The Improvement of Stress Coping Behaviour and Learning Engagement Artificial Intelligence Personalized Mental Health Education

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ABSTRACT

Background: *Mental health problems and declining learning engagement among university students have become major concerns within digitally intensive higher education environments. Although artificial intelligence (AI) technologies have increasingly been integrated into educational systems, previous studies have rarely combined personalized mental health education, adaptive coping recommendations, and behavioral engagement analytics within a single intervention framework. Therefore, this study aimed to examine the effectiveness of AI. personalized mental health education in improving stress coping behavior and learning engagement among university students.*
Method: *This study employed a sequential explanatory mixed methods intervention design involving 289 undergraduate students from Universitas Hang Tuah Pekanbaru and Institut Kesehatan Payung Negeri Pekanbaru, Indonesia, during 2025. Data were collected using structured questionnaires and behavioral engagement analytics from digital learning activities. Quantitative data were analyzed using paired sample t tests and SEM PLS, while qualitative data were analyzed thematically.*
Result: *The findings demonstrated statistically significant improvements across all psychosocial and academic engagement dimensions ($p<0.001$). It induced positive changes in students stress coping behavior and learning engagement following the intervention. SEM PLS analysis additionally revealed significant direct and indirect effects of AI personalized mental health education on stress coping behavior, emotional wellbeing, and learning engagement. Qualitative findings further indicated that students perceived the intervention as adaptive, emotionally supportive, and beneficial for improving self regulation and academic motivation. These findings provide preliminary evidence that AI personalized mental health education may contribute to improved stress coping behavior and learning engagement among university students.*

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INTRODUCTION

Mental health problems among university students have become a growing global public health concern, particularly within digitally intensive higher education environments. Increasing academic pressure, prolonged online learning exposure, emotional exhaustion, and psychosocial adaptation difficulties have substantially affected students' wellbeing and academic participation in recent years. Recent evidence indicates that university students frequently experience elevated levels of stress, anxiety, emotional dysregulation, and learning disengagement associated with academic workload and digital learning demands.(1)(2) Furthermore, psychologically vulnerable students often demonstrate lower motivation, reduced classroom participation, and weaker self--regulated learning behaviors, potentially affecting long term academic achievement and psychosocial wellbeing.

Learning engagement has increasingly been recognized as a critical factor influencing academic success, emotional adaptation, and educational sustainability in higher education settings. Students with poor emotional regulation and ineffective stress coping strategies frequently experience cognitive fatigue, decreased participation consistency, and reduced academic motivation. Previous studies demonstrated that emotional wellbeing significantly influenced behavioral, emotional, and cognitive engagement among university students within technology supported learning environments.(3)(4) Consequently, higher education institutions are increasingly required to develop adaptive intervention strategies capable of simultaneously addressing psychosocial wellbeing and academic engagement challenges.

In Indonesia, mental health concerns among university students have received increasing attention following the expansion of digital and blended learning practices in higher education. Recent studies have reported that Indonesian students frequently experience academic stress, emotional exhaustion, anxiety, and difficulties adapting to technology intensive learning environments. The rapid integration of digital learning platforms has provided greater educational flexibility; however, it has also increased psychological demands associated with academic workload, self regulation, and continuous online engagement. These challenges may negatively affect students' emotional wellbeing and learning participation if appropriate psychosocial support mechanisms are not available. Consequently, Indonesian universities are increasingly encouraged to develop innovative and scalable mental health promotion strategies capable of supporting both student wellbeing and academic engagement within digitally mediated learning environments.

