Mental Health Trends Among Tertiary Education Students: A Bibliometric and Machine Learning Approach

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Abstract

Mental health challenges among tertiary education students have become a pressing global concern, necessitating innovative approaches to early detection and intervention. This study explores the application of machine learning (ML) techniques to predict mental health trends within this vulnerable population. Using a comprehensive dataset extracted from the Web of Science (WoS), a bibliometric analysis was conducted to map the evolution and research hotspots in the field from 2003 to 2023. Complementing this, a systematic review following the PRISMA framework evaluated the performance of thirty classification algorithms applied to five major mental health conditions, including anxiety, depression, bipolar disorder, schizophrenia, and post-traumatic stress disorder. Models such as Random Forest, Support Vector Machines (SVM), and Convolutional Neural Networks (CNN) demonstrated promising predictive accuracy, with CNN achieving up to 99.75% in detecting bipolar disorder. The study further discusses ethical challenges associated with ML applications, particularly concerning bias in clinical data, privacy issues, and the equitable treatment of diverse student populations. Findings underscore the potential of AI-driven approaches to deliver more personalised, timely, and effective mental health interventions tailored to university students' unique circumstances. By integrating bibliometric insights with empirical evaluation of ML models, this research contributes a comprehensive perspective on the state-of-the-art and future directions in AI-assisted mental health care within higher education contexts.

Keywords: Machine Learning, Mental Health, University Students, Artificial Intelligence, Predictive Modelling, Systematic Review, Ethical AI

1. Introduction

1.1 Background of the Study

Tertiary education students represent a population increasingly vulnerable to mental health challenges due to a complex interplay of academic, social, and environmental stressors (Zhou et al., 2023). Over the past two decades, the prevalence of conditions such as anxiety, depression, and post-traumatic stress disorder (PTSD) among students has risen significantly, leading to concerns regarding academic performance, personal well-being, and long-term societal impact (Nguyen et al., 2021). Conventional mental health interventions, including counselling and pharmacological treatments, have not kept pace with the growing demand or the need for early, personalised support mechanisms.

Simultaneously, advancements in artificial intelligence (AI), particularly in machine learning (ML), have opened new avenues in mental health research and care. ML algorithms can analyse vast and diverse datasets, ranging from clinical records to behavioural signals captured via smartphones, to detect patterns associated with psychological distress. Bibliometric analyses have shown a marked increase in the application of ML in mental health studies, especially from research hubs like the United States and China (Yuan et al., 2024). Keywords such as "deep learning," "predictive modelling," and "digital biomarkers"

have become increasingly prominent in the literature, indicating a shift toward data-driven and proactive mental health strategies.

1.2 Problem Statement

Despite the growing burden of mental health disorders among university students, current diagnostic and support systems are reactive rather than predictive. Traditional methods often fail to identify early warning signs or provide real-time, individualised intervention. Furthermore, existing ML research has not been fully contextualised within the academic setting or systematically evaluated for effectiveness, fairness, and practical applicability. Ethical concerns, such as bias in clinical datasets, privacy risks, and disparities in mental health outcomes across race and gender, remain unresolved. As such, there is a critical need for robust, interpretable, and ethically grounded ML systems tailored to the mental health needs of university students.

1.3 Aim and Objectives

The aim of this study is to evaluate the applicability and performance of machine learning approaches in predicting mental health trends among university students.

The objectives are to:

i. Review and compare commonly used ML algorithms in mental health research.
ii. Evaluate the predictive performance of these algorithms using relevant metrics such as accuracy, precision, recall, and AUC-ROC.
iii. Identify the most influential behavioural and contextual features that contribute to mental health outcomes.
iv. Analyse the ethical considerations and limitations associated with AI use in student mental health prediction.
v. Recommend strategies for implementing fair, data-driven, and scalable predictive models in academic institutions.

1.4 Significance of the Study

This study contributes to the evolving intersection of AI and mental health by focusing on an underserved but critical demographic: tertiary education students. By providing a systematic analysis of ML model performance and associated challenges, the research informs educators, mental health professionals, and policymakers on how to harness AI for early detection and intervention. The findings offer a pathway toward personalised mental health support systems that can improve student well-being, academic outcomes, and institutional readiness. Moreover, by addressing ethical implications, the study encourages the development of AI frameworks that prioritise equity, transparency, and user trust.

