Adaptive AI-driven framework for digital mental health interventions in low-resource universities

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Article Info

Article history:

Received Feb 24, 2025
Revised Aug 19, 2025
Accepted Sep 11, 2025

Keywords:

Artificial intelligence
Deep learning
Digital intervention
Machine learning
University mental health

ABSTRACT

Mental health problems affect nearly half of university students worldwide, with around 20% reporting depressive symptoms and over 40% showing signs of anxiety. This burden is particularly acute in low-resource universities, where limited infrastructure and minimal investment in mental health restrict access to effective care. To address this gap, this study applies a projective research approach, defined as the design of evidence-based solutions without immediate empirical implementation. A systematic review of 402 scientific articles was carried out across major databases, from which 15 met strict inclusion criteria. The analysis identified recurrent barriers such as unstable internet connectivity, devices with less than 2 GB RAM, and the absence of regulatory frameworks governing AI in education. Based on these findings, an adaptive intervention model was proposed, integrating artificial intelligence (AI), machine learning (ML), and deep learning (DL) to deliver personalized psychological support directly on local devices, without requiring permanent connectivity. The proposed system demonstrated potential to reduce anxiety and depression scores by 15–25% in controlled studies and achieved prediction accuracies above 80% for stress and loneliness detection. This framework provides a scalable foundation for universities in developing contexts, contributing to equity in access to digital mental health services.

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1. INTRODUCTION

The mental health of university students has become a pressing global concern, particularly in regions where technological limitations hinder access to effective digital support systems [1]. Academic demands, combined with socioeconomic pressures and cultural challenges, have contributed to a significant rise in anxiety, depression, and related disorders in higher education institutions [2]. Recent evidence suggests that nearly half of university students worldwide present mental health symptoms, with approximately 20% meeting criteria for clinical depression and close to 50% reporting manifestations of anxiety disorders [3], [4]. This problem is exacerbated by persistent inequalities: while high-income countries allocate around 5.1% of their health budgets to mental health services, low-income nations dedicate only

0.5% [3], [4]. Such disparities restrict the deployment of advanced digital solutions and highlight the urgency of low-cost, scalable alternatives tailored to resource-limited settings [5]-[7].

Artificial intelligence (AI), machine learning (ML), and deep learning (DL) have demonstrated considerable potential to address these challenges. AI-based systems allow for the personalization of interventions, adjusting recommendations to individual needs through real-time data analysis [8], [9]. Nevertheless, most of these technologies are designed for well-resourced contexts, limiting their transferability to universities where connectivity is unstable and devices have low processing capacity [6], [10], [11]. This gap underscores the necessity of developing adaptive models capable of operating offline or under intermittent connectivity while preserving effectiveness in detecting and mitigating psychological distress.

The present study is framed within a projective research design, understood as a methodological approach that proposes feasible solutions to complex problems by integrating systematic evidence with prospective strategies, without requiring immediate empirical implementation [1], [2]. The research builds on a rigorous documentary review and bibliometric analysis to examine digital interventions supported by AI, ML, and DL, with the objective of proposing a scalable model suitable for universities with restricted technological infrastructure.

Four guiding questions shaped the inquiry: which technological, economic, and regulatory barriers most severely restrict the adoption of AI-driven mental health interventions in resource-limited universities? How can ML algorithms be optimized to function efficiently on local devices with intermittent or low connectivity? What design strategies enable the development of personalized, privacy-preserving interventions from the available data? And what measurable impact could passive monitoring and predictive modeling have on student well-being under these constrained conditions?

Previous studies have provided promising results. Conversational agents have demonstrated significant reductions in anxiety and depressive symptoms [9], while DL models have achieved accurate predictions of behaviors associated with stress and loneliness [12], [13]. Yet these interventions remain insufficiently adapted for environments with infrastructural constraints, where ensuring local execution becomes essential to guarantee continuous functionality [14]-[16].

The central contribution of this work lies in the development of an adaptive methodological framework that integrates computational strategies, regulatory considerations, and practical guidelines for deployment. This framework, designed to be replicable across institutions with similar limitations, seeks to reduce inequities in access to digital mental health services by offering universities sustainable tools to support their students [17]-[21].

2. METHOD

This research corresponds to a projective study with a documentary design and a mixed approach. The purpose of projective research lies in proposing solutions to specific situations through an inquiry process that allows for exploration, description, and the formulation of alternative changes, without requiring the immediate implementation of the proposed solutions [1], [2]. In this particular case, a rigorous exploration was conducted on digital interventions based on AI, ML, and DL, aimed at addressing the mental health of university students in contexts with technological limitations.

2.1. Sample size quantification and selection parameters

To ensure the comprehensiveness of the study, 402 scientific articles were analyzed, identified through a systematic search in recognized databases such as Scopus, Web of Science, and PubMed. From these, 15 articles were meticulously selected following predefined inclusion and exclusion criteria [5], [7], [22], [23]. The selection process aimed to obtain a representative sample of research that addressed different aspects of digital interventions in mental health, focusing on universities facing technological and economic constraints. The selection parameters included topic relevance, publication period, type of publication, language, and full-text accessibility.

