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Implementation of Artificial Intelligence to Enhance the Effectiveness of Adaptive Learning in Psychological Education in Schools

Sutikno[1*], Junita Sipahelut[2], Isep Djuanda[3]
[1]Universitas Negeri Jakarta, Indonesia
[2]Institut Agama Kristen Negeri (IAKN) Ambon, Indonesia
[3]Universitas Islam Depok, Indonesia
Corresponding Author: Sutikno sutikno_1119925002@mhs.unj.ac.id

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A B S T R A C T
The advancement of Artificial Intelligence (AI) in education offers significant potential to address the limitations of conventional instructional approaches, which tend to be uniform and insufficiently responsive to students' diverse learning characteristics, particularly in psychological education that requires both conceptual understanding and the development of emotional regulation skills. This study aims to examine the effectiveness of implementing AI-based adaptive learning in improving students' comprehension of psychological concepts and their emotional regulation abilities at the senior high school level. The research employed a quasi-experimental approach with a pretest–posttest control group design involving 60 tenth-grade students from a public senior high school in Papua, divided into experimental and control groups. Data were collected through a psychological comprehension test, an emotional regulation scale, and a learning engagement questionnaire, and were analyzed using independent samples t-tests and effect size calculations. The findings indicate that students in the AI-based adaptive learning group demonstrated significantly greater improvement compared to those in the conventional learning group, both in cognitive achievement and emotional regulation, along with higher levels of learning engagement. These results suggest that integrating AI into psychological education effectively supports differentiated instruction and strengthens students' emotional competencies.

INTRODUCTION

The development of Artificial Intelligence (AI) in education has changed the learning paradigm from a uniform approach to a more personalized and responsive system to the individual needs of students. Globally, the integration of Artificial Intelligence in the context of education is seen as able to improve the quality of learning through real-time learning data analysis and the provision of more precise adaptive feedback (Prajapati, 2024). This digital transformation is increasingly relevant post-pandemic when educational institutions are encouraged to accelerate the adoption of effective and inclusive learning technologies. However, the effectiveness of AI implementation is not only determined by the sophistication of its technology, but also by its suitability with the development characteristics of students. In the context of psychology education in schools, learning challenges are not only cognitive, but also include affective aspects such as emotional regulation and social-emotional skills.

At the global level, AI-based adaptive learning has been widely applied to science, math, and language subjects with results showing significant improvements in academic performance (Sari et al., 2024). This technology works by mapping students' learning profiles, adjusting the difficulty level of the material, and providing automated interventions according to individual needs. Despite this, most of the research still focuses on the cognitive domain and mastery of academic content, while the psychological dimension of students has received relatively little attention. In fact, the educational psychology literature confirms that learning success is greatly influenced by the ability to regulate emotions and self-regulated learning (Balashov, 2022) Thus, the integration of AI in psychology education is a scientific urgency that needs to be explored systematically.

In the context of Indonesia, especially in the Papua region, the gap in the quality of learning is still a strategic issue due to limited resources, variations in students' abilities, and uneven access to technology. National data show that the disparity in learning outcomes between regions is still quite significant, so adaptive and contextual pedagogical innovations are needed (Banda, 2024). The use of adaptive learning-based AI has the potential to be a solution to accommodate the heterogeneity of students' abilities without excessively increasing the workload of teachers. Nevertheless, the implementation of smart technologies in regions with limited infrastructure requires realistic and empirically tested models. Therefore, research that tests the effectiveness of AI in the context of schools in Papua has local relevance as well as national contribution.

Conceptually, adaptive learning relies on the theory of learning differentiation and a constructivistic approach that emphasizes the importance of adjusting learning experiences to individual characteristics of students (Yang, 2025). AI integration strengthens this approach through predictive analytics capabilities and automated personalization based on learning behavior data. Study by Tumblr (2022) emphasized that AI in education has the potential to support the development of cognitive and social-emotional competencies if designed with the right pedagogical approach. However, implementation that is

not accompanied by empirical evaluation risks creating a gap between theoretical potential and field practice. Therefore, research that examines the relationship between the use of AI adaptive learning and the improvement of students' emotion regulation is important to strengthen its theoretical and applicable foundation.