2. Methodology

2.1 Data Sources

This study conducted a comprehensive bibliometric analysis using four databases, namely Web of Science, PubMed, Scopus, and Google Scholar. The Web of Science was selected as the primary data source due to its high citation accuracy and peer-reviewed integrity (Falagas et al., 2008; Yuan et al., 2024). Search terms included “machine learning,” “mental health,” “university students,” and related keywords from 2003 to 2024.

2.2 Machine Learning Algorithms

A variety of ML algorithms were assessed, including:

- **Supervised learning**: Random Forest (RF), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Decision Trees, Logistic Regression, and Naïve Bayes.
- **Unsupervised learning**: Principal Component Analysis (PCA), K-means clustering (used less frequently due to clinical limitations).
- **Exclusion of Reinforcement Learning (RL)**: RL was excluded as it has not yet found strong applicability in mental health prediction contexts (Tate, 2021).

Feature sets included behavioural indicators from smartphone usage, sleep patterns, and GPS location data. In particular, the CES dataset, containing 45 manually curated features, was leveraged to improve model performance.

2.3 Systematic Review

A systematic review was conducted using PRISMA guidelines, applying strict inclusion and exclusion criteria. The final dataset included 128 articles that employed classification algorithms to predict five common mental health conditions. The review evaluated 30 algorithms, with key metrics analysed including precision, recall, specificity, AUC-ROC, and MCC.

2.4 Performance Evaluation

Model performance was validated using 5-fold cross-validation with K repeats. Hyperparameter tuning was conducted using a Tree-structured Parzen Estimator (TPE). Evaluation metrics included log-loss, Brier score, AUC-ROC, AUC-PR, sensitivity, and MCC (Zhang et al., 2023).

3. Results

3.1 Model Performance

The analysis revealed that supervised learning methods consistently outperformed unsupervised approaches in nearly all evaluated metrics. Among the models examined, Convolutional Neural Networks (CNN) achieved the highest predictive accuracy at 99.75% in detecting bipolar disorder, owing to their deep architecture and capacity to model complex patterns in behavioural data (Lekkas et al., 2021). Similarly, Support Vector Machines (SVM) demonstrated strong performance, achieving an F1-score of 0.90 in the classification of schizophrenia.

Random Forest (RF) models showed robust generalisability across heterogeneous datasets, particularly in identifying common trends in anxiety and depression. RF's ensemble approach and built-in feature importance measures made it both effective and interpretable. Light Gradient Boosting Machines (LightGBM) also performed competitively, with accuracy between 88% and 91%, especially when hyperparameters were optimised using the Tree-structured Parzen Estimator.

In contrast, Logistic Regression (LR), while offering a lower accuracy of around 78%, retains value due to its transparency and ease of deployment in real-world applications. Decision Trees (DT), despite being highly interpretable, suffered from overfitting and yielded slightly lower accuracy (75%).

At the lower end of the spectrum, Naive Bayes (NB) models achieved an accuracy of 72%, performing adequately for keyword-based text classification, though limited by their assumption of feature independence. K-Nearest Neighbours (KNN), with 74% accuracy, proved simple to implement but was sensitive to feature scaling and data imbalance—issues common in behavioural datasets.

These findings are summarised in Table 1 below.

Table 1: Summary of Machine Learning Model Performance for Predicting Mental Health Trends

Model	Accuracy (%)	Precision	Recall/F1-Score	AUC-ROC	Key Features Used	Interpretations/ Remarks
Convolutional Neural Network (CNN)	99.75	0.98	0.99	0.99	Sleep duration, phone time, and social time	Highest performance in detecting bipolar disorder
Support Vector Machine (SVM)	90.00	0.89	0.90	0.93	GPS data, activity labels, behavioural traits	Strong in predicting schizophrenia and PTSD
Random Forest (RF)	85.00 – 92.00	0.86	0.87	0.91	Sleep, phone use, location entropy	Balanced performance across all mental health categories
Logistic Regression (LR)	78.00	0.77	0.76	0.82	Time-based usage patterns, stress levels	Interpretable but less accurate than tree-based models
Decision Tree (DT)	75.00	0.74	0.73	0.79	Activity duration, device usage	Simple but prone to overfitting
Naive Bayes (NB)	72.00	0.70	0.68	0.76	Keyword features from survey responses	Assumes feature independence; lower performance on correlated datasets
K-Nearest Neighbours (KNN)	74.00	0.72	0.70	0.77	Sleep cycles, interaction patterns	Sensitive to feature scaling and data imbalance
Light Gradient Boosting (LightGBM)	88.00 – 91.00	0.88	0.89	0.92	Phone usage, me time, social interaction	Performed well with hyperparameter tuning using Tree-structured Parzen Est.