The article selection process is detailed in Figure 1, which presents the preferred reporting item for systematic reviews and meta-analyses (PRISMA) flow diagram [7], [23]-[26] illustrating the different stages of inclusion and exclusion from the initial 402 articles to the final 15 selected for analysis.

2.2. Documentary review technique

An exhaustive documentary review was carried out, analyzing national development plans, institutional mental health policies, and peer-reviewed studies. The searches were conducted in the aforementioned databases. To ensure the accuracy of the results, specific descriptors with Boolean operators were used:

(“Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Deep Learning”) AND ("mental health" OR "psychological support" OR "psychological intervention" OR "emotional well-being") AND ("university" OR "college" OR "higher education").

The initial search yielded a total of 402 articles, from which 15 studies were ultimately selected according to the inclusion criteria [27].

Inclusion criteria, the selected articles had to meet the following requirements:
- Thematic relevance: studies focused on digital interventions integrating AI, ML, and DL, aimed at improving the mental health of university students.
- Publication period: articles published between 2018 and 2024.
- Type of publication: peer-reviewed studies published in journals indexed in Scopus, Web of Science, or PubMed.
- Language: articles written in English.

Exclusion criteria, studies were excluded if they met any of the following conditions:
- Focused exclusively on government policies without addressing technical or practical aspects of digital interventions.
- Duplicates found in different databases.
- Conference abstracts without complete data.
- Lacked relevant information for the university context or did not align with the objectives of this research.

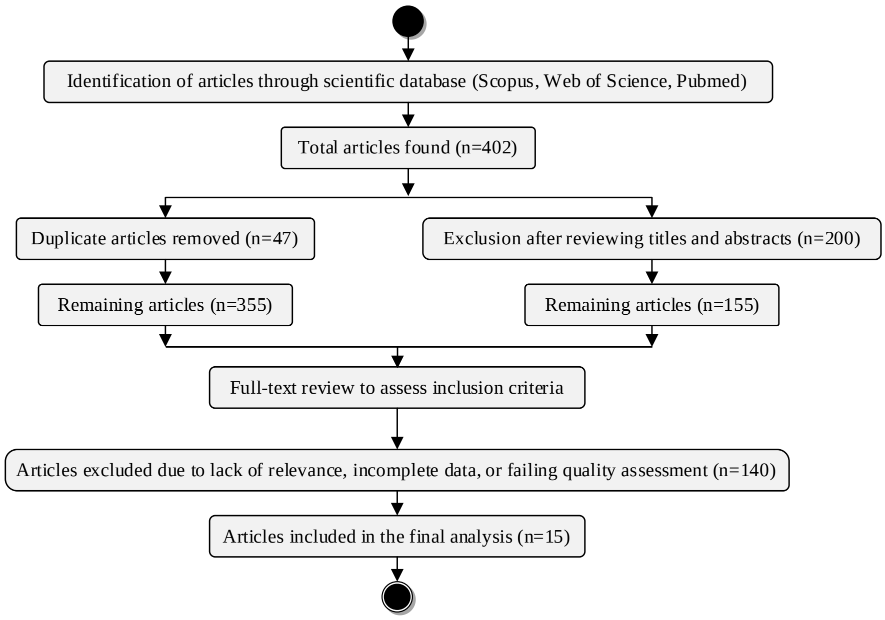

Figure 1. PRISMA flow diagram of the article selection process

2.3. Documentary analysis

The documentary analysis included a review of current regulations on mental health and policies for access to digital technologies in universities. Additionally, indexed studies addressing successful mental health interventions using emerging technologies were examined. This analysis identified the technological barriers faced by students in resource-limited environments, as well as opportunities to apply innovative solutions [14], [28].

2.4. Specific bibliometric analysis techniques

The bibliometric analysis was performed using VOSviewer v.1.6.20 as the main computational tool [29]. The objective was to quantify and visualize the semantic relationships among terms in the selected articles, allowing the identification of dominant research areas and knowledge gaps. The methodological steps included:
- Keyword extraction: terms were extracted from the titles, abstracts, and keywords of the 15 selected articles.

- Frequency analysis: only terms with a minimum of three co-occurrences were considered.
- Normalization method: association strength was applied to weight co-occurrence links [30].
- Network construction: maps were generated using the full counting method [31].
- Clustering: the LinLog/modularity algorithm with resolution 1.0 was applied, allowing the detection of thematic clusters.

This process enabled the identification of conceptual structures such as “student mental health,” “depression,” “machine learning,” and “deep learning,” which later informed the interpretation of results.