Although a number of studies have reported on the effectiveness of AI in improving learning outcomes, there are significant research gaps in two key aspects. First, most studies use experimental designs on exact subjects and rarely evaluate their impact on students' emotional competence (Guo et al., 2025). Second, research conducted in developing countries is still limited, so the generalization of global findings is not necessarily relevant to the local social and cultural context (Laurence, 2025). In addition, there have not been many studies that have simultaneously measured improvements in conceptual understanding and emotion regulation within a single AI-based intervention framework. This gap is the basis for the need for further research that is contextual and comprehensive.

Based on these backgrounds and gaps, this study aims to analyze the effectiveness of the implementation of adaptive learning-based AI in improving the understanding of psychology materials and the ability to regulate emotions of high school students. In particular, this study examined the difference in learning outcomes between the group that used AI adaptive learning and the group that used conventional methods through quasi-experimental design. In addition, this study also evaluates the level of student learning involvement as a supporting variable in understanding the dynamics of technology implementation. With a quantitative approach and inferential statistical analysis, this research is expected to produce measurable and academically accountable empirical findings.

The contribution of this research is theoretical and practical. Theoretically, this study expands the study of the application of AI in psychology education by integrating cognitive and affective aspects in an evaluation model. This research also enriches the literature on adaptive learning in the context of developing regions that are still rarely represented in international publications. Practically, the results of this study offer a contextual and adaptive AI implementation model for schools with a heterogeneity of student abilities, especially in Papua. Thus, this research is expected not only to contribute to the development of education and psychology, but also to become a policy reference in the responsible and sustainable use of smart technology.

LITERATURE REVIEW

Artificial Intelligence in Education: Conceptualization and Cutting-edge Development

Artificial Intelligence (AI) in education is understood as a computational system that is able to mimic human cognitive processes through data analysis, machine learning, and automatic adaptive feedback. This development is driving a pedagogical transformation from a uniform approach to personalized and dynamic data-driven learning. A systematic study conducted by Ravichandran

(2024) shows that the integration of AI in education contributes to improved learning efficiency, accuracy in the diagnosis of learning difficulties, as well as the optimization of instructional interventions. Furthermore, research by Fan et al. (2025) emphasized that generative AI and machine learning-based systems have the potential to support the process of metacognitive reflection and learning differentiation if designed with a strong pedagogical foundation. Nonetheless, the literature also reminds of the importance of context-based empirical evaluation to ensure that AI implementation is not just a technological innovation, but actually has a significant impact on student learning outcomes.

Adaptive Learning and Learning Differentiation

Adaptive learning is an approach that adjusts the content, strategies, and difficulty level of material based on individual characteristics and performance of students. Theoretically, this approach is rooted in the principle of learning differentiation and the theory of social constructivism that emphasizes the importance of learning experiences that are relevant to the needs of learners. Research by Sari et al. (2024) shows that AI-based adaptive learning systems are able to improve academic achievement through a personalized material recommendation mechanism. On the other hand, a meta-analytical study by Sibley et al. (2025) found that the effectiveness of adaptive learning was strongly influenced by the quality of instructional design and the integration of formative feedback. This shows that the success of adaptive learning depends not only on algorithms, but also on the alignment between technology and pedagogical strategies. Thus, the development of adaptive learning AI models in psychology education requires the integration of the principles of differentiation and comprehensive empirical validation.

Psychology Education and Emotion Regulation in the School Context

Psychology education at the secondary school level has a strategic role in shaping students' social-emotional competencies, including emotional regulation skills. Emotion regulation is seen as an individual's ability to manage affective responses adaptively in academic and social situations. Longitudinal study by Shengyao et al. (2024) showed that the ability to regulate emotions was positively correlated with academic achievement and students' psychological well-being. In addition, research by Lynn et al. (2024) affirms that social-emotional learning-based interventions can significantly improve self-efficacy and learning engagement. However, most of these interventions still use conventional approaches without the support of smart technologies. The integration of AI in psychology education has the potential to strengthen the process of developing emotion regulation through personalized feedback and real-time analysis of student responses.

AI Integration, Learning Engagement, and Affective Impact

Learning engagement is an important indicator in evaluating the effectiveness of technology-based learning. AI adaptive learning allows for continuous monitoring of student learning behavior, which can increase intrinsic

participation and motivation. Research by Villegas-Ch et al. (2024) Found that the use of artificial intelligence-based learning systems was positively related to increased engagement and material retention. Meanwhile, a study by Sajja et al. (2025) emphasizes that interactive design and data-driven personalization contribute to a more meaningful learning experience. However, there is still limited research that examines the simultaneous impact of AI on cognitive and affective aspects in learning psychology. Therefore, empirical testing that integrates the variables of conceptual understanding, emotion regulation, and learning engagement is essential to enrich the literature and ensure the sustainability of the implementation of AI in education.

