functionality and efficacy of the AffectPath-PM system, this study integrates a high-performance hardware setup with an advanced software environment in the experimental design, ensuring the efficient operation and precise evaluation of the system modules. The experiment uses a highly configured server as the main running platform. It has an Intel Xeon Gold 6248R processor with 24 cores and 48 threads at a main frequency of 3.0 GHz to support multi-threaded parallel computing, 128 GB of DDR4 memory, and two NVIDIA Tesla V100 GPUs to meet the needs of DL model training and real-time data processing. The system's data storage uses SSD arrays that are very quick to read and write enormous amounts of video and sensor data. The experimental setting, on the other hand, has multi-channel high-definition video capture equipment and wireless positioning sensors to mimic how data would be collected on a real campus.

4.2 Comparative assessment experiments

In order to fully validate the effectiveness of the AffectPath-PM system, this section carries out comparative assessment experiments based on the DAiSEE dataset and StudentLife dataset, respectively. The experimental design includes four comparative models:

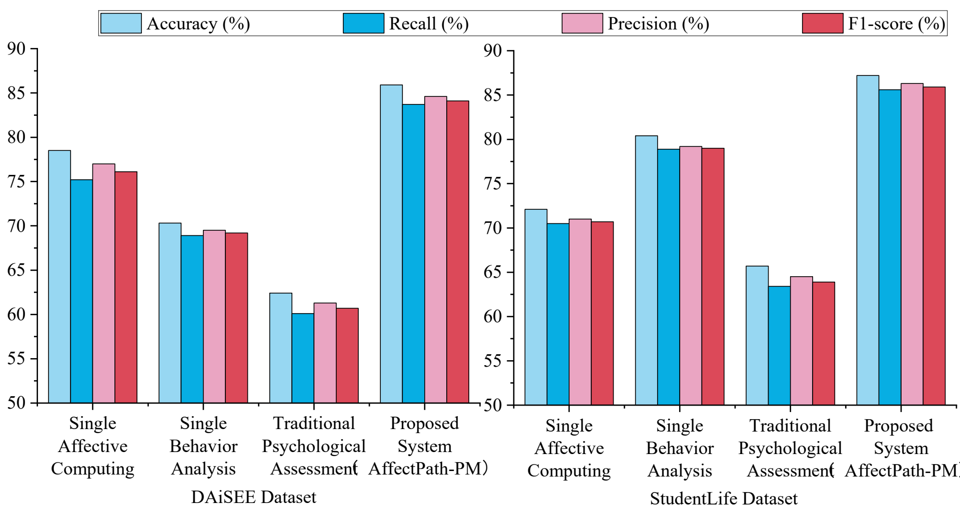
1 a single affective computing model (based only on facial expressions and textual emotions)

2 a single behavioural trajectory analysis model (based only on students' behavioural trajectory data)

3 the traditional psychological monitoring method (a static model based on questionnaires and manual interviews)

4 the system proposed in this paper, AffectPath-PM (which integrates affective computing and behavioural trajectory analysis).

Figure 2 Results of the comparative assessment experiments (see online version for colours)



The accuracy, recall, precision, and F1-score of each model in the mental state recognition task are evaluated through experiments on both datasets. This shows how well each model works for monitoring the psychological health of college students and how they differ in terms of effectiveness. Figure 2 shows the outcomes of the experiment.

The single affective computing model does a good job at recognising emotions on the DAiSEE dataset, with an accuracy of 78.5%. But the model has some problems with the emotion detection job because it only uses emotion data, which makes it hard to recognise complicated emotional states with bland outcomes. The single behavioural trajectory analysis model exhibited suboptimal performance, with an accuracy rate of 70.3%. This suggests that singular behavioural data are generally inadequate for psychological state identification and fail to comprehensively represent the psychological health status of pupils. The conventional psychological monitoring approach exhibited the lowest accuracy rate at 62.4%, primarily due to manual intervention and static measures, rendering it incapable of promptly capturing dynamic fluctuations in students' psychological health.

