Behavior-Transformer for Early Risk Detection and Monitoring in Students' Social Media Activity

ArunaDevi Karuppasamy, Rolou Lyn Maata and Abbas Fadhil Aljuboori
Gulf College, Oman

arunadevi@gulfcollege.edu.om,
rolou@gulfcollege.edu.om,
abbas.aljuboori@gulfcollege.edu.om

Abstract: In the digi talized world, examining students' behavior through social media activity has become an important issue for organizations trying to detect early signs of depression, anxiety, and performance deterioration. Despite numerous records of inspirational guidance and rewards in educational environments, a significant gap remains in flexible, understandable strategies for real-time risk identification on professional social media platforms. We propose a Behavior-Transformer (Behav-T), a hybrid deep learning model designed to identify student mental health risk from self-reported social media behaviour. Digital transformation activities necessitate and create opportunities for ethical monitoring of individuals. The results obtained by the proposed model show 0.77 accuracy and 0.77 F1-score, outperforming traditional models, including Support Vector Machine (SVM), Gradient Boosting, Logistic Regression, Random Forest, and a Multi-Layer Perceptron (MLP). The results show that the proposed model performs well for early mental health risk screening in student populations. Future work should use multimodal data and cross-cultural validation across organizational contexts to achieve equitable, culturally responsive risk detection.

Keywords: Social Media Analysis, Clustering, Transformer, Stress Detection, Neural Network, Student Behavior Analysis

1. Introduction

Mental health problems have become so widespread among students in universities that they have become an international issue. According to the earlier studies, the prevalence of the symptom's indicative of clinical depression, anxiety, or stress among the student population is estimated to be about 30-40 per cent of all students throughout their academic career, although only 25-30 per cent of them seek professional assistance (Jadhav and Chavan, 2025). A significant association was observed between the outcomes of mental stress and hours of social media use per day. The use of social media has become part of everyday life, totally changing how people interact, exchange information, and socialize. The increase of social media platforms has already formed a network where billions of users can access Facebook, Instagram, Twitter, YouTube, TikTok, and new platforms every day (Sardar, Jana, and Paria, 2025). A study used to conduct a sentiment analysis of Twitter data discuss the insights of customer to support digital marketing strategy and business decision-making in Oman (Maata et al., 2021). This global application, however, is accompanied by accumulating information about mental health problems in users, especially student groups that are developmentally vulnerable to social comparison processes and validation-seeking processes that are peer-based. The mean mental stress score was found to be 2.16 in participants who spent less than 1 hour a day, 2.85 in those who spent 1–2 hours a day, 3.19 in those who spent 3 hours a day, 3.5 in those who spent 4 hours a day, 3.46 in those who spent 5 hours or more a day. The study demonstrates that the length of time spent on social media is a significant predictor of mental health outcomes. Recent large-scale scoping reviews examining factors in social media use among college students all indicate that long-term exposure to social media is predictive of poor mental health. The main underlying mechanisms have been identified as fear of missing out, sleep quality, and overconsumption (Fatima et al., 2025). The processes by which the use of social media creates mental distress are not fully understood, but it is assumed that they entail several interactive channels. The patterns of social media use, which were differentiated by pointless use, distraction in work, easy distractibility, and restlessness in the absence, were significantly related to the mental stress indices, and these patterns reflect the impact of addiction-related engagement in creating psychological stress by replacing restorative activities. Research on network analysis has been done on Chinese college students, and this research has found that depression is the most central node in the network of relationships between social media addiction, academic burnout, and psychological stress; excessive use of social media distracts students, thus leading to increased anxiety and depression (Feng et al., 2025). Additionally, mental stress was significantly linked with the frequency of social comparison and validation-seeking behaviour, and these psychological processes were also clarified as the etiology of the symptoms associated with stress (Azazz, 2025). In this research paper, the researcher will provide an in-depth analysis of the connection between social media use trends and mental pressure among student groups. It will look at the frequency of engagement, addictive behavior patterns, social comparison, and validation-seeking

behaviors and evaluate the relationship between the specified factors and specific mental-health outcomes. The main research questions will be: To outline how widespread and intensive the symptoms of mental-stress distress, to define the characteristics of the usage, which best predict the experience of psychological distress, to outline how exposure to social media produces measurable mental-health effects, and to generalize empirical findings, which can be used to implement mental-health interventions aimed at protecting vulnerable student populations.