METHODOLOGY

Research Type and Design

This study uses a quantitative approach with a quasi-experimental design of the pretest–posttest control group design. This design was chosen because it allows researchers to compare the effectiveness of Artificial Intelligence (AI)-based interventions with conventional learning in a naturally formed classroom context without a full randomization process. Quasi-experimental approaches are relevant in educational research because they consider administrative, ethical, and structural limitations in formal school settings. Through this design, researchers can measure changes in scores before and after treatment and make comparisons between groups to test the effect of interventions empirically (Gabr et al., 2025).

Population and Sampling Techniques

The research population is all class X students at one of the public high schools in Papua in the 2024/2025 school year. The sampling technique uses non-probability sampling with a purposive sampling approach, which is to select two classes that have relatively equivalent academic characteristics based on the previous semester's report card scores. The number of participants was 60 students who were divided into two groups, namely the experimental group (n = 30) and the control group (n = 30). The selection of class X students is based on considerations of the psychological development of early adolescents who are in the social and emotional transition phase so that they are relevant to emotional regulation interventions. The number of samples was considered adequate for statistical analysis of the difference test of two independent groups in quantitative education research (Buckley, 2024).

Data Collection Instruments and Techniques

Data collection is carried out through three main instruments. First, the multiple-choice psychological material comprehension test developed based on the national curriculum and psychology learning competency indicators. This test is validated by three psychology education experts to ensure the validity of the content and the suitability of the measurement indicators. Second, the scale of emotion regulation is adapted from the adolescent emotion regulation model and adjusted to the local cultural context through the process of language

adaptation and construct validation. Third, a five-point Likert scale-based learning engagement questionnaire that measures cognitive, emotional, and behavioral dimensions in the learning process. The reliability test of all instruments was performed using Cronbach's Alpha coefficient with a minimum limit of 0.70 to ensure internal consistency (Kennedy, 2022).

Research Implementation Procedure

The research procedure was carried out systematically in four main stages. The first stage is preparation, which includes research licensing, the preparation of AI adaptive learning modules, and short training for accompanying teachers related to the use of the system. The second stage is the implementation of a pretest in both groups to measure students' initial ability to understand psychology and emotional regulation. The third stage was the implementation of a six-week intervention, where the experimental group used an AI adaptive learning system that automatically adjusted materials and exercises based on student performance, while the control group followed conventional lecture-based learning and discussions. The fourth stage is the implementation of posttests and filling out learning engagement questionnaires. The entire research process is carried out by paying attention to the ethical principles of research, including written consent from the school and the student's parents.

Data Analysis Techniques

Data analysis was performed quantitatively using IBM Statistical Package for the Social Sciences software version 26 (Babbie et al., 2022). The initial stage includes a normality test and a variance homogeneity test to ensure that the assumptions of parametric analysis are met. Furthermore, an independent samples t-test was carried out to compare the increase in scores between the experimental group and the control group. The effect size calculation using Cohen's d was carried out to determine the magnitude of the effect of the intervention practically. In addition, gain score analysis is used to evaluate the change in an individual's score from pretest to posttest. The interpretation of the results was based on statistical significance ($p < 0.05$) and the strength of the effect to provide a comprehensive picture of the effectiveness of the implementation of AI in learning psychology.

RESEARCH RESULTS

Equality of Initial Ability of the Group

In the early stages, the analysis was performed to ensure that the experimental group and the control group had relatively equivalent initial conditions before the six-week intervention was applied. Equivalence of initial conditions is important in quasi-experimental design because there is no full randomization, so potential initial differences between groups should be minimized. The results of the pretest showed that the average scores of psychological comprehension and emotion regulation in both groups were in a similar range, with relatively comparable score variations. Statistically, independent t-tests on pretest scores showed no significant differences between

groups. These findings confirm that changes in the posttest stage are more likely to be influenced by treatment (AI adaptive learning) than by differences in initial ability.

Table 1. Pretest Baseline Comparison Between Groups (n=60)

Variable	Group	Mean	SD	t	p
Psychological Comprehension (0–100)	Experimental (n=30)	55.20	8.10	0.26	0.795
	Control (n=30)	54.70	7.90		
Emotional Regulation (1–5)	Experimental (n=30)	2.98	0.41	0.34	0.736
	Control (n=30)	2.95	0.39		

Source: Primary Data (Pretest), 2025.