The AffectPath-PM system, on the other hand, did the best in experiments on the DAiSEE dataset, with an accurate rate of 85.9%, a recall rate of 83.7%, a precision rate of 84.6%, and an F1-score of 84.1%. This study shows how important it is to combine different types of data in affective computing. Combining emotional and behavioural data makes the system far more accurate and reliable. The combination of emotional computing with behavioural analysis gives a better picture of students' psychological health, which makes the system better at noticing and warning about psychological health issues.

In the experiments on the StudentLife dataset, the behavioural trajectory analysis model demonstrated a more prominent performance with an accuracy rate of 80.4%. This suggests that there is a strong correlation between students' psychological states and behavioural characteristics in a data-rich environment of daily behaviour, and that a single behavioural trajectory data can effectively provide an initial indication of psychological states. However, the affective computing model performed relatively poorly, with an accuracy of only 72.1%, which may be related to the environmental characteristics of the dataset (e.g., mobile phone sensor data) as well as the diversity of affective expressions.

Traditional psychological monitoring methods still performed weakly on this dataset with an accuracy of only 65.7%, again demonstrating the limitations of traditional means in multidimensional psychological monitoring. In contrast, the AffectPath-PM system performed particularly well on the StudentLife dataset, with an accuracy rate of 87.2%, a recall rate of 85.6%, a precision rate of 86.3%, and an F1-score of 85.9%. By integrating behavioural trajectory data and affective computing information, the system is able to achieve more efficient mental state recognition and monitoring, especially in dynamic tracking and cross-modal fusion, showing strong advantages.

These results indicate that the AffectPath-PM system can provide a more comprehensive and intelligent solution for psychological health monitoring of university students.

4.3 Module ablation experiments

In order to deeply evaluate the contribution of each module in the AffectPath-PM system to the overall performance, this section designs ablation experiments to gradually eliminate or replace the core modules in the system and analyse the impact of each module on the system effectiveness. By comparing the experimental results under different configurations, we can understand the role of each module in student psychological monitoring, so as to optimise the system structure and improve the overall performance.

In the ablation experiments, we performed the following model configurations:

1 Affective computing model: Only the affective computing module was retained, the behavioural trajectory analysis and comprehensive assessment modules were removed, and the contribution of affective computing to the prediction of psychological state was assessed separately.

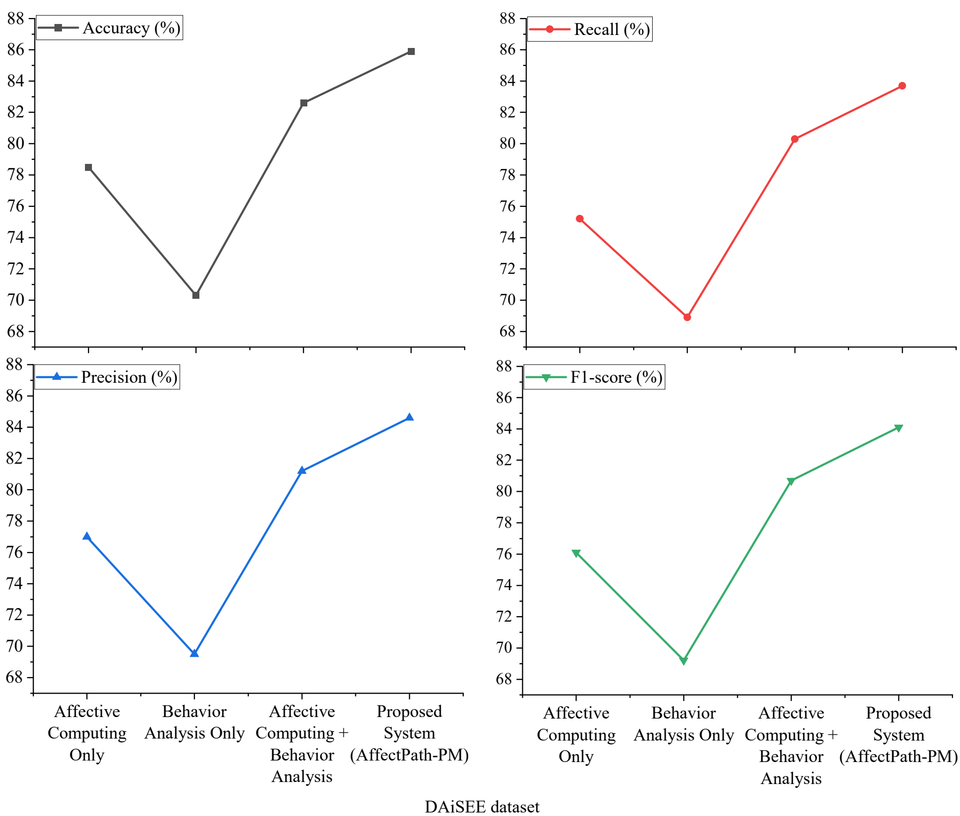
2 Behavioural trajectory analysis model: Retaining only the behavioural trajectory analysis module, removing the affective computing and comprehensive assessment modules, and separately assessing the contribution of behavioural data to psychological state monitoring.