The rapid advancement of artificial intelligence (AI) technologies has recently transformed educational and mental health support systems within higher education. AI based educational tools, intelligent tutoring systems, and adaptive digital learning environments have demonstrated substantial potential for improving personalized learning experiences, emotional support accessibility, and student engagement outcomes. AI driven mental health systems additionally offer opportunities for personalized emotional guidance, adaptive coping recommendations, and scalable psychosocial support mechanisms capable of addressing increasing student mental health concerns.(5) Previous studies also reported that AI supported educational environments positively influence emotional resilience, self- efficacy, and adaptive learning behavior among university students.(6)

Despite these promising developments, several important limitations remain within the existing literature. First, many previous studies primarily focused on generalized AI learning systems or academic chatbot utilization without specifically integrating personalized mental health education and adaptive psychosocial intervention mechanisms.(7) Second, existing studies often examined student engagement, emotional wellbeing, or AI acceptance separately, resulting in limited understanding regarding the multidimensional relationships among AI personalized intervention, stress coping behavior, emotional wellbeing, and learning engagement.(8) Third, relatively few studies have combined behavioral engagement analytics, adaptive emotional support, and AI driven coping recommendations within a single intervention framework.(9) Moreover, previous research has predominantly employed cross sectional or correlational approaches, thereby limiting deeper understanding regarding intervention effectiveness and psychosocial adaptation mechanisms among university students.(10)(11)

Another critical issue concerns the growing dependence on AI technologies within higher education without sufficient integration of emotionally responsive and psychologically adaptive educational frameworks.(12) Several recent studies warned that excessive AI dependence may negatively affect students' critical thinking, emotional interaction, and learning authenticity if not accompanied by appropriate psychosocial support systems.(13)(14) Therefore, there is an urgent need to develop AI driven educational interventions that not only support academic performance but also strengthen emotional wellbeing, adaptive coping behavior, and engagement sustainability within higher education environments.

To address these gaps, the present study developed and evaluated an AI personalized mental health education intervention integrating adaptive coping recommendations, emotional support guidance, and behavioral engagement analytics within blended higher education environments. Unlike previous studies focusing primarily on generalized AI learning support, the current study employed a sequential explanatory mixed methods intervention design to examine both the direct and indirect relationships among AI personalized mental health education, stress coping behavior, emotional wellbeing, and learning engagement among university students. The study additionally explored students' perceptions and psychosocial adaptation experiences following participation in the personalized intervention program. The findings are expected to contribute theoretically and practically to the growing field of AI driven educational wellbeing interventions by providing an integrated psychosocial adaptation framework capable of supporting emotional resilience and academic engagement sustainability within digitally intensive higher education environments.

METHOD

Design and participants

This study employed a sequential explanatory mixed methods intervention design to examine the effectiveness of AI Personalized Mental Health Education on stress coping behavior and learning engagement among university students. The quantitative phase utilized a one-group pretest–posttest quasi-experimental design, followed by a qualitative phase to explore participants' experiences and perceptions of the intervention. Pretest was conducted one week before the intervention, while posttest was administered immediately after the completion of the eight-week intervention program. Subsequently, semi-structured interviews were conducted with 20 purposively selected participants representing varying levels of intervention engagement and outcome changes.

The study was conducted between March and August 2025 involving undergraduate students from Universitas Hang Tuah Pekanbaru and Institut Kesehatan Payung Negeri Pekanbaru, Indonesia. These institutions were selected because both had implemented blended learning and digital educational platforms, providing a suitable context for evaluating AI-based mental health education. A total of 289 students participated in the study. 157 students were from Universitas Hang Tuah Pekanbaru and 132 students were from Institut Kesehatan Payung Negeri Pekanbaru.

Participants were selected using stratified random sampling based on faculty affiliation and academic year to ensure proportional representation across academic backgrounds and study levels. Student enrollment records served as the sampling frame, and participants were randomly selected within each stratum using a computer-generated randomization procedure. Eligibility criteria included active undergraduate enrollment, participation in blended learning activities, and willingness to complete all study procedures. The study followed a sequential explanatory mixed methods procedure in which quantitative data collection and analysis were conducted first, followed by a qualitative phase designed to explain and expand the quantitative findings. After the completion of the post, a subset of participants was purposively selected to participate in semi- structured interviews based on their engagement levels during the intervention and observed changes in stress coping behavior as well as learning engagement scores. Thise view enabled a deeper exploration of students' experiences, perceptions, and psychosocial adaptation processes following participation in the AI personalized intervention.