Based on Table 1, the difference in mean pretest between groups on the two main variables is relatively small and insignificant. This pattern shows that the two classes selected through purposive sampling actually have comparable academic characteristics, as per the sample selection objective that emphasizes initial equivalence based on previous academic indicators. Thus, the interpretation of posttest results and gain scores can be carried out with stronger methodological confidence.

These baseline results are consistent with the research procedure that places pretest as an internal control mechanism in the pretest–posttest control group design. In quasi-experimental designs, the pretest serves as a comparator of the initial conditions as well as helps to ensure that the post-intervention changes are not distorted by the initial differences. An independent t-test on pretest scores is used to verify this equivalence before effectiveness analysis is performed on both posttest and gain score data. Overall, the equivalence of early abilities strengthens the internal validity of the research and serves as a foundation for assessing the impact of the implementation of AI-based adaptive learning more objectively on student learning outcomes and psychological aspects.

Improvement of Cognitive Learning Outcomes in Psychology Materials

After the intervention lasted six weeks, the experimental group showed a greater improvement in understanding of psychological material than the control group. Descriptively, the posttest score of the experimental group increased significantly from the pretest score, while the control group also increased but by a smaller amount. This difference in improvement indicates that adaptive learning AI systems that adjust materials and exercises based on student performance provide more effective differentiation support than conventional learning. The gain score analysis made it clear that the average score increase in the experimental group was higher and more consistent between students. Inferentially, independent t-tests on gain scores showed significant differences, with effect sizes in the medium to large category.

Table 2. Psychological Comprehension Outcomes: Pretest, Posttest, Gain, and Effect Size

Measure	Group	Mean	SD
Pretest (0–100)	Experimental	55.20	8.10
	Control	54.70	7.90
Posttest (0–100)	Experimental	78.40	7.20
	Control	66.10	8.00
Gain Score (Post–Pre)	Experimental	23.20	6.80
	Control	11.40	6.50

Independent Samples t-test on Gain Score: t (58)=6.87, p<0.001
Effect Size (Cohen's d): 1.77
Source: Primary Data (SPSS Output), 2025.

Table 2 shows that the experimental group experienced an increase in material comprehension by 23.20 points, while the control group increased by 11.40 points. The difference in gain of 11.80 points indicates a substantive impact of the intervention, not just a natural improvement due to the usual learning process. The Cohen's effect measure d = 1.77 shows that the difference in improvement is in a large category, so the impact of adaptive learning AI is not only statistically significant, but also practically relevant in the classroom context.

These findings are in line with the design of a method that uses pretest and gain score analysis to capture individual changes. An independent t-test was used as per the analysis plan to compare the mean changes between groups. With this approach, the interpretation does not only focus on the posttest value alone, but on the magnitude of the development of the initial condition, so that it is consistent with the research objective of empirically testing the effectiveness of the intervention. In summary, the results on the cognitive aspect confirm that AI-based adaptive learning supports more targeted learning, accelerates the understanding of psychological concepts, and narrows the achievement gap between students through differentiation of materials and exercises.

Strengthening Emotional Regulation as an Affective Impact of Learning

In addition to cognitive achievement, this study assesses the affective dimension in the form of emotion regulation which is an important target in psychology education in schools. The results showed that the experimental group experienced a higher increase in emotion regulation than the control group. This increase was reflected in the increase in the emotion regulation scale score on the larger posttest in the experimental group. Conceptually, adaptive learning that provides immediate and appropriate feedback can help students manage learning frustration, increase their sense of competence, and improve coping strategies. The difference between groups was also seen in the gain score, which showed a more stable pattern of improvement in the experimental group.

Table 3. Emotional Regulation Outcomes: Pretest, Posttest, Gain, and Effect Size

Measure	Group	Mean	SD
Pretest (1–5)	Experimental	2.98	0.41
	Control	2.95	0.39
Posttest (1–5)	Experimental	3.72	0.38
	Control	3.22	0.40
Gain Score (Post–Pre)	Experimental	0.74	0.34
	Control	0.27	0.30

Independent Samples t-test on Gain Score: t (58)=5.67, p<0.001
Effect Size (Cohen's d): 1.46
Source: Primary Data (SPSS Output), 2025.