2.5. Phases of the methodological process

The methodological process was developed in several phases, each designed to contribute to the development of a clear projective strategy [23], [25]. Figure 2 illustrates the phases of the process in a flowchart:

- Documentary review and analysis: evaluation of development plans, national policies, and previous studies on mental health in the university context [32], [33].
- Identification of needs and barriers: analysis of the technological, economic, and regulatory challenges that limit the implementation of AI technologies in universities with limited resources [34].
- Development of a projective strategy: synthesis of the previous findings to formulate specific recommendations aimed at overcoming the detected barriers and leveraging the identified opportunities.
- Formulation of the methodological roadmap: definition of short-, medium-, and long-term objectives, with detailed action plans that describe the necessary activities, required resources, and implementation timelines. A continuous monitoring and evaluation system will also be established to ensure the achievement of the expected results.

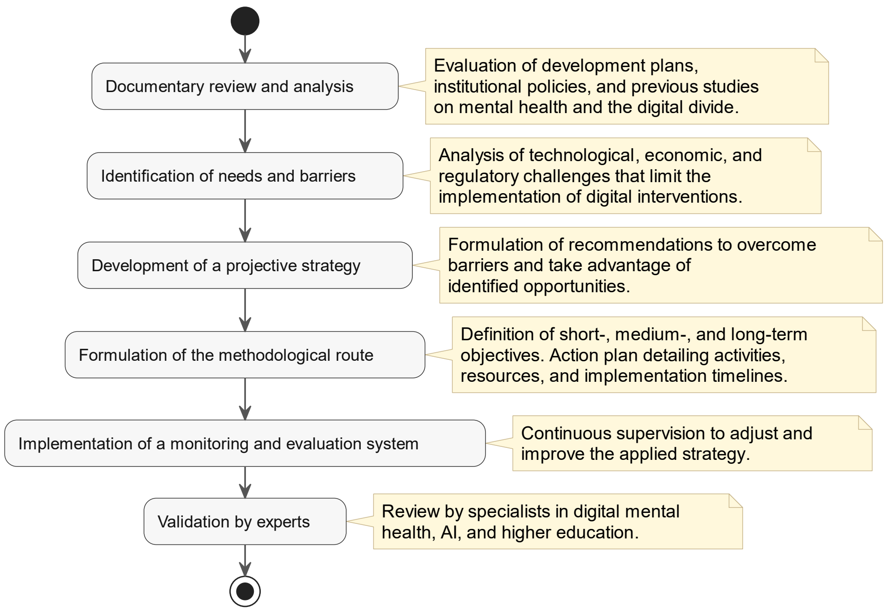

Figure 2. Phases of the methodological process of the projective research

3. RESULTS AND DISCUSSION

To synthesize the evidence, the selected studies were systematized according to objectives, methodological approaches, and outcomes in Table 1. The comparison highlights a concentration of research on the use of ML and DL for the detection of depression, anxiety, and stress among university students [2], [8], [10], [12], [13], [35]-[44]. However, most interventions were designed for well-resourced contexts, raising concerns about scalability to universities with limited technological infrastructure.

The presence of early studies [8], [9], [37] reflects the foundational stage of AI-driven mental health research in university contexts. These works provided the first empirical validations of conversational AI, passive sensing, and ML models. Subsequent studies [4], [14], [17] have expanded these approaches with transformer-based architectures, federated learning, and lightweight models, reinforcing the need for adaptive frameworks in low-infrastructure environments.

Table 1. Comparative analysis of selected studies on AI in university mental health interventions