Sample adequacy was evaluated based on Structural Equation Modeling Partial Least Squares (SEM PLS) and intervention research. Previous methodological literature suggests that SEM PLS can be reliably conducted with sample sizes exceeding 200 participants, particularly when the structural model includes multiple latent constructs and mediation pathways. The final sample of 289 participants exceeded the minimum recommended threshold and was therefore considered sufficient to ensure stable parameter estimation, adequate statistical power, and reliable model evaluation.

Variables and data collection

The primary independent variable was AI Personalized Mental Health Education, defined as an adaptive intervention providing individualized mental health information, emotional support, stress coping recommendations, and engagement enhancement strategies. The dependent variables included stress coping behavior and learning engagement, while emotional wellbeing served as an intervening construct in the SEM analysis. Stress coping behavior was measured using a structured questionnaire consisting of 12 assessment items covering emotional regulation, adaptive coping, stress management, help seeking, and self regulation dimensions. Emotional wellbeing was assessed through emotional balance, positive emotional experiences, psychological comfort, and perceived ability to manage academic challenges.

Whereas learning engagement was assessed using a 15-item questionnaire covering behavioral, emotional, and cognitive engagement, participation consistency, assignment completion, and learning motivation. Learning engagement was assessed using a 15-item questionnaire covering three core dimensions commonly used in student engagement research, namely behavioral engagement, emotional engagement, and cognitive engagement within digital learning environments. Behavioral engagement reflected participation consistency, classroom interaction, and assignment completion behaviors, while emotional and cognitive engagement assessed students affective involvement and investment in learning activities. All questionnaire items employed a five point Likert's scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating more favorable outcomes.

The intervention conducted in this study was, an adaptive digital mental health education program designed to provide individualized learning content, stress coping recommendations, emotional support guidance, and engagement enhancement strategies for university students. The intervention was delivered through an AI-assisted platform that adapted educational materials and support messages according to participants' self-reported psychological conditions, coping needs, and learning engagement profiles. The intervention system was designed to provide adaptive mental health education, individualized stress coping recommendations, emotional support guidance, and personalized engagement strategies based on students' psychological responses and learning participation patterns.

The intervention was conducted over an eight-week period and consisted of eight structured educational modules delivered through the AI personalized platform. Each module focused on specific topics, including mental health awareness, stress identification, emotional regulation, adaptive coping strategies, self regulation, help seeking behavior, academic resilience, and learning engagement enhancement. Participants completed one module per week and received personalized recommendations, emotional support messages, and engagement reminders generated by the AI system according to their assessment responses and participation patterns.

Prior to the intervention, validity and reliability testing of the research instruments was conducted involving 40 undergraduate students outside the primary study sample. The validity test demonstrated that all questionnaire items achieved a correlation coefficient value greater than 0.300, indicating acceptable construct validity. Reliability analysis additionally showed Cronbach's alpha values exceeding 0.700 across all assessment dimensions, confirming satisfactory internal consistency reliability. Supporting demographic variables included age, gender, academic year, faculty background, daily digital learning duration, and frequency of AI platform access during the intervention period. Frequency of AI platform access was measured based on participants' self-reported use of the intervention platform during the eight-week intervention period. Access frequency was categorized as low (1–2 accesses per week), moderate (3–5 accesses per week), and high (more than 5 accesses per week). This classification was used to describe participants' engagement with the intervention platform and was not included as a primary outcome variable in the effectiveness analysis. Age was recorded in years based on self-report, while gender was categorized as male or female. Academic year was classified into first, second, third, and fourth year levels, and faculty background was obtained from institutional enrollment records. Daily digital learning duration was categorized as <3 hours, 3–5 hours, or >5 hours per day. Frequency of AI platform access during the intervention period was categorized as low, moderate, or high based on participants' self-reported usage patterns.

The AI personalization system utilized data obtained from participants questionnaire responses and digital learning activity records to generate individualized educational recommendations throughout the intervention period. Questionnaire-based assessments included stress coping behavior, emotional wellbeing, and learning engagement measures administered before and during the intervention. Behavioral engagement indicators were derived from learning activity records, including attendance consistency, participation frequency in online learning activities, and assignment completion behavior. These indicators were used by the system to adapt educational content, coping recommendations, and engagement support messages according to participants learning and psychosocial profiles.