2. Literature Review

A recent study shows the effects of using social media on the mental health of students found that the main negative effects were anxiety, depression, and stress, and the positive effect was social support and self-expression, which was neutralized by the negative effects, which are cyberbullying, social comparison, and validation-seeking behaviour (Jadhav and Chavan, 2025). The mobile social engagement enabled by the widespread introduction of smartphones and the growth of social media platforms in the early-to-mid 2010s created opportunities previously unavailable. Recent studies of mental health outcomes and social media adoption have reported similar parallel rises in teenage depression and anxiety in times of steep adoption of social media, even though causality is a topic of current discussion. A recent scoping review investigating behavioural, demographic and psychosocial factors of social media use in college students summarized the results of 22 peer reviewed articles and discovered consistent relationships between social media overuse and depression, anxiety, stress, and emotional dysregulation symptoms, with fear of missing out, poor sleep, and extended use consistently proving valuable predictors of negative mental health consequences (Fatima et al., 2025). There is significant heterogeneity in how various audiences respond to social media exposure. In a cross-sectional study of social media and sleep levels in college students, it was shown that women reported more fear of missing out, anxiety, depression, and perceived stress than men and had a higher frequency of checking social media (Lust and Danzey, 2025). Such results indicate that women users might be more susceptible to the negative psychological impact of social media, which might be due to a disparate susceptibility to the effects of appearance anxiety and social comparison on image-focused media. Problematic social media use has been discussed as a behavioural addiction that satisfies all criteria similar to substance use disorders, such as tolerance (an increasing amount of time is needed to achieve satisfaction), withdrawal symptoms (anxiety and restlessness when limited access is available), and use regardless of harm (Shannon et al., 2024) . The addiction index included in the study at hand, namely aimless usage, distracting when performing a task, restlessness when there is no access, and being readily distracted, reflects high levels of addiction-related engagement among all the participants. It is also worth noting that, according to the addiction index, 48.6 per cent of the respondents had a score of above 3.25, which means that problematic patterns of engagement are used by half of the participants. The result that the signs of addiction are significantly related to mental stress confirms the postulate that indicators of addiction are converted into psychological distress, potentially through loss of sleep, academic participation, and face-to-face socialization. Students using more than 5 hours per day reveal significantly higher addiction indices and mental distress, indicating that intensive use turns compulsive and disturbing to large subgroups. Recent studies on digital stress in Chinese university undergraduates revealed that the level of digital stress was correlated with the degree of problematic social media use, both directly and indirectly via anxiety and depression, with cognitive reappraisal reducing the intensity of the two (Zhan, Luo, and Hu, 2025). A cross-sectional research of secondary school students in Saudi Arabia on the relationship between social media use and sleep quality showed that the use of Tik Tok, the duration of social media use, and the presence of moderate to severe symptoms of depression were all significant independent predictors of poor sleep quality that highlights the relationship between long-term social media use and poor sleep quality (Al-Garni et al., 2024). Recent research has used machine learning to forecast students' mental health outcomes using different feature sets. A systematic review found 48 studies that used machine learning to detect depression, anxiety, and stress in undergraduate students, and reported the accuracies of 63 to 100% (Schaab et al., 2024). An analysis of 11,943 college students who had taken the Symptom Checklist-90 showed that tree-based ensemble techniques (Light Gradient Boosting Machine, Random Forest, XGBoost) performed better than non-ensemble techniques, with the LGBM achieving only 6 misclassifications on 2,388 test data (Liu et al., 2025).