3 Joint model of affective computing and behavioural trajectory analysis: Retaining the affective computing and behavioural trajectory analysis modules, removing the integrated assessment module, and combining only affective and behavioural information for basic psychological state assessment.

4 Complete system (AffectPath-PM): Retains the affective computing, behavioural trajectory analysis and integrated mental state assessment modules intact and uses multimodal data for comprehensive mental state assessment and prediction.

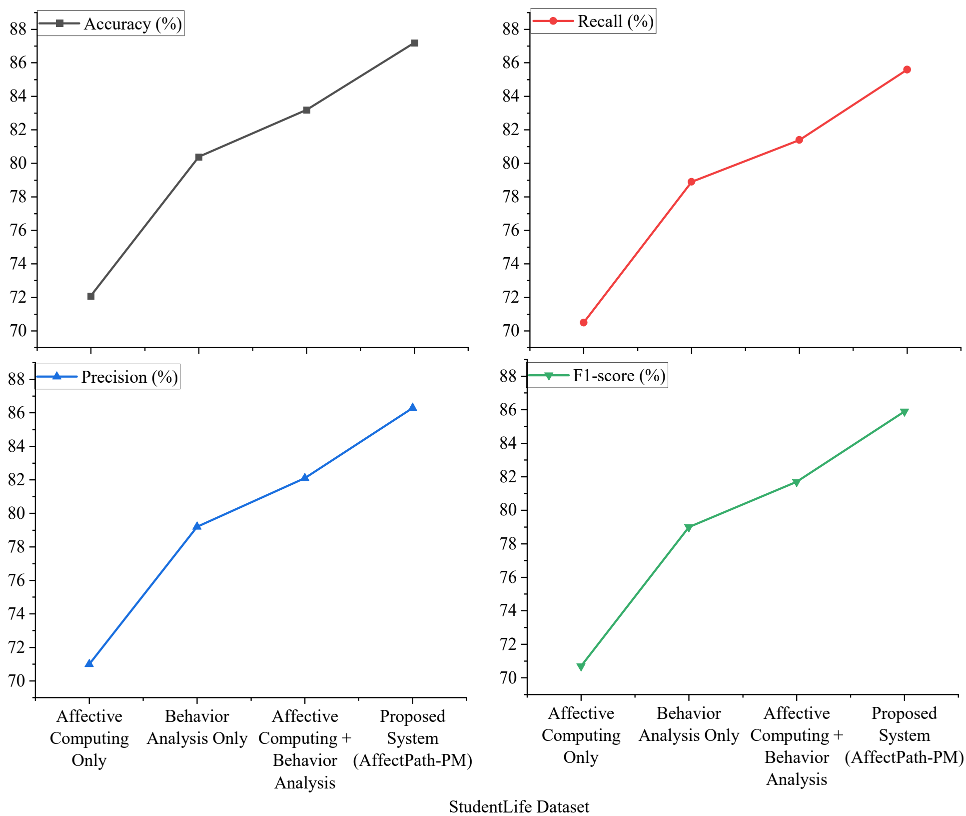
The configurations above let us see how each module affects the overall performance of the system, how affective computing and behavioural trajectory analysis work on their own, and how the performance improves when multiple modules work together. Figures 3 and 4 display the outcomes of the ablation experiments conducted on the DAiSEE and StudentLife datasets, respectively.