To enable structural model analysis, participants perceptions of the AI Personalized Mental Health Education intervention were assessed using an 8-item evaluation questionnaire administered at the end of the intervention period. The instrument measured four dimensions of the intervention experience, namely perceived personalization of educational content, relevance of adaptive coping recommendations, usefulness of emotional support guidance, and effectiveness of engagement enhancement support. All items were evaluated using a five-point Likert scale ranging from strongly disagree to strongly agree. Higher scores indicated more positive perceptions regarding the quality and usefulness of the AI Personalized Mental Health Education intervention.

Semi-structured interviews were conducted individually within two weeks following completion of the posttest. Each interview lasted approximately 30–45 minutes and was conducted either face to face or through online video conferencing platforms according to participant preference. The interviews were guided by a semi structured interview protocol developed from the study objectives and quantitative findings. Key topics included participants experiences using the AI Personalized Mental Health Education platform, perceived changes in stress coping behavior, emotional wellbeing, learning engagement, and overall perceptions of the intervention. Follow up probing questions were used to explore participants responses in greater depth and clarify emerging experiences. With participants' consent, all interviews were audio recorded and transcribed verbatim prior to thematic analysis.

Data Analysis

Quantitative and qualitative data were analyzed using a sequential explanatory mixed methods analytical framework to evaluate the effectiveness of AI Personalized Mental Health Education on students' stress coping behavior and learning engagement. Quantitative data processing was performed using IBM SPSS Statistics version 30 and SmartPLS version 4. Prior to hypothesis testing, all data were screened for missing values, outliers, normality, and multicollinearity assumptions. Normality of the pretest–posttest difference scores was assessed using the Shapiro–Wilk test and visual inspection of histograms and Q–Q plots. The results indicated that all primary outcome variables satisfied the normality assumption ($p > .05$), supporting the application of parametric paired sample t-test analyses. Descriptive statistics, including means, standard deviations, frequencies, and percentages, were calculated to summarize participant characteristics and variable distributions.

Paired sample t tests analyses were conducted to examine differences between pre-intervention and post intervention outcomes. Structural Equation Modeling Partial Least Squares (SEM PLS) was additionally employed to evaluate direct and indirect relationships among intervention effectiveness, stress coping behavior, emotional wellbeing, and learning engagement. Instrument validity was assessed using convergent and discriminant validity, while reliability was evaluated using Cronbach's alpha and composite reliability coefficients. Statistical significance was established at $p < .05$.

Meanwhile, the qualitative data analysis was conducted after the completion of the quantitative analysis to facilitate explanatory integration between both data sets. Interview transcripts were analyzed using thematic analysis involving open coding, theme identification, and category refinement. Integration occurred during interpretation of the findings, where qualitative themes were used to explain, contextualize, and strengthen the quantitative results. Specifically, students' narratives regarding emotional support, adaptive coping, self regulation, and learning participation were compared with the quantitative outcomes obtained from pretest–posttest analyses and SEM PLS modeling. This integration enhanced the overall validity and comprehensiveness of the study findings.

Ethics

This study received ethical approval from the Ethics Committee of Universitas Hang Tuah Pekanbaru (Ethical Approval No. 014.B/KEPK/UNIV-HTP/II/2025) prior to data collection and intervention implementation. All research procedures were conducted in accordance with the ethical principles outlined in the Declaration of Helsinki for research involving human participants. Participation was entirely voluntary, and all respondents were informed regarding the study objectives, confidentiality procedures, and their right to withdraw from the study at any stage without academic consequences. Written informed consent was obtained electronically before participation. To ensure participant privacy and psychological safety, all collected data were anonymized and securely stored using password protected digital systems accessible only to the research team.

RESULTS AND DISCUSSION

Participant demographic characteristics and baseline distributions were analyzed to examine the initial psychosocial conditions, digital learning behaviors, and engagement patterns of students prior to the implementation of the AI Personalized Mental Health Education intervention. The baseline assessment additionally provided contextual insights regarding students' readiness for adaptive digital mental health learning within blended higher education environments. Detailed participant characteristics and baseline distributions are presented in Table 1.