3. Method

Initially, the proposed method converts selected mental-health Likert items (distraction, worries, concentration, depression, interest, sleep) into standardized numeric features for each student. A small autoencoder then compresses these features into a 2-dimensional latent vector and reconstructs the original input. The model is trained to make the reconstruction close to the original:

$$\mathcal{L}_{\text{AE}} = \sum_{i} \| x_i - \hat{x}_i \|_2^2.$$

Where x_i is the original mental-health feature vector of the i^{th} student, $\hat{x}_i$ is the reconstructed vector produced by the autoencoder, and $\mathcal{L}_{\text{AE}}$ is the squared difference between them. This loss decreases when the model correctly captures the student's main mental-health pattern. On the learned 2-D latent space, we apply K-means clustering with $k = 3$ to obtain three natural groups and then label them as low, medium, and high risk based on average depression and sleep scores in each cluster. For each student, we construct three types of social media features: (i) a sequence of platform tokens, (ii) a categorical token for daily time spent, and (iii) a numeric vector of social media usage Likert items (e.g., purposeless use, distraction, restlessness, self-comparison, validation seeking, fluctuating interest). Together, these are represented as a single combined feature vector:

$$f_i = [p_i, t_i, u_i],$$

where $p_i$are platform features, $t_i$is time-spent encoding, and $u_i$is the usage-Likert vector. This representation aligns with each student's identified risk level (low/medium/high). Finally, a Transformer-based classifier takes the combined social media features and predicts the discovered risk level. The model maps the input features of the student i to a 3-class output (low, medium, high risk), and we represent this simply as a function:

$$\hat{y}_i = \mathcal{F}(p_i, t_i, u_i),$$

where $\mathcal{F}(\cdot)$ denotes the Transformer-based network. In words, the network jointly learns patterns from platform sequences, time spent, and usage behaviour to estimate the probability of each risk category for every student.

4. Results and Discussion

4.1 Dataset

The Kaggle study on social media and mental health, which is a publicly available dataset, was used for this study (Ahmed and Syeda, 2023). It consists of time-stamped survey responses that contain information related to mental health, social media behavior, and demographic data. Each row represents an individual, and each column encodes a demographic characteristic, a social media behavior variable, or a mental health item on an ordinal scale (usually 1–5 Likert). The variables contain the information whether the respondent uses social media, which platforms they use most frequently (e.g., Facebook, Twitter, Instagram, YouTube, Discord, Reddit, Snapchat, TikTok, Pinterest), and how much time they spend on social media on average daily. These factors are reported in categorical ranges, such as "Less than an hour," "Between 2 and 3 hours," and "More than 5 hours." In addition to more general measures of well-being, the mental health section contains variables that analyze behavioral and psychological impacts of social media use. These questions address behaviors such as aimlessly using social media, letting it divert attention from work, becoming agitated when not using it, comparing oneself to more successful people online, and seeking acceptance from social media platforms. On a scale of 1 to 5, other variables measure mental health-related behaviors, such as the prevalence of sleep issues, ease of distraction, amount of worry, difficulty concentrating, the rate of feeling down or depressed, and changes in interest in daily activities.

4.2 Experimental Analysis

The proposed model was applied to the dataset to analyse the higher-educational system, in which a system could support early, low-cost digital screening by highlighting students with elevated predicted risk for further assessment, while also surfacing which aspects of social media behaviour (heavy purposeless use, high validation-seeking, long daily duration, etc.) are most prevalent among higher-risk groups. Training the autoencoder on the six defined mental health items performed well, with the reconstruction loss decreasing from about 0.87 at epoch 50 to about 0.44 at epoch 200. These results show that the two-dimensional bottleneck captured the main differences in students' symptom profiles. The use of k-means clustering on the resultant latent space created three distinct groups with an increase in the mean score of the items: feeling