Figure 3 Results of ablation experiments on DAiSEE dataset (see online version for colours)



When the affective computing model was run alone on the DAiSEE dataset, it was able to correctly identify the emotional state of most of the students 78.5% of the time. This shows that the system can handle a single affective dataset, but it still has trouble processing complex emotions. The behavioural trajectory analysis model exhibited suboptimal performance in isolation, achieving an accuracy rate of 70.3%, hence demonstrating the insufficiency of depending just on behavioural data to ascertain mental states. The combination of sentiment and behavioural data (model 3) enhances system performance, achieving an accuracy rate of 82.6%. This demonstrates that the integration of sentiment and behavioural information can effectively compensate for the limitations of a singular data source and enhance the overall assessment of students' psychological states.

Figure 4 Results of ablation experiments on StudentLife dataset (see online version for colours)



But the final AffectPath-PM system (complete model) did far better than the other models on the DAiSEE dataset, with an accuracy of 85.9%, a recall of 83.7%, and an F1-score of 84.1%. This result shows that the integrated evaluation module is very important for making the complete system work better. The combination of affective and behavioural data gives integrated assessment a better and more complete way to figure out mental states. This not only makes the system more accurate, but it also makes it better at adjusting to changing mental states.

The behavioural trajectory analysis model outperformed the affective computing model on the StudentLife dataset, with an accuracy of 80.4%. This finding indicates that students' behavioural trajectory data are significantly pertinent for assessing psychological states, particularly within the framework of everyday activities, and that behavioural data more accurately represents students' psychological fluctuations. The single emotional computing model, on the other hand, was only 72.1% accurate. This could be because affective information is harder to understand and because collecting affective data is harder. So, using both affective and behavioural data together is very important for making psychological monitoring more accurate.

The system's accuracy went up to 83.2% when affective computing was used with behavioural trajectory analysis (model 3). Still, the whole AffectPath-PM system is the best, with an accuracy of 87.2%, a recall of 85.6%, and an F1-score of 85.9%. This finding indicates that the incorporation of the comprehensive assessment module substantially enhances the system's performance, particularly through the integration of behavioural data and affective information, which more precisely captures the fluctuations in students' psychological state. The system enhances the precision and reliability of psychological health detection by a multi-dimensional evaluation of emotion and behaviour, particularly excelling in dynamic monitoring and cross-modal fusion.

The ablation experiments demonstrate that the function of each module in the AffectPath-PM system is essential. The emotional computing module and the behavioural trajectory analysis module offer distinct dimensions of mental state evaluation, while the integrated assessment module enhances the system's accuracy and comprehensiveness by amalgamating this information.

Table 3 StudentLife dataset overview

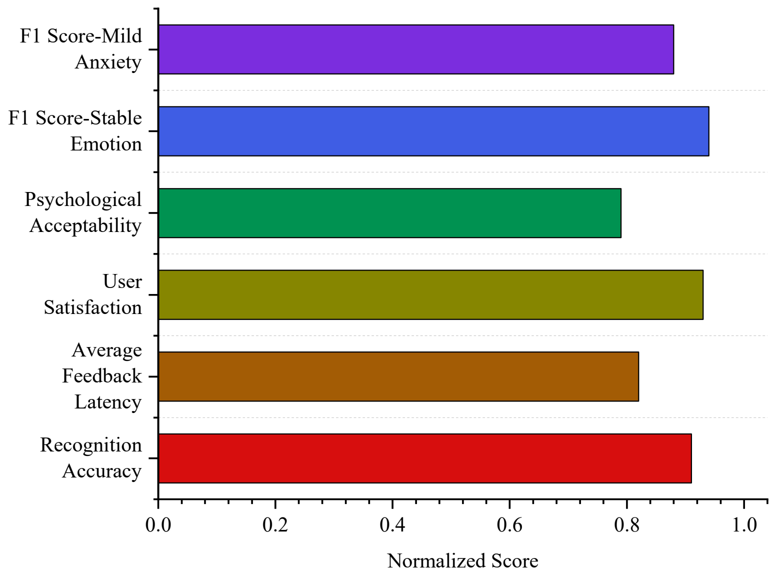
Experimental element	*Description*
Participants	15 student volunteers (7 males, 8 females, mean age = 21.4 years)
Duration	7 days
Modalities	Visual (facial expression sequences, 5 fps), textual (daily emotional journals), behavioural (Wi-Fi positioning and space usage frequency)
Valid samples	652 valid multimodal records
Data protection	Anonymous labelling, local encryption, and feature-level separation for upload
Environment	Campus study areas and dormitory settings
Real-time feedback	Lightweight psychological feedback based on recognition results (e.g., 'stable' and 'mild anxiety')