Table 1 demonstrates that the study population was predominantly female (59.2%) and primarily consisted of students with moderate daily digital learning exposure ranging from 3–5 hours (51.6%). The mean participant age was 20.84 ± 1.63 years, indicating that most respondents were within the transitional developmental stage frequently associated with heightened academic adaptation challenges. Baseline findings further revealed moderate levels of stress coping behavior (2.94 ± 0.61) and learning engagement (3.08 ± 0.58), suggesting that many students initially experienced psychosocial and academic participation difficulties prior to the intervention. Relatively lower emotional regulation and self regulation scores additionally indicated the need for adaptive mental health education and personalized psychosocial support mechanisms among university students. Pretest and posttest analyses were conducted to evaluate changes in stress coping behavior and learning engagement following the implementation of AI Personalized Mental Health Education intervention. Preliminary assumption testing confirmed that the distributions of pretest–posttest difference scores were approximately normal, thereby supporting the use of paired sample t-test procedures for intervention outcome evaluation. Detailed intervention outcome comparisons are presented in Table 2.

Table 1. Participant characteristics and baseline distribution (n=289)

Variable	n	%	Mean ± SD
Gender			
Male	118	40.8	–
Female	171	59.2	–
Institution			
Universitas Hang Tuah Pekanbaru	157	54.3	–
Institut Kesehatan Payung Negeri Pekanbaru	132	45.7	–
Academic Year			
First Year	71	24.6	–
Second Year	86	29.8	–
Third Year	79	27.3	–
Fourth Year	53	18.3	–
Daily Digital Learning Duration			
< 3 hours	74	25.6	–
3–5 hours	149	51.6	–
> 5 hours	66	22.8	–
Frequency of AI Platform Access			
Low	63	21.8	–
Moderate	141	48.8	–
High	85	29.4	–
Age (years)	–	–	20.84 ± 1.63
Baseline Stress Coping Behavior	–	–	2.94 ± 0.61
Emotional Regulation	–	–	2.87 ± 0.64
Adaptive Coping Strategy	–	–	3.02 ± 0.59
Self Regulation Ability	–	–	2.91 ± 0.66
Baseline Learning Engagement	–	–	3.08 ± 0.58
Behavioral Engagement	–	–	3.14 ± 0.62
Emotional Engagement	–	–	3.01 ± 0.60
Cognitive Engagement	–	–	3.09 ± 0.57
Attendance Consistency	–	–	3.22 ± 0.63
Assignment Completion Behavior	–	–	3.17 ± 0.61

Table 2. Pretest and posttest comparison of intervention outcomes

Variable	Pretest Mean ± SD	Posttest Mean ± SD	Mean Difference	*t value*	P- value	Effect Size (Cohen's d)
Stress coping behavior	2.94 ± 0.61	4.08 ± 0.54	1.14	18.472	< .001	1.31
Emotional regulation	2.87 ± 0.64	4.02 ± 0.56	1.15	17.936	< .001	1.27
Adaptive coping strategy	3.02 ± 0.59	4.15 ± 0.51	1.13	18.105	< .001	1.29
Self regulation ability	2.91 ± 0.66	4.06 ± 0.55	1.15	17.614	< .001	1.25
Learning engagement	3.08 ± 0.58	4.19 ± 0.49	1.11	19.284	< .001	1.37
Behavioral engagement	3.14 ± 0.62	4.23 ± 0.50	1.09	18.733	< .001	1.33
Emotional engagement	3.01 ± 0.60	4.11 ± 0.52	1.10	18.064	< .001	1.28
Cognitive engagement	3.09 ± 0.57	4.21 ± 0.48	1.12	19.011	< .001	1.35
Attendance consistency	3.22 ± 0.63	4.28 ± 0.47	1.06	17.856	< .001	1.26
Assignment completion behavior	3.17 ± 0.61	4.24 ± 0.46	1.07	18.294	< .001	1.30

Table 2 demonstrates statistically significant improvements across all psychosocial and academic engagement dimensions following the intervention program ($p < .001$). The largest effect sizes were observed in learning engagement ($d = 1.37$), cognitive engagement ($d = 1.35$), and behavioral engagement ($d = 1.33$), indicating substantial intervention impacts on students' academic participation and adaptive learning behavior. Stress coping behavior additionally increased from 2.94 ± 0.61 to 4.08 ± 0.54, reflecting enhanced emotional regulation and self management capacity after receiving personalized mental health education. These findings support recent evidence suggesting that adaptive AI based educational interventions positively influence emotional wellbeing, self regulation, and student engagement within higher education environments(15)(16).