depressed or down, and sleep issues. The observed pattern provides empirical evidence for classifying the clusters into low-, medium-, and high-risk groups. Furthermore, it implies that the autoencoder has learned a clinically relevant latent space, rather than random groupings. The discovered risk-label distribution was even, with about 130 students in the low-risk group, 171 in the high-risk group, and 180 in the medium-risk group. The given balance is beneficial to prospective multi-class training, as it shows that the unsupervised process did not produce an uneven majority-to-minority split and that there are sufficient examples of each of the three risk groups. The given balance is beneficial to prospective multi-class training, as it shows that the unsupervised process did not produce an uneven majority-to-minority split and that there are sufficient examples of each of the three risk groups. The produced social media functionalities, when considered alongside the inferred risk labels, displayed several trends. The platform vocabulary was supported by a wide range of trendy services, such as Facebook, Twitter, Instagram, YouTube, Snapchat, Reddit, Tik Tok, Pinterest, and so on. Most students reported using more than one platform simultaneously, indicating their activity across different media settings. Categories of time spent included less than an hour and more than 5 hours; most respondents were in the intermediate category, with the most widespread category being between 3 and 4 hours. The high-risk students were more likely to occupy the highest time-use categories and use several platforms simultaneously that are visual and socially intensive at the same time (e.g., Instagram, Tik Tok, Snapchat). Conversely, less risky students were more likely to use fewer platforms and use less cumulative time per day. However, this trend was not always consistent, suggesting the need to account for interaction effects in the model. The social-media-use Likert-based, purposeless browsing, distraction, restlessness, not using social media, self-comparison, validation seeking, and variability in interest gave another view on behaviour. Students in the high-risk group reported higher scores on these items, consistent with previous literature on problematic social-media behaviour, whereas low-risk students reported more moderate responses. The correspondence between unsupervised risk levels and self-reported online behaviours, therefore, confirms the construct validity of the assigned labels. The model was trained on a multimodal representation comprising a platform sequence, a time-spend token, and a usage Likert vector, using an 80/20 train-test split. The training loss showed a steady drop over epochs, and the validation loss dropped at the beginning of epoch 1 to about 0.96 and at the end of epoch 16, at which point early stopping was called. These findings demonstrate the effectiveness of the AdamW optimizer, cosine learning rate schedule, and gradient clipping in reducing underfitting and overfitting.