Based on Table 3, the experimental group increased by an average of 0.74 points on a scale of 1–5, while the control group increased by 0.27 points. The difference in gain of 0.47 points on this psychological scale can be understood as a meaningful change in the context of a relatively short educational intervention. The Cohen's effect d size of 1.46 indicates a strong influence, so the results show not only small differences, but also noticeable affective shifts in the group learning with the adaptive system.

These results are consistent with the research procedure that explicitly places emotion regulation as the main outcome in addition to material understanding. The use of pretest and gain score comparison allows for a fairer evaluation of development because it takes into account the student's initial position. An independent t-test on the gain score was the appropriate analytical choice in this design to test whether the mean change in the experimental group significantly exceeded the change in the control group. Thus, the implementation of AI adaptive learning not only impacts the cognitive aspect, but also strengthens students' emotional competence, which is a typical goal of psychology education in schools.

Learning Engagement as an Indicator of Process and Support for Differentiation

Learning engagement is analyzed to capture the quality of the learning process, not just the end result. The findings showed that students in the experimental group reported higher learning engagement than the control group on cognitive, emotional, and behavioral dimensions. In the process, adaptive systems tend to improve focus as the material adjusts abilities, reducing boredom for high-ability students and reducing anxiety for students who need basic reinforcement. Increased engagement was also seen from better consistency of participation and exercise completeness in the experimental group during the intervention period. This confirms that AI adaptive learning supports differentiation of learning not only through content, but also through more meaningful learning experiences.

Table 4. Learning Engagement Comparison After Intervention (Posttest Only)

Dimension (1–5)	Group	Mean	SD	t	p	Cohen's d
Cognitive Engagement	Experimental	4.05	0.45	4.12	<0.001	1.06
	Control	3.48	0.60			
Emotional Engagement	Experimental	3.92	0.50	3.71	<0.001	0.96
	Control	3.39	0.60			
Behavioral Engagement	Experimental	4.10	0.42	4.44	<0.001	1.15
	Control	3.50	0.62			

Source: Primary Data (Engagement Questionnaire), 2025.

Table 4 shows that the overall dimension of learning engagement in the experimental group was higher than in the control group with significant differences. The size of the effect that is in the near large range suggests that engagement is not just a slight increase, but a noticeable increase. This increase is practically important because learning engagement is the "motor" that bridges learning interventions with cognitive and affective outcomes. In other words, learning engagement serves as a process indicator that explains why the experimental group showed improved understanding and stronger regulation of emotions.

These learning engagement findings remained consistent with the research method, although engagement was measured post-intervention as a process indicator. In a quasi-experimental framework, intergroup comparisons on engagement scores were performed using an independent t-test to assess the mean difference between the treatment receiving the treatment and the comparison class. The use of effect size helps ensure that the difference is practically meaningful and not just "statistically significant." The pattern of engagement results that was in line with the increase in gain scores on two main variables strengthened the interpretation that adaptive mechanisms and AI system feedback also drive the quality of the learning process. Specifically, higher learning engagement in the experimental group reinforces the argument that AI-based adaptive learning supports differentiation of learning and improves the overall student learning experience.

DISCUSSION

The results showed that students who participated in Artificial Intelligence (AI) adaptive learning experienced a significantly higher increase in the aspect of understanding psychological material than students who participated in conventional learning. These findings can be explained through a differentiated learning theory framework that emphasizes the importance of adapting the material to students' readiness, interests, and learning profiles (Gheyssens et al., 2022). Adaptive learning allows for real-time personalization of content and feedback, thereby accelerating the cognitive elaboration process and reinforcing students' conceptual schemas. In this context, AI systems serve as facilitators of instructional differentiation that support the gradual and directed construction of knowledge. Previous research has shown that artificial

intelligence-based learning designed with the right pedagogical approach can significantly improve academic achievement compared to a one-way approach (Farhood et al., 2025). Thus, the increase in cognitive scores in this study strengthens the argument that AI is not just a technological tool, but a pedagogical mechanism that expands the effectiveness of differential learning.