The consistent large effect sizes observed across multiple outcomes may be explained by the multidimensional design of the intervention, which simultaneously targeted emotional support, adaptive coping, self regulation, and academic engagement. Unlike conventional mental health education programs that typically focus on information delivery alone, the AI Personalized Mental Health Education system continuously generated individualized recommendations and adaptive guidance based on students' psychological responses and learning participation patterns. This personalized approach may have strengthened the interconnected processes underlying emotional adaptation and academic functioning. Improvements in emotional regulation and coping behavior likely contributed to enhanced motivation, participation consistency, and cognitive engagement, thereby producing reinforcing effects across several psychosocial and educational dimensions. The strong intervention effects therefore appear to reflect the synergistic influence of personalized emotional support and adaptive learning engagement strategies operating simultaneously throughout the intervention period.

Structural Equation Modeling Partial Least Squares (SEM PLS) analysis was subsequently performed to evaluate the direct and indirect relationships among AI Personalized Mental Health Education, stress coping behavior, emotional wellbeing, and learning engagement outcomes among university students. The structural pathway analysis and hypothesis testing results are presented in Table 3

Table 3 demonstrates that AI Personalized Mental Health Education exerted significant positive effects on stress coping behavior (β = 0.742, $p < .001$), emotional wellbeing (β = 0.691, $p < .001$), and learning engagement (β = 0.486, $p < .001$). Stress coping behavior additionally showed a strong positive influence on learning engagement (β = 0.533, $p < .001$), indicating the important mediating role of psychosocial adaptation within the intervention framework. The significant indirect pathways further suggest that adaptive AI based mental health education may enhance academic participation through improvements in emotional regulation and coping capacity. These findings are consistent with recent studies emphasizing that personalized digital mental health interventions positively influence student wellbeing, emotional resilience, and academic engagement in higher education environments.(17)

Measurement model evaluation and qualitative thematic exploration were subsequently conducted to strengthen the interpretative validity of the intervention findings. Detailed construct reliability and structural model evaluation are presented in Table 4, while qualitative themes of student experiences after the AI personalized intervention are presented in Table 5.

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Table 3. SEM PLS structural model results

Hypothesis Path	Path Coefficient (β)	t statistic	P-value	Decision
AI Personalized Mental Health Education → Stress Coping Behavior	0.742	15.381	< .001	Supported
AI Personalized Mental Health Education → Emotional Wellbeing	0.691	13.947	< .001	Supported
AI Personalized Mental Health Education → Learning Engagement	0.486	8.764	< .001	Supported
Stress Coping Behavior → Learning Engagement	0.533	10.128	< .001	Supported
Emotional Wellbeing → Learning Engagement	0.417	7.915	< .001	Supported
Stress Coping Behavior → Emotional Wellbeing	0.578	11.036	< .001	Supported
AI Personalized Mental Health Education → Stress Coping Behavior → Learning Engagement	0.395	8.487	< .001	Supported
AI Personalized Mental Health Education → Emotional Wellbeing → Learning Engagement	0.288	6.941	< .001	Supported

Table 4. Measurement and Structural Model Evaluation

Construct	Cronbach's Alpha	Composite Reliability	AVE	R^2	Q^2
AI Personalized Mental Health Education	0.887	0.908	0.663	-	-
Stress Coping Behavior	0.894	0.912	0.684	0.551	0.403
Emotional Wellbeing	0.901	0.924	0.701	0.587	0.426
Learning Engagement	0.913	0.931	0.719	0.672	0.511

Table 5. Qualitative themes of student experiences after artificial intelligence personalized intervention