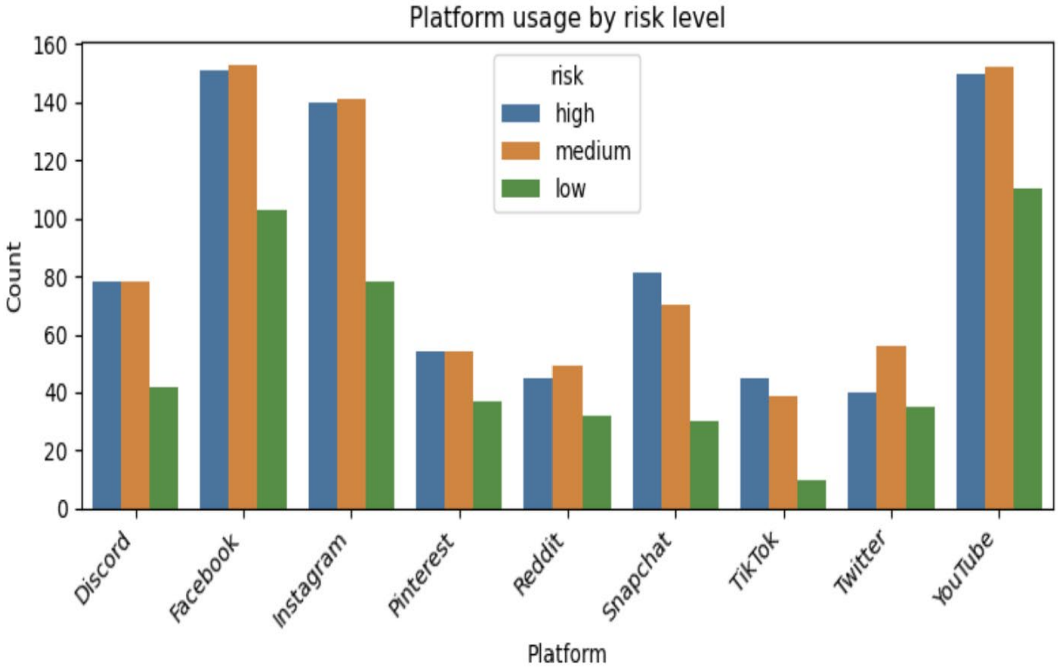

Figure 1: Social Media Platform Usage by Risk Level

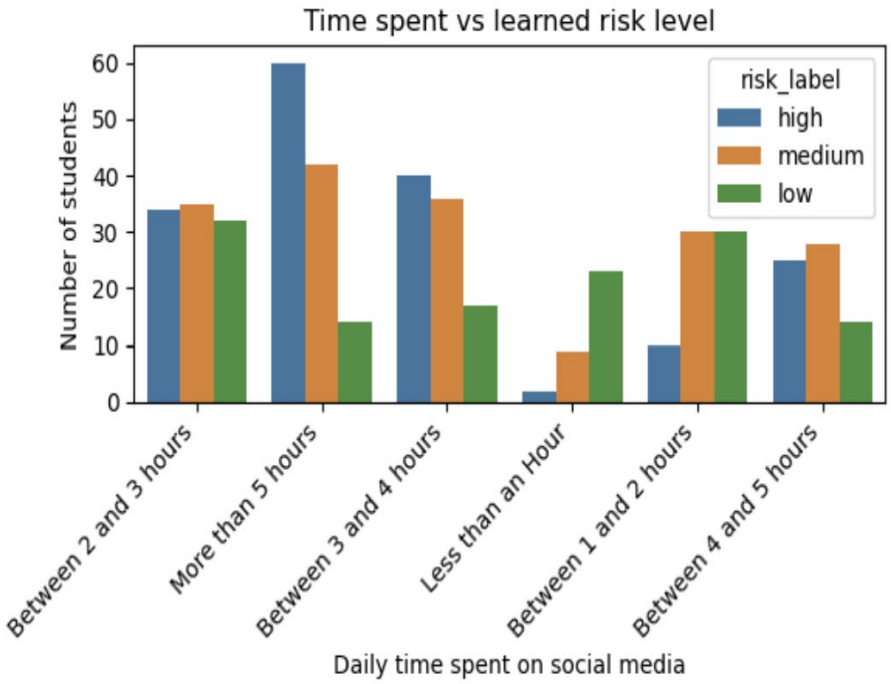

Figure 2: Daily Time Spent on Social Media vs. Learned Risk Level

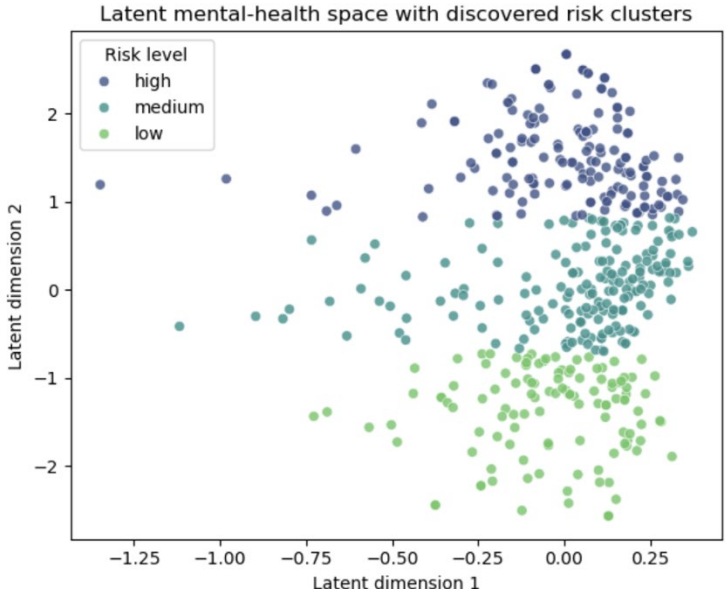

Figure 3: Mental-Health Space with Discovered Risk Clusters

Figure 1 demonstrates platform-specific usage distributions according to the level of mental health risk. The bar chart indicates the number of students in high, medium and low risk group who use each of the major social media platforms. It also presents various patterns of usage by various platforms and therefore it indicates that certain platforms are more prevalent among students at risk. Figure 2 illustrates the correlation between the acquired level of mental health risk and how much time a person spends on social media daily. The bars grouped together, indicating the number of students who can be considered to be at high, medium, and low risk, according to each of the time use categories forming the x-axis, indicate that a greater proportion of the students who fall in the higher risk categories are associated with the heavier use of social media. The two-dimensional latent mental health space that the proposed model was trained on is presented in Figure 3, with each point on the plot corresponding to an individual student that is projected to the latent space and colour-coded depending on the risk cluster identified (high, medium, low). According to the plot, meaningful structure in underlying