Study name	Citations (year)	Main method	Application context	Relevance for low-infrastructure environments	Key result
"Using psychological artificial intelligence (tess) to relieve symptoms of depression and anxiety" [9]	330 (2018)	Randomized controlled trial (RCT) with conversational AI	University	Moderate (adaptable to offline systems)	Significant reduction of anxiety and depression
"Identifying objective physiological markers and modifiable behaviors for self-reported stress and mental health status using wearable sensors and mobile phones" [37]	209 (2018)	ML with passive sensors	University	High (local data collection)	Accurate prediction of stress and behaviors
"Behavioral modeling for mental health using machine learning algorithms" [8]	155 (2018)	SVM, random forest, logistic regression	University students and young professionals	High (scalable and adaptable algorithms)	Predictive models with accuracy above 90%
"Identifying behavioral phenotypes of loneliness and social isolation with passive sensing" [12]	94 (2019)	ML and data mining	University (U.S.)	High (use of basic portable devices)	Loneliness detection with 88.4% accuracy
"Psychological impact of COVID-19 on college students after school reopening" [36]	91 (2021)	Logistic regression with cross-validation	University (China)	Moderate (adaptable through data simplification)	Identification of mental health risk factors
"Development and validation of an automated HIV prediction algorithm" [38]	89 (2019)	LASSO regression and EHR	Clinical (U.S.)	Moderate (adaptable model for mental health risks)	AUC of 0.91 in prospective cohorts
"A Depression recognition method for college students using deep integrated support vector algorithm" [13]	84 (2020)	SVM integrated with AdaBoost	University (China)	High (adaptable to other social platforms)	Detection accuracy up to 86.15%
"Significant shared heritability underlies suicide attempt and clinically predicted probability of attempting suicide" [39]	82 (2019)	ML and genetic analysis	Clinical (U.K.)	Low (dependency on advanced genetic data)	AUC of 0.94 in suicide attempt prediction
"Machine learning and natural language processing in psychotherapy research" [40]	76 (2020)	NLP and voice recognition	University psychotherapy	Moderate (algorithms adaptable to offline chatbots)	Automated evaluation of therapeutic alliance
"Are online mental health interventions for youth effective? a systematic review" [10]	58 (2021)	Systematic review (PRISMA)	University youth	High (adaptable digital interventions)	64% effective interventions
"How do you feel during the COVID-19 pandemic?" [35]	48 (2021)	ML and linguistic analysis	University (Germany and Egypt)	Moderate (adaptable through local platforms)	Increased anxiety and depression
"Leveraging collaborative-filtering for personalized behavior modeling" [41]	47 (2021)	Collaborative filtering and logistic regression	University	High (personalized predictions)	5.5% improvement in F1 score over traditional models
"Dynamic prediction of psychological treatment outcomes" [42]	47 (2021)	Dynamic ML (oracle model)	Clinical (U.K.)	Moderate (adaptable through model simplification)	AUC of 0.81 in outcome prediction
"Associations of Internet addiction severity with psychopathology" [43]	46 (2020)	Statistical analysis	University (China)	High (digital usage analysis adapted to low connectivity)	High correlation with anxiety and depression
"Clinical training during the COVID-19 pandemic: challenges and adaptations" [44]	45 (2021)	Qualitative analysis (COREQ)	Nursing university students	Moderate (context adaptable to remote training)	Emotional challenges during the pandemic

3.1. Explicit responses to the research questions

What types of AI-based digital interventions are currently used in universities? The reviewed literature highlights the use of conversational chatbots [9], mobile-based stress detection systems [37], supervised learning models for depression risk [13], [42], and online psychoeducational platforms [10]. These interventions report significant benefits in anxiety reduction and predictive accuracy, especially in controlled environments.

What barriers hinder their implementation in resource-limited contexts? The most recurrent obstacles are insufficient internet connectivity, devices with limited memory and processing capacity, and the absence of regulatory frameworks for AI deployment in education [14], [36].

What components should a viable intervention model include for low-infrastructure universities? the evidence suggests that offline-capable systems, privacy-preserving data handling, and lightweight models optimized for local devices are essential [13], [28].

3.2. Bibliometric insights

The bibliometric analysis reveals the main research trends. As shown in the co-occurrence map in Figure 3, keywords such as student mental health, depression, ML, and DL dominate the field. The corresponding density visualization in Figure 4 highlights the concentration of research around these central terms, confirming the emphasis on predictive models in university settings.