3.2 Feature Importance

The most influential features included:

- Sleep duration
- Location entropy
- Phone usage time
- Social interaction time
- "Me Time" indicators

Random Forest-based feature selection revealed that the inclusion of these behavioural indicators significantly enhanced model performance, achieving up to 60% accuracy despite challenges posed by high feature correlation and individual variability.

3.3 Comparative Analysis

SVMs appeared in 35.41% of the reviewed literature, followed by RF (28%) and CNN (17%). While LightGBM showed high precision in multiple classification tasks, it underperformed in sparse or highly variable datasets.

4. Discussion

4.1 Addressing Individual Variability

The accuracy limitations observed can be attributed to treating the dataset as homogeneous. Mental health experiences are highly individualised, influenced by contextual, cultural, and genetic factors. Future studies should adopt clustering or stratification techniques to account for demographic and psychographic diversity among students (Torous & Roberts, 2022).

4.2 Ethical Considerations

The ethical implications of AI-driven mental health interventions require urgent attention. Algorithmic bias—often rooted in skewed training datasets—can perpetuate disparities, particularly affecting students of marginalised racial, gender, or socioeconomic backgrounds. Implementing ethical AI frameworks grounded in autonomy, beneficence, and justice is imperative (Zhou et al., 2023).

4.3 Emerging Trends

AI-based psychotherapy applications are gaining traction as an alternative to traditional therapy. As conventional modalities exhibit limitations, especially in resource-constrained academic environments, AI offers scalable, real-time, and personalised support mechanisms. However, data privacy and the need for clinically validated AI systems remain obstacles (Nguyen et al., 2021).

4.4 Limitations and Future Research

This study is limited by its reliance on publications indexed in WoS, potentially excluding relevant grey literature. Furthermore, the absence of a standardised quality metric for ML research in mental health impedes consistent evaluation. Future research should explore multimodal data integration, improved stratification techniques, and user-centred AI model co-design with students and clinicians.

5. Conclusion and Recommendations

5.1 Conclusion

This study has demonstrated the potential of machine learning (ML) models in predicting mental health trends among university students, addressing a critical need for early intervention and personalised support. Through a systematic evaluation of supervised learning algorithms—including Convolutional Neural Networks, Support Vector Machines, Random Forest, and LightGBM—the research highlighted their strong predictive capabilities across conditions such as bipolar disorder, schizophrenia, anxiety, and depression. CNN achieved the highest accuracy (99.75%), while SVM and Random Forest models showed robust and generalisable performance.

In addition to technical evaluation, this study addressed the ethical, methodological, and contextual challenges of applying AI in student mental health. Key behavioural features such as sleep duration, phone usage, social activity, and location patterns were identified as critical indicators of mental well-being. Furthermore, the analysis revealed the limitations of data quality, algorithmic bias, and the need to account for individual differences in mental health experiences.

The findings affirm the value of integrating AI-based solutions into mental health care frameworks for university students, while also underscoring the importance of ethical considerations in their design and deployment.

5.2 Recommendations

To ensure responsible and effective adoption of AI-driven mental health prediction systems in academic institutions, the following recommendations are proposed:

1. **Institutional Integration**
   Universities should consider integrating ML models into existing student support systems, such as counselling services and wellness apps. These systems can offer early alerts for at-risk students based on behavioural patterns, subject to ethical safeguards.
2. **Cross-Disciplinary Collaboration**
   Collaboration between data scientists, psychologists, academic administrators, and IT professionals is essential to ensure models are both technically sound and contextually relevant.
3. **Ethical Oversight and Data Governance**
   Institutions must establish ethical frameworks to manage data privacy, informed consent, and fairness. Bias audits, explainable AI tools, and anonymised data practices should be mandated.
4. **Customisation and Personalisation**
   ML models should be trained using context-specific data and designed to account for individual variability, cultural sensitivity, and demographic diversity.
5. **Capacity Building and Training**
   Staff and student training on AI tools, mental health literacy, and digital ethics will improve adoption, trust, and responsible use of predictive systems.
6. **Ongoing Monitoring and Evaluation**
   Institutions should implement continuous performance evaluation and feedback mechanisms to refine models, address emerging ethical concerns, and ensure continued relevance.

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