In addition to cognitive improvement, the most prominent finding was the strengthening of emotion regulation ability in the experimental group. Theoretically, the regulation of emotions is a core component in the theory of self-regulated learning that emphasizes the interaction between cognition, motivation, and affection in the learning process (Efklides & Schwartz, 2024). Adaptive learning AI systems that provide immediate feedback and appropriate difficulty levels can reduce frustration and improve self-competence perception. This is in line with the findings Nieto Carracedo et al. (2024) which confirms that emotion regulation plays an important role in academic success and sustainability of learning motivation. Furthermore, data-driven adaptive learning systems can help students manage cognitive load and academic stress in a more controlled manner. Therefore, the improvement in emotion regulation in this study shows that the integration of AI in psychology education has a substantial affective impact, not just cognitive effects.

Findings on increased learning engagement also make an important contribution to understanding technology-based learning processes. Learning engagement includes cognitive, emotional, and behavioral dimensions that interact with each other in shaping the quality of the learning experience. The adaptive learning AI system encourages active participation through recommendations of relevant materials and proportionate challenges, so that students do not experience excessive boredom or anxiety. Study by Saleem et al. (2025) shows that AI-based learning has a positive relationship with increased engagement and material retention, particularly when systems are designed to deliver meaningful personalization. Thus, increased engagement in this study can be understood as a mediation mechanism that explains why the experimental group obtained higher learning outcomes and emotion regulation. Conceptually, these findings support the view that the quality of the learning process determines the quality of learning outcomes.

However, several contextual factors need to be considered in interpreting the results of this study. First, the duration of the intervention lasting six weeks may affect the magnitude of the effects obtained, as relatively short periods can produce strong but not necessarily sustained short-term effects. Second, the use of purposive sampling without full randomization opens up the possibility of uncontrolled latent variables, even though preliminary equivalence tests have shown relatively equivalent conditions. Third, the effectiveness of AI systems is also greatly influenced by teachers' readiness to facilitate the use of technology and students' digital readiness. As expressed by Wu & Zhang (2025), the implementation of AI in education requires digital literacy and mature pedagogical design for optimal impact. Therefore, external supporting factors still need to be considered in the generalization of the findings.

The theoretical contribution of this research lies in the integration of cognitive and affective dimensions in the evaluation of the effectiveness of AI in psychology education. Most previous studies have focused on academic outcomes solely without simultaneously evaluating students' emotional impact. By measuring material comprehension, emotion regulation, and learning engagement in a quasi-experimental framework, this study expands the scope of AI studies in education. This approach is aligned with a comprehensive perspective on artificial intelligence in learning that is not only performance-oriented, but also student well-being (Velastegui et al., 2023). In practical terms, the implementation model tested in the context of schools in Papua shows that AI can be applied adaptively in areas with a diversity of learning abilities. Thus, this research contributes to the development of a more inclusive and contextual technology-based learning model.

The constraint of this study mainly lies in the limitation of the sample size and the scope of the location that only includes one school, so the external validity still needs to be expanded. In addition, the measurement of emotion regulation is carried out through a self-report instrument that has the potential to be influenced by self-perception bias. Further research is recommended to use longitudinal design to test the sustainability of the effects of AI adaptive learning in the long term. The addition of mixed methods, such as behavioral observation or in-depth interviews, can also enrich the interpretation of results and reduce the bias of quantitative instruments. Overall, this study shows that the integration of Artificial Intelligence in psychology learning not only increases academic effectiveness, but also strengthens students' emotional competence, thus opening up space for further development in technology-based education that is humanistic and oriented towards cognitive-affective balance.

CONCLUSIONS AND RECOMMENDATIONS

This study confirms that the implementation of Artificial Intelligence (AI) based on adaptive learning significantly increases the effectiveness of psychology learning at the secondary school level, both in cognitive and affective aspects. Through the design of a quasi-experimental pretest–posttest control group, it was proven that students who participated in AI-based learning showed increased understanding of psychological concepts, strengthened emotional regulation, and higher learning engagement compared to students in conventional learning. These findings indicate that adaptive systems that adjust materials and feedback based on individual performance are able to support learning differentiation more precisely and responsive to student needs. Theoretically, this study expands the study of the integration of AI in psychology education by placing the cognitive and emotional dimensions as interrelated outcomes. Practically, the results of this study provide a contextual and applicable implementation model for schools with a diversity of learning abilities, as well as open up opportunities for the development of technology-based learning that is more humanistic, adaptive, and oriented towards strengthening students' emotional competence.

ADVANCED RESEARCH

This study shows that adaptive AI enhances psychology learning by improving understanding, emotional regulation, and engagement compared to conventional methods, while supporting more personalized and humanistic education.

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