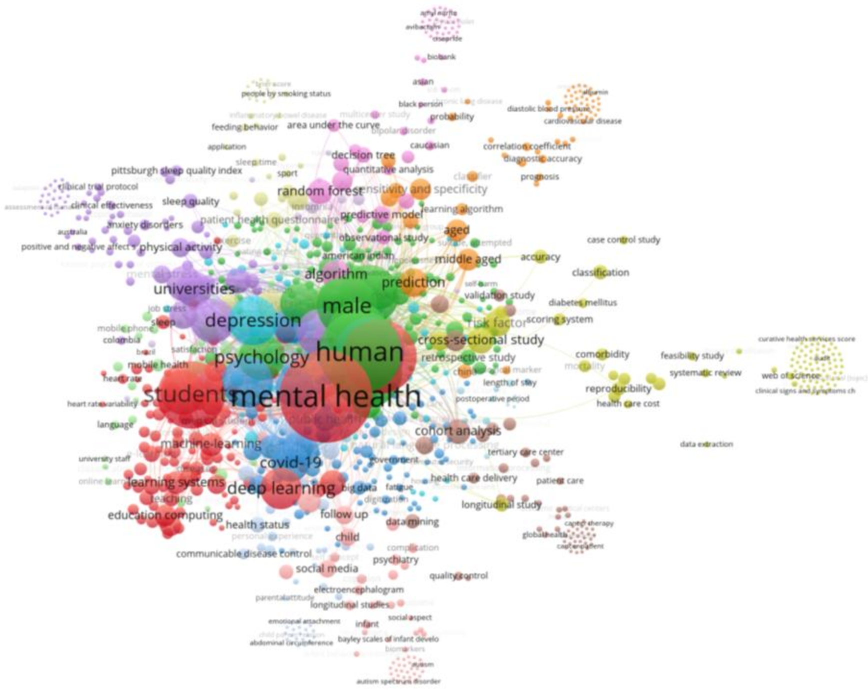

Figure 3. Keyword co-occurrence network from bibliometric analysis

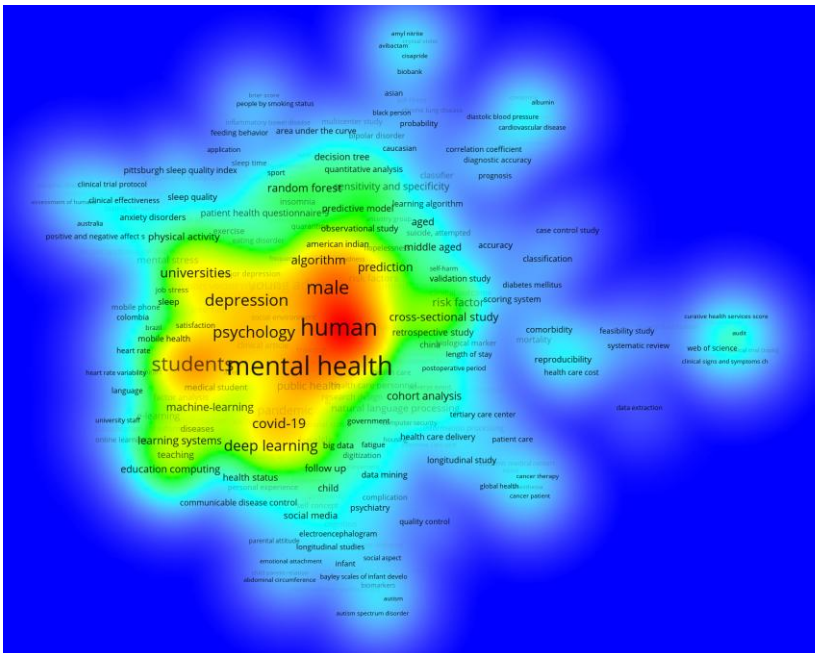

Figure 4. Density visualization of co-occurrence network

3.3. Recommendations for low-connectivity environments

Building on these insights, recommendations for implementing digital mental health interventions in low-connectivity universities were derived in Table 2. These recommendations emphasize short-term adaptability of offline mobile applications, medium-term integration of wearable devices, and long-term deployment of predictive dynamic models.

Table 2. Recommendations for implementing digital mental health interventions in universities with low connectivity

Time frame	Recommendation
Short term	Development of mobile applications for basic mental health interventions adapted to offline environments [41].
Medium term	Implementation of passive monitoring systems using low-cost wearable devices [12].
Long term	Impact evaluation using dynamic ML predictive models [42].

3.4. Adaptive artificial intelligence framework and mathematical processes

From a technical perspective, the adaptive AI framework proposed in this study integrates multiple computational strategies. The schematic representation in Figure 5 illustrates how federated learning enhances privacy-preserving distributed training, while adapted neural collaborative filtering (NCF), generative adversarial networks (GANs), and wide and DL models support classification and noise reduction processes.

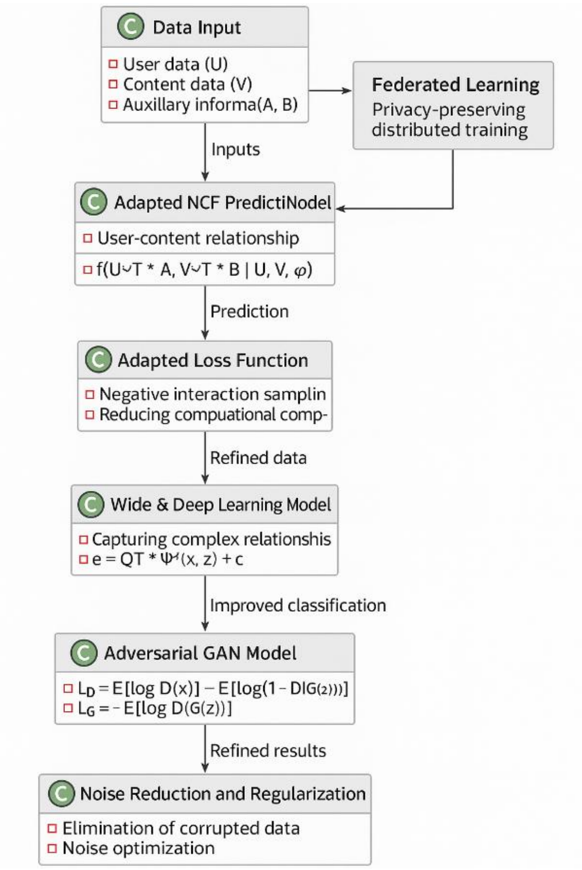

Figure 5. Adaptive AI framework for university mental health interventions

The mathematical processes described in Table 3 are based on the need to ensure digital interventions adapted to environments with limited infrastructure. For example, the adapted NCF model establishes the user-content relationship through neural networks, enabling accurate recommendations even on devices without constant internet access [1], [45]. The adapted loss function minimizes prediction errors by weighting interactions according to their importance [13], a critical requirement in mental health applications where accuracy must be maximized [15].