Theme	Description	Representative Statements
Personalized Emotional Support	Students reported that the AI system delivered individualized recommendations based on their self-reported stress conditions and learning challenges. Participants explained that the intervention provided emotional regulation guidance, stress management suggestions, and adaptive study strategies that helped them identify stress triggers, manage emotional responses, and cope more effectively with academic workload demands.	"The system felt more personal because the recommendations matched my stress condition and learning difficulties."
Improved Stress Coping and Emotional Regulation	Participants described increased awareness of emotional reactions during stressful academic situations. Many students reported applying the coping strategies suggested by the system, such as stress monitoring, relaxation techniques, and problem-focused coping approaches, which contributed to improved emotional control and psychological adjustment.	"I became more aware of how to control stress and manage academic pressure more effectively."
Increased Learning Motivation and Participation	Students reported that personalized reminders, progress feedback, and adaptive learning recommendations encouraged greater participation in learning activities. Several participants indicated that the intervention helped them maintain study consistency, improve class participation, and increase motivation to complete academic tasks.	"The personalized reminders and coping guidance motivated me to participate more actively during classes."
Adaptive Learning and Self Regulation	Participants perceived that the intervention supported self regulated learning behaviors, including time management, study consistency, and adaptive learning strategies during academic activities.	"The intervention helped me organize study schedules and improve my learning discipline."
Positive Perceptions Toward AI Based Mental Health Education	Students expressed favorable attitudes toward the integration of AI within mental health education, particularly regarding accessibility, personalization, and interactive educational experiences.	"AI based education made mental health learning feel more interactive, practical, and easier to understand."
Enhanced Emotional Wellbeing and Academic Confidence	Several participants reported improvements in emotional wellbeing, confidence, and academic resilience after participating in the AI personalized intervention program.	"I felt calmer, more confident, and less overwhelmed when facing assignments and academic responsibilities."

Table 4 demonstrates satisfactory measurement and structural model performance across all latent constructs included in the SEM analysis. Cronbach's alpha values ranged from 0.887 to 0.913, while composite reliability coefficients exceeded the recommended threshold of 0.70, indicating strong internal consistency reliability. The AVE values ranging from 0.663 to 0.719 additionally confirmed adequate convergent validity for all constructs, including AI Personalized Mental Health Education, Stress Coping Behavior, Emotional Wellbeing, and Learning Engagement. Furthermore, the R^2 values revealed moderate to substantial explanatory power for Stress Coping Behavior (0.551), Emotional Wellbeing (0.587), and Learning Engagement (0.672), while Q^2 values exceeding 0.400 indicated strong predictive relevance of the structural model. Complementing these quantitative findings, Table 5 revealed that students consistently perceived the AI personalized intervention as adaptive, emotionally supportive, and beneficial for strengthening self regulation, emotional adaptation, and academic participation. These findings further support the effectiveness of personalized digital mental health interventions in promoting emotional resilience, learning engagement, and psychosocial wellbeing among university students.(15)(18)

The present study examined the effectiveness of AI Personalized Mental Health Education in improving stress coping behavior and learning engagement among university students within blended learning environments. Overall findings demonstrated that the intervention significantly improved stress coping behavior and learning engagement among university students. These results indicate that AI based personalized mental health education may serve as an effective digital health promotion strategy for supporting students facing academic stress and emotional challenges in higher education settings.

Baseline findings revealed moderate levels of stress coping behavior and learning engagement prior to intervention implementation, suggesting that many students initially experienced emotional regulation and academic participation difficulties. This finding aligns with previous studies reporting that digitally intensive learning environments may increase psychological vulnerability, academic fatigue, and disengagement among university students.(1)(19) The current study, therefore, addressed an important educational and public health issue through the integration of adaptive AI driven mental health education.

The pretest and posttest comparison demonstrated statistically significant improvements across all intervention outcomes, particularly in learning engagement (d = 1.37), cognitive engagement (d = 1.35), and behavioral engagement (d = 1.33). These findings suggest that AI personalized intervention effectively strengthened students' academic participation, adaptive learning behavior, and emotional coping capacity. Similar studies have reported that AI enhanced educational interventions positively influence emotional wellbeing, self regulation, and engagement sustainability among university students.(20)(21)(22) However, unlike previous research primarily emphasizing general AI learning systems, the present study specifically integrated adaptive mental health education and individualized coping recommendations within the intervention framework.