mental health risk patterns is reflected in the latent representation, with students with comparable inferred levels of mental health risk well-separated in regions.

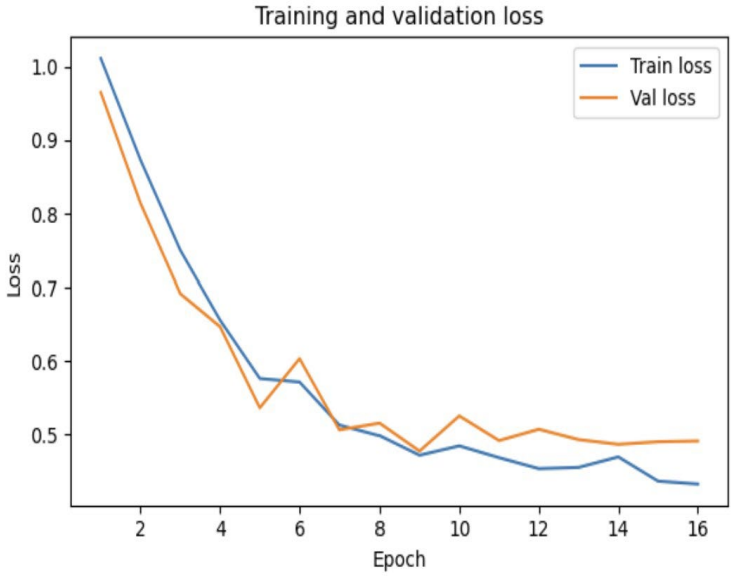

Figure 4: Training and Validation Loss Across Epochs

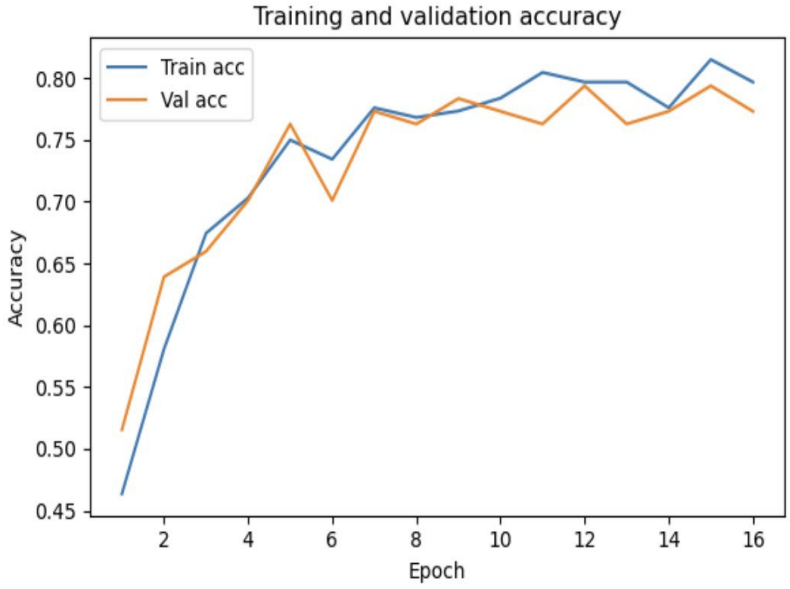

Figure 5: Training and Validation Accuracy Across Epochs

The curves in figure 4 indicate that the convergence behaviour is stable. The training and validation loss decrease rapidly in the first four epochs of the training. This indicates the optimization process using the gradient-based model is on track and the errors are being reduced at a fast rate. This preliminary drop is an indication that the model can learn helpful feature representations. In epoch 5-8, the validation loss can be observed to have small changes. Probably, these changes are introduced by random mini-batch updates and the invariance of the dataset is not guaranteed. It should be mentioned that the later epochs do not show long-term increase in validation loss. Following approximately epoch 8, the two curves become flat. The training loss decreases gradually, and the validation loss remains constant in a small range. The low-level of generalization indicates that the model is not overfitting excessively and that the variance is manageable. Figure 5 demonstrates that the curves of accuracy are still moving in the direction of stability of learning. Training accuracy increases gradually with an initial accuracy of approximately 46 percent in the first epoch and an average of more than 80 percent in subsequent epochs. The same happens to validation accuracy which culminates at approximately 78 to 79. The proximity between the training and validation accuracy indicates that the model can be generalised

with ease and that the balance of bias and variance is good. The intermediate epochs have the small changes in the performance between training and validation, however, there is no divergence, which indicates that convergence is high. The general trends in the loss and accuracy indicate that the proposed model can accomplish stable optimisation, predictive reliability, and generalisation to mental health risks classification.

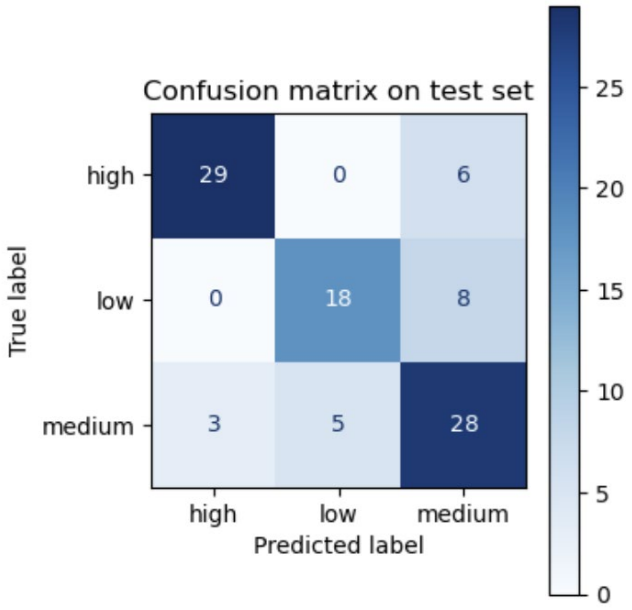

Figure 6: Confusion Matrix of Mental-Health Risk Classification on the Test Dataset