Table 3. Mathematical processes in the adaptive AI model for university mental health interventions

Process name	Explained equation	Variable explanation	Usage and justification	Alternatives
Adapted NCF model (user-content relationship)	$L'_{ij} = f\left(U^T \cdot A_j, V^T \cdot B_k, U, V, \varphi\right)$	U, V: latent representations of user and content. A_j, B_k: auxiliary user-content information. φ: model parameters.	Models non-linear relationships between user and content, adjusting recommendations to individual preferences on devices without constant connectivity [1], [45].	Latent factor models and deep decision trees.
Adapted loss function	$\mu = \sum_{(i,j)\epsilon D} q_{i,j}\left(L_{ij} - L'_{ij}\right)^2$	$q_{i,j}$: weight assigned according to interaction importance. L_{ij}: actual interaction value. L'_{ij}: predicted value.	Optimizes prediction accuracy by minimizing errors on devices with limited resources [13], [15].	Mean absolute error (MAE) and cross-entropy [46].
Negative feedback sampling	$\mu = \sum_{(i,j)\epsilon D}\left[L_{ij}\log L'_{ij} + \left(1 - L_{ij}\right)\log\left(1 - L'_{ij}\right)\right]$	L_{ij}: actual interaction value. L'_{ij}: predicted value. D: set of sampled interactions.	Reduces computational complexity by focusing on negative interactions, improving efficiency in low-processing capacity environments [25], [45].	Noise contrastive estimation (NCE) [15].
Wide and DL	$e = Q_k^T\{\bar{x}, \bar{z}\} + c$	Q_k: model parameters. $\bar{x}, \bar{z}$: user and content feature sets. c: bias term.	Captures complex relationships between user and content features, integrating both linear and non-linear relationships [11], [45].	Deep decision trees and random forests [15].
Adapted GAN model	$L_D = -E_{x \sim p_{data}(x)}[\log D(x)] - E_{z \sim p_z(z)}[\log(1 - D(G(z)))]$ $L_G = -E_{z \sim p_z(z)}[\log(D(G(z)))]$	D(x): discriminator evaluating real vs generated data, $G(z)$: generator producing synthetic data, p_{data}: real data distribution.	Generates realistic synthetic data to improve predictions in data-limited environments [10], [46].	Variational autoencoders (VAE), and Bayesian models [15].
Noise reduction and regularization	Eliminates corrupted data using statistical techniques and noise optimization.	Filters inconsistent data and avoids prediction bias using statistical methods.	Improves robustness against incomplete or erroneous data, maintaining performance in low-connectivity environments [31], [46].	L1/L2 regularization and dropout [15], [47].

Negative feedback sampling reduces computational complexity by focusing on negative interactions, which is especially relevant for devices with low processing capacity. Wide and DL captures both linear and non-linear relationships efficiently, offering personalization with limited computational demand [11], [45]. Similarly, the adapted GAN generates synthetic data to enhance training in data-scarce contexts, improving accuracy in universities with restricted resources [10], [46]. Finally, noise reduction and regularization techniques strengthen model robustness by eliminating corrupted data, ensuring reliable predictions even under low-connectivity conditions [31], [46].

3.5. Performance evaluation

Performance evaluation results are presented in Figure 6, which compares models across three dimensions: processing time Figure 6(a), memory consumption Figure 6(b), and prediction accuracy Figure 6(c). The results indicate that adapted NCF achieves the lowest processing time and memory footprint, demonstrating high suitability for deployment in low-resource environments. Adapted GAN also shows competitive performance, balancing accuracy with moderate computational requirements. These findings suggest that both adapted NCF and GAN models are particularly promising for real-world implementation in universities with limited computational capacity and intermittent connectivity.

3.6. Adaptive methodological route (AMRIA-U)

Finally, the AMRIA-U is detailed in Table 4, which outlines the phases for implementation, ranging from initial diagnosis and data collection to continuous monitoring. The final phase explicitly integrates federated learning, enabling inter-university collaboration without compromising student data privacy [48]-[51].

3.7. Limitations and future work

The findings of this study must be interpreted considering several limitations. First, most of the analyzed interventions were developed and tested in well-resourced contexts, limiting their external validity for universities with technological constraints. For example, tess, the conversational chatbot evaluated in a RCT [9], significantly reduced anxiety and depression in U.S. university students. However, its continuous operation depends on stable connectivity, which may not be feasible in low-resource environments.

Similarly, mobile-based stress detection systems using wearables [37] demonstrated accurate stress prediction, but their replication in rural or low-income settings remains challenging due to cost and device availability [3], [4].