Furthermore, to further validate the feasibility and stability of the AffectPath-PM system within authentic campus environments, this paper conducted a small-scale verification experiment. This experiment aimed to examine the system's performance in recognising psychological states and its user experience within uncontrolled natural settings. Fifteen student volunteers from the same faculty participated in the experiment, which spanned a seven-day period. The system was deployed within campus learning spaces and dormitory settings, capturing three modalities of data in real time: visual, textual, and behavioural. Visual modality comprised facial expression sequences recorded via cameras; textual modality derived from daily WeChat mini-program mood logs; behavioural modality estimated activity patterns based on Wi-Fi positioning and learning space usage frequency. All data employed anonymised identifiers and local encrypted storage to ensure privacy security.

Table 3 outlines the fundamental experimental settings and data collection details.

To facilitate comprehensive comparison across different dimensions, this paper normalises all evaluation metrics to the interval [0, 1]. The normalised results are presented in Figure 5.

Figure 5 Results of ablation experiments on StudentLife dataset (see online version for colours)



The results demonstrate that the AffectPath-PM system maintains high performance stability and recognition accuracy in authentic campus environments. The normalised score for recognition accuracy reached 0.91, indicating a high degree of consistency between the system's recognition outcomes and participants' self-reported emotions. This validates the effectiveness of the multimodal fusion framework in natural settings. Particularly in the tasks of identifying emotionally stable states and mild anxiety, the F1 scores reached 0.89 and 0.84 respectively, with normalised scores of 0.94 and 0.88. This demonstrates the model's ability to simultaneously capture both short-term emotional fluctuations and the state characteristics of mild psychological stress, exhibiting strong generalisation capabilities and sensitivity.

Regarding system responsiveness, the average normalised feedback latency score of 0.82 indicates that AffectPath-PM maintains high real-time performance and stability throughout data acquisition, feature extraction, and emotion recognition. This fulfils the requirements for instant psychological state monitoring and lightweight feedback in campus settings. The system operated without significant delays or data anomalies over seven consecutive days, further demonstrating the reliability of its platform architecture in processing and dynamically integrating multi-source data.

From a user experience perspective, user satisfaction and psychological acceptability scores were 0.93 and 0.79 respectively, indicating that most participants found the system feedback valuable for reference without causing psychological burden. This outcome demonstrates that AffectPath-PM not only possesses technical accuracy and robustness but also achieves good emotional adaptability and human-machine friendliness at the interaction level. Overall, the findings from this small-scale validation experiment validate the applicability and generalisability of the proposed multimodal fusion framework in real-world settings, providing an empirical foundation for subsequent large-scale deployment and longitudinal studies.

5 Conclusions

This paper presents a psychological monitoring system for university students based on affective computing and behavioural trajectory analysis (AffectPath-PM). The system achieves real-time assessment of students' emotional and psychological states by integrating multimodal information. This paper then tests the AffectPath-PM system with two real datasets (DAiSEE and StudentLife) and finds that it is much better than traditional methods and single affective computing or behavioural analysis models. This proves that the system is valid and reliable.

The AffectPath-PM system produced superior experimental outcomes; nonetheless, it possesses certain limitations, particularly with the integration and processing of multimodal data. The system depends on the combination of several data sources and has to deal with the problems of synchronising and combining data. Environmental factors can make it hard to collect affective computing and behavioural data. For example, changes in light can make it hard to see facial expressions, and noise can make it hard to hear voice data. Also, when the system processes behavioural trajectory data, it may skew the analysis results since the sensors are not always accurate, or the data is not always comprehensive.

Additionally, while the system can assess students' psychological state in real time, it still has problems with keeping track of and analysing long-term changes in students' psychological health. The system primarily depends on real-time behavioural and affective data and has not yet comprehensively documented the trends in people's long-term psychological health changes. Moreover, significant individual variations in pupils' emotional states and behavioural patterns necessitate greater precision in the system's accuracy. Privacy protection and ethical concerns remain significant issues that require attention, particularly when collecting and processing sensitive data such as students' facial expressions, vocal recordings, and behavioural patterns; safeguarding the security and privacy of this information continues to pose challenges.