The SEM PLS analysis further demonstrated strong direct effects of AI Personalized Mental Health Education on stress coping behavior (β = 0.742) and emotional wellbeing (β = 0.691). Moreover, stress coping behavior significantly influenced learning engagement (β = 0.533), indicating that psychosocial adaptation plays an important mediating role in supporting academic participation and engagement sustainability. These findings are consistent with previous literature emphasizing that personalized AI based educational systems may improve emotional resilience and adaptive learning experiences through individualized support mechanisms.(3)(23)

The qualitative findings provided important explanatory insights into the quantitative patterns observed throughout the study. For example, the substantial improvement in stress coping behavior (d = 1.31) was reflected in students' narratives describing increased emotional awareness, better stress management, and greater confidence in handling academic pressures. Similarly, the significant increase in learning engagement (d = 1.37) was supported by participants' reports of stronger learning motivation, improved participation consistency, and enhanced self regulated learning behaviors. Students frequently emphasized that personalized recommendations and adaptive emotional support helped them translate mental health knowledge into practical coping actions during academic activities. These qualitative experiences help explain why improvements were consistently observed across both psychosocial and academic dimensions following the intervention. Participants consistently reported improved emotional regulation, stronger academic motivation, adaptive self regulation, and positive perceptions toward AI based mental health education. Students perceived that personalized recommendations and emotional guidance helped them manage academic stress more effectively while simultaneously improving participation consistency and learning discipline. Similar findings have been reported in recent studies demonstrating that AI supported emotional feedback systems positively influence students' psychological wellbeing and self efficacy.(24)(25)

An important contribution of the present study lies in the integration of behavioral engagement analytics and adaptive mental health recommendations within a multidimensional intervention framework. Previous studies often examined AI based learning engagement systems and mental health support separately.(26)(27) In contrast, the current study simultaneously integrated emotional support, stress coping guidance, and engagement reinforcement, thereby strengthening the intervention's predictive relevance for learning engagement outcomes ($R^2 = 0.672$).

Despite these promising findings, several limitations should be acknowledged. First, the quasi experimental design may limit causal generalizability compared with randomized controlled studies. Second, the study relied primarily on self reported assessments, potentially introducing response bias. Future studies are therefore encouraged to employ longitudinal experimental designs, multimodal behavioral analytics, and cross cultural validation approaches to further investigate the long term effectiveness of AI personalized mental health education.

Overall, the present study contributes to the growing literature regarding AI driven educational wellbeing interventions by demonstrating that adaptive AI personalized mental health education may significantly improve stress coping behavior, emotional wellbeing, and learning engagement among university students in blended higher education environments.

CONCLUSION

This study demonstrated that AI Personalized Mental Health Education significantly improved stress coping behavior, emotional wellbeing, and learning engagement among university students within blended higher education environments. Participants demonstrated improvements in stress coping behavior, emotional wellbeing, and learning engagement following participation in the AI Personalized Mental Health Education program. Significant pretest–posttest differences were observed across multiple psychosocial and academic dimensions, while the SEM PLS analysis identified significant associations among AI Personalized Mental Health Education, stress coping behavior, emotional wellbeing, and learning engagement. The findings suggest that integrating adaptive coping recommendations, emotional support guidance, and behavioral engagement analytics within a digital learning environment may provide a promising approach for supporting students' psychosocial adaptation and academic engagement. However, given the study design and contextual limitations, the findings should be interpreted as preliminary evidence, and further controlled studies are required to confirm the effectiveness and generalizability of the intervention.

Qualitative findings indicated that students generally perceived the AI based intervention as adaptive, interactive, and supportive of their learning and emotional experiences during the intervention period. These findings provide contextual insights into participants experiences with the program but do not establish the specific mechanisms underlying the observed quantitative outcomes. Overall, this study contributes theoretically and practically to the growing field of AI driven educational wellbeing interventions by proposing an integrated psychosocial adaptation framework capable of supporting emotional resilience and engagement sustainability among university students in digitally intensive learning environments.

Conflict of Interest

The authors declare no conflict of interest.

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