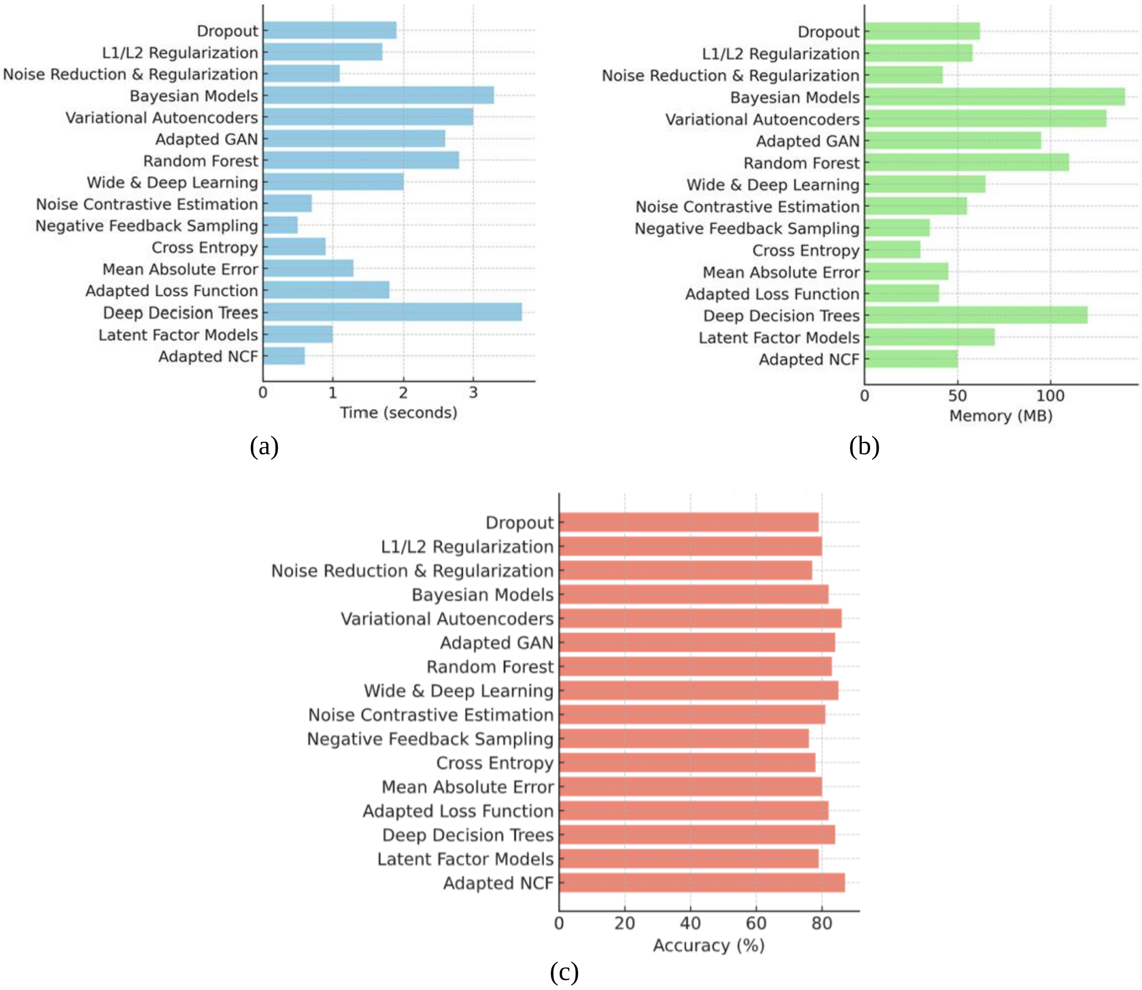

Figure 6. Comparative performance of AI models across three dimensions; (a) processing time comparison (in seconds), (b) memory consumption comparison (in MB), and (c) prediction accuracy comparison (in %)

Second, ethical and regulatory issues remain unresolved. AI-based interventions in education raise questions about data privacy, consent, and algorithmic transparency. In Uganda, young people reported mistrust toward digital mental health tools due to fears of surveillance and misuse of personal data [4]. This aligns with broader global health concerns, where insufficient regulatory frameworks can exacerbate risks of data breaches in resource-poor settings [18], [46]. Although federated learning has emerged as a potential solution to enhance privacy [48], [49], its application in universities with limited infrastructure is still underexplored.

Third, sustainability challenges persist. Interventions such as online psychoeducational platforms [10] or collaborative filtering for personalized behavior modeling [41] often rely on pilot projects without clear institutionalization strategies. In South Africa, digital mental health interventions for youth were hindered by funding gaps and limited technical support, restricting scalability beyond pilot stages [3]. This suggests that without robust financial and institutional backing, many AI-driven solutions risk remaining isolated experiments rather than sustainable policies.