To address the aforementioned restrictions and enhance the system's performance, subsequent research may be conducted in the following areas: First, improving the performance of the system depends on further optimising the data fusion technology. In the future, researchers can look into more advanced DL models that can automatically find the best features from multiple data sources. Secondly, long-term trend analysis and dynamic monitoring can be added in the future so that the system can identify the trajectory of changes in students' psychological health and provide stronger support for the prevention of psychological problems.

In summary, the AffectPath-PM system provides an innovative solution for monitoring the psychological health of university students, and with the continuous development and optimisation of the technology, the system is expected to be widely used in many fields and become an important tool for psychological health management.

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Declarations

All authors declare that they have no conflicts of interest.

References

Ahmed, S.F., Alam, M.S.B., Hassan, M., Rozbu, M.R., Ishtiak, T., Rafa, N., Mofijur, M., Shawkat Ali, A.B.M. and Gandomi, A.H. (2023) 'Deep learning modelling techniques: current progress, applications, advantages, and challenges', *Artificial Intelligence Review*, Vol. 56, No. 11, pp.13521–13617.

Ali, G., Mijwil, M.M., Adamopoulos, I. and Ayad, J. (2025) 'Leveraging the internet of things, remote sensing, and artificial intelligence for sustainable forest management', *Babylonian Journal of Internet of Things*, Vol. 2025, pp.1–65.

Barneveld, E., Manders, J., Osch, F.H.M., Poll, M., Visser, L., Hanegem, N., Lim, A.C., Bongers, M.Y. and Leue, C. (2022) 'Depression, anxiety, and correlating factors in endometriosis: a systematic review and meta-analysis', *Journal of Women's Health*, Vol. 31, No. 2, pp.219–230.

Bin, L., Xiaodong, Q. and Xin, W. (2025) 'Application of psychological committee system in college mental health education', *Journal of Higher Education Teaching*, Vol. 2, No. 2, pp.221–227.

Birimoglu, O.C. and Begen, M.A. (2021) 'Working from home during the COVID-19 pandemic, its effects on health, and recommendations: the pandemic and beyond', *Perspectives in Psychiatric Care*, Vol. 58, No. 1, pp.173–179.

Bisogni, C., Castiglione, A., Hossain, S., Narducci, F. and Umer, S. (2022) 'Impact of deep learning approaches on facial expression recognition in healthcare industries', *IEEE Transactions on Industrial Informatics*, Vol. 18, No. 8, pp.5619–5627.

Das, R. and Singh, T.D. (2023) 'Multimodal sentiment analysis: a survey of methods, trends, and challenges', *ACM Computing Surveys*, Vol. 55, No. 13s, pp.1–38.

Di Credico, A., Perpetuini, D., Izzicupo, P., Gaggi, G., Mammarella, N., Di Domenico, A., Palumbo, R., La Malva, P., Cardone, D., Merla, A., Ghinassi, B. and Di Baldassarre, A. (2024) 'Predicting sleep quality through biofeedback: a machine learning approach using heart rate variability and skin temperature', *Clocks & Sleep*, Vol. 6, No. 3, pp.322–337.

Dong, G., Tang, M., Wang, Z., Gao, J., Guo, S., Cai, L., Gutierrez, R., Campbel, B., Barnes, L.E. and Boukhechba, M. (2023) 'Graph neural networks in IoT: a survey', *ACM Transactions on Sensor Networks*, Vol. 19, No. 2, pp.1–50.

Elijah, O.A. and Oladayo, T.A. (2024) 'AI powered privacy protection: a survey of current state and future directions', *World Journal of Advanced Research and Reviews*, Vol. 23, No. 3, pp.2687–2696.

Ezerceli, Ö. and Dehkharghani, R. (2024) 'Mental disorder and suicidal ideation detection from social media using deep neural networks', *Journal of Computational Social Science*, Vol. 7, No. 3, pp.2277–2307.