The confusion matrix of the proposed classifier on the test set appears in Figure 6. The true mental health risks labels are depicted in the y-axis, and the predicted labels are depicted in the x-axis. According to the matrix, the classes of high and medium risk performed very well. It further indicates that not all the low-risk cases are correctly identified as such and not all the medium-risk cases are correctly forecasted as high or low-risk cases. This indicates the key causes of classification errors. The model achieved an overall accuracy of 0.77, macro-averaged precision of 0.81, recall of 0.76, and F1 score of 0.77. The obtained results show that it worked well for all three risk levels. The results of the high/low risk categories were especially good, with the precision to recall ratio (precision/recall ≈ 0.90/0.80 for high risk and 0.90/0.62 for low risk). The medium-risk group showed slightly lower precision of 0.65 but a higher recall of 0.86 which gave an F1 score of 0.74. This pattern fits with the idea that profiles with intermediate risk are more varied and harder to separate clearly than profiles with clear low or high risk. The inference routine explains the decision process of the model on the individual cases. An example test student was with a true latent cluster label of medium, the model placed the medium latent cluster label in the correct model with a very high posterior probability of about 0.91, compared to either the high or low latent cluster label, which had an approximation of 0.05 and 0.04, respectively. It further determined that the student used various platforms and as such Facebook, Twitter, Instagram, YouTube, Snapchat, Reddit, Pinterest, and stated that they spend between three to four hours a day on social media. This example shows that the system can provide both a discrete risk label and calibrated probabilities, along with information about how much time is spent and which platforms are used. This is useful for practical screening. The risk labels are generated by an unsupervised autoencoder K-means stage rather than predefined thresholds. This means that the classifier can learn to map complex patterns of social media behaviour onto a hidden mental health category based on characteristics. This approach makes it easier for practitioners to connect predicted risk levels to specific questionnaire items (such as depression and sleep) and observable digital behaviours, rather than vague numerical thresholds. The experiments demonstrate that a collection of mental health data is adequate for deriving a significant 2D latent representation that categorises individuals into clinically relevant low-, medium-, and high-risk groups. Furthermore, a Transformer-based model can accurately predict these risk levels utilizing only self-reported social media usage.