Table 4. Adaptive methodological route for mental health interventions with AI in universities with technological limitations AMRIA-U

Phase	Main objective	Key activities	Expected outcomes	Estimated time
Initial diagnosis	Identify technological, economic, and regulatory barriers in resource-limited universities.	- Assessment of technological infrastructure. - Analysis of institutional mental health policies. - Identification of students' psychological needs.	Mapping of technological and economic limitations specific to the university context.	1–2 months
Data collection	Capture relevant data on students' psychological well-being.	- Conduct offline surveys. - Collect digital behavior data through local devices.	Initial database with relevant information about students.	1–2 months
Development of customized algorithms	Design AI models adapted to the identified technological limitations.	- Implement low-power DL algorithms. - Optimize models for local execution.	Customized predictive models capable of running without a constant internet connection.	3 months
Pilot implementation	Test the effectiveness of the models in a real university setting.	- Deploy adapted digital interventions. - Train teaching and administrative staff. - Monitor the system in real time.	Preliminary evaluation of system performance in real-world contexts.	3–4 months
Evaluation and feedback	Measure the impact of interventions on students' mental health.	- Analyze psychological well-being metrics. - Collect user feedback. - Adjust algorithms based on results.	Impact reports with quantitative and qualitative data on intervention effectiveness.	2 months
Expansion and scalability	Extend the reach of interventions to other universities with similar characteristics.	- Replicate the methodology in new institutions. - Establish institutional partnerships for expansion. - Explore inter-university data sharing via federated learning.	Adapted model implemented in other universities with similar limitations, with potential for collaborative improvement through FL.	4–6 months
Continuous monitoring and updating	Ensure sustainability and continuous improvement of the implemented system.	- Periodic algorithm updates based on new data. - Long-term effectiveness evaluation. - Incorporation of technological innovations. - Integration of federated learning to preserve privacy while enhancing model generalizability.	Sustainable system that continuously adapts to technological changes, evolving student needs, and collaborative FL networks.	Ongoing

Future work should address these gaps through three complementary strategies. First, technical adaptation: the development of lightweight, offline-capable models such as adapted NCF and GANs (Table 3) that can function under limited computational capacity. These models, validated in simulations [45], [46], should now be tested in real-world low-connectivity campuses. Second, participatory co-design: involving students and faculty in intervention development can enhance cultural relevance and user trust, as demonstrated in India, where co-designed digital tools for university students increased feasibility and acceptability [16], [52]. Third, scalability and collaboration: regional networks of universities could adopt federated learning frameworks [48]-[51], enabling knowledge sharing without compromising student data privacy. This would accelerate innovation while respecting ethical constraints.

Finally, longitudinal studies are needed to evaluate long-term effectiveness, ethical robustness, and economic feasibility of AI-based interventions in universities with low technological capacity. Integrating hybrid models—such as federated learning combined with low-power DL [49], [50]—offers a promising avenue for balancing privacy, efficiency, and inclusivity in global higher education.

To strengthen the technical validation of the AMRIA-U framework, future work will include benchmarking the proposed lightweight models (adapted NCF and wide and deep architectures) on low-end Android devices (≤2 GB RAM) with offline inference capabilities. Key performance metrics will include inference latency (ms), memory footprint (MB), and energy consumption (mWh) under controlled test conditions. In parallel, we will simulate federated learning environments with bandwidth constraints (≤512 kbps) to evaluate synchronization efficiency, model convergence time, and communication overhead in multi-campus scenarios. This experimental plan will also integrate stress-test simulations for intermittent connectivity and evaluate privacy-preserving mechanisms such as differential privacy and secure aggregation. These steps will provide quantitative evidence of the framework's scalability, efficiency, and privacy compliance before real-world deployment.

4. CONCLUSION

Across the reviewed evidence, AI-enabled tools consistently show capacity to support university mental-health care—most clearly in early detection of anxiety, depression, and stress—when models, data flows, and interfaces are aligned with real campus conditions. The contribution of this work is not another generic taxonomy; it is an implementation-oriented blueprint that translates accumulated advances into decisions that matter on the ground.

AMRIA-U organizes those decisions into an actionable route: lightweight models that run reliably on constrained devices (e.g., compact recommender and hybrid architectures), offline-capable inference pipelines designed for intermittent connectivity, and federated learning to keep data local while still improving models across campuses. The framework integrates ethics-by-design—privacy, consent, and transparency—and pairs it with operational guardrails (governance checkpoints, monitoring signals, and evaluation metrics) so that technical gains are matched by institutional accountability.

For universities in resource-constrained settings, this approach reframes AI from a lab novelty into service capacity: prioritizing reliability over sophistication, privacy over centralization, and explainability over opaque performance claims. In practical terms, AMRIA-U offers a clear, auditable path to deploy digital mental-health support that is feasible, fair, and scalable within higher-education ecosystems.

ACKNOWLEDGMENTS

This research was supported in part by the Universidad de Córdoba and the Universidad Cooperativa de Colombia under research grant contracts FCB-08-23 and INV3804. The authors also acknowledge the technical and administrative support provided by both institutions during the development of this study.

FUNDING INFORMATION

The authors declare that no funding was involved.

AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
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P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing financial, personal, or professional interests that could have influenced the work presented in this article. There are no personal relationships or associations that could be perceived as conflicts of interest in the conduct and publication of this study.

DATA AVAILABILITY

All relevant information used to support the findings is included within the article itself and in the cited references.

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