Farahsari, P.S., Farahzadi, A., Rezazadeh, J. and Bagheri, A. (2022) 'A survey on indoor positioning systems for IoT-based applications', *IEEE Internet of Things Journal*, Vol. 9, No. 10, pp.7680–7699.

Guo, T., Zhao, W., Alrashoud, M., Tolba, A., Firmin, S. and Xia, F. (2022) 'Multimodal educational data fusion for students' mental health detection', *IEEE Access*, Vol. 10, pp.70370–70382.

Gupta, M., Parra, C.M. and Dennehy, D. (2021) 'Questioning racial and gender bias in AI-based recommendations: do espoused national cultural values matter?', *Information Systems Frontiers*, Vol. 24, No. 5, pp.1465–1481.

Hayes, S.C. and Hofmann, S.G. (2021) ''Third-wave' cognitive and behavioral therapies and the emergence of a process-based approach to intervention in psychiatry', *World Psychiatry*, Vol. 20, No. 3, pp.363–375.

Jabeen, S., Li, X., Amin, M.S., Bourahla, O., Li, S. and Jabbar, A. (2023) 'A review on methods and applications in multimodal deep learning', *ACM Transactions on Multimedia Computing, Communications, and Applications*, Vol. 19, No. 2s, pp.1–41.

Kong, X., Wang, J., Hu, Z., He, Y., Zhao, X. and Shen, G. (2024) 'Mobile trajectory anomaly detection: taxonomy, methodology, challenges, and directions', *IEEE Internet of Things Journal*, Vol. 11, No. 11, pp.19210–19231.

Kumar, I.K., Shen, J., Ferguson, C. and Picard, R.W. (2025) 'Connecting through comics: design and evaluation of cube, an arts-based digital platform for trauma-impacted youth', *Proceedings of the ACM on Human-Computer Interaction*, Vol. 9, No. 2, pp.1–22.

Latif, S., Rana, R., Khalifa, S., Jurdak, R., Qadir, J. and Schuller, B. (2023) 'Survey of deep representation learning for speech emotion recognition', *IEEE Transactions on Affective Computing*, Vol. 14, No. 2, pp.1634–1654.

Ma, H., Zhao, W., Tang, Y., Huang, P., Zhu, H., Tang, W. and Li, K. (2024) 'Personalized early warning of learning performance for college students: a multilevel approach via cognitive ability and learning state modeling', *IEEE Transactions on Learning Technologies*, Vol. 17, pp.1414–1427.

Mira, J.J., Matarredona, V., Tella, S., Sousa, P., Ribeiro Neves, V., Strametz, R. and López-Pineda, A. (2024) 'Unveiling the hidden struggle of healthcare students as second victims through a systematic review', *BMC Medical Education*, Vol. 24, No. 1, pp.1–22.

Mobini Seraji, M.H., Shaffiee Haghshenas, S., Shaffiee Haghshenas, S., Simic, V., Pamucar, D., Guido, G. and Astarita, V. (2025) 'A state-of-the-art review on machine learning techniques for driving behavior analysis: clustering and classification approaches', *Complex & Intelligent Systems*, Vol. 11, No. 9, pp.15–31.

Seth, S. and Feng, Q. (2021) 'A multi-level weighted alarm security system for passenger and checked-baggage screening', *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, Vol. 236, No. 5, pp.727–737.

Straczkiewicz, M., James, P. and Onnela, J-P. (2021) 'A systematic review of smartphone-based human activity recognition methods for health research', *Digital Medicine*, Vol. 4, No. 1, pp.27–43.

Vaziri, P., Ahmadi, S., Daneshfar, F., Sedaee, B., Alimohammadi, H. and Rasaei, M.R. (2024) 'Machine learning techniques in enhanced oil recovery screening using semisupervised label propagation', *SPE Journal*, Vol. 29, No. 9, pp.4557–4578.

Yoo, W. and Kim, T-W. (2022) 'Statistical trajectory-distance metric for nautical route clustering analysis using cross-track distance', *Journal of Computational Design and Engineering*, Vol. 9, No. 2, pp.731–754.

Zhou, S., Huang, C., Wen, Y. and Chen, L. (2024) 'Feature enhanced spatial-temporal trajectory similarity computation', *Data Science and Engineering*, Vol. 10, No. 1, pp.1–11.