Table 1: The performance of different traditional models and the proposed model on the Social Media and Mental Health dataset.

Models	Accuracy	F1-score
Support Vector Machine (SVM)	0.66	0.65
Multi-Layer Perceptron	0.67	0.67
Gradient Boosting	0.71	0.69
Logistic Regression	0.73	0.72
Random Forest	0.75	0.74
Proposed Model	**0.77**	**0.77**

The proposed model shows good performance in terms of precision, recall, and F1, with approximately 0.90, 0.80, 0.85 for high-risk; 0.89, 0.62, 0.73 for low-risk; and 0.65, 0.86, 0.74 for medium-risk, yielding a precision of 0.81 and a recall of 0.76. This result shows that the identification of high and medium-risk students, and a moderate decrease in recall of the low-risk group. Other models achieve lower F1 scores and tend to be less effective at discriminating the medium-risk group, suggesting that they do not sufficiently exploit the platform mix, time spent, and usage behaviours encoded in the proposed models' learned features. These findings support the claim that the implemented two-stage architecture, which includes an autoencoder-style latent risk discovery phase and a Transformer, achieves a measurable increase in performance that can be compared to the traditional machine-learning methods and simpler deep-learning baselines in applying them to the same dataset and label space. This enhancement is particularly relevant to the early detection of students at increased risk, where high F1 scores and the increased achievement on the high and moderate risk courses have greater marginal returns than marginal gains on the high-risk students who align with the majority in the low-risk category.

5. Conclusion

The study proposed a deep learning model for classifying students' mental health risks based on social media activity. In the initial phase, an autoencoder trained on mental health data created a 2-D latent representation. Applying K-means clustering to the representation yields three clinically interpretable categories (low, medium, and high risk) based on depression and sleep scores. In the second stage, the proposed model used social media platform sequences, time-spent categories, and usage-related similarity features simultaneously to infer these unsupervised risk labels. The proposed model achieved an accuracy of 0.77 and an F1-score of 0.77 on the public social media and Mental Health Kaggle dataset. This result was better than those of other models, such as Random Forest, Logistic Regression, Gradient Boosting, SVM, and an MLP, whose F1-scores ranged from 0.65 to 0.74. The improvement is significant for the high- and medium-risk categories, which are the most important for early intervention. The results show that combining latent representation learning with Transformer-based multimodal modelling provides an efficient technique for identifying mental health risks in higher education institutions. Although the present research confirms that social media behavioural patterns can be used to determine the level of mental health risks, the practical implementation of the given model will involve liaising with campus counselling centres and mental health workers. Possible uses would be creating anonymized early-warning dashboards to signal the at-risk groups, implementing the model into wellness platforms to give individualized advice, and helping institutes to make decisions regarding student wellbeing. Nevertheless, there are still several challenges. To begin with, larger and more varied datasets are needed in instances of generalization across platforms and across cultures. Second, there are ethical and privacy and consent issues associated with using self-reported or publicly accessible social media data. Third, the latent clusters though interpretable would need more clinical verification to obtain reliable attribution of risks. Lastly, longitudinal analysis is required to determine the correspondence between the anticipated degree of risks and the reality in terms of mental health modifications across a period. As a necessary action to transition research to practice, the solution to these limitations will result in a central area of future work.

Ethics Declaration

The study utilizes publicly available, anonymized datasets that do not contain personally identifiable information. As the research did not involve direct human participation or intervention, institutional ethical approval was not required.

AI Declaration

AI-assisted tools were utilized only to improve linguistic quality and readability.

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