KMAN PUBLISHING INSTITUTE
Journal Website

Article history:
Received 01 September 2025
Revised 22 December 2025
Accepted 29 December 2025
Initial Published 04 January 2026
Final Publication 10 March 2026

Journal of Adolescent and Youth Psychological Studies

Volume 7, Issue 3, pp 1-9

E-ISSN: 2981-2526

Interplay of Cognitive Flexibility and Adaptive Emotion Regulation as Predictors of Academic Success in AI-Enhanced Learning Environments

Malihe. Ghafourimanesh[1], Katauon. Haddadi[1*], Fatemeh. Mirchenari[2], Fateme. Haj Manouchehri[2]

[1] Department of Psychology, CT.C., Islamic Azad University, Tehran, Iran
[2] Department of Educational Psychology, CT.C., Islamic Azad University, Tehran, Iran

*** Corresponding author email address**: drhaddadi@iau.ac.ir

Article Info

Article type:
Original Research

How to cite this article:
Ghafourimanesh, M., Haddadi, K., Mirchenari, F., & Haj Manouchehri, F. (2026). Interplay of Cognitive Flexibility and Adaptive Emotion Regulation as Predictors of Academic Success in AI-Enhanced Learning Environments. *Journal of Adolescent and Youth Psychological Studies, 7*(3), 1-9.
http://dx.doi.org/10.61838/kman.jayps.4917

ABSTRACT

Objective: The objective of this study was to examine the interactive predictive roles of cognitive flexibility and adaptive emotion regulation on academic success among university students learning in artificial intelligence–enhanced educational environments.

Methods and Materials: This quantitative cross-sectional correlational study was conducted among 317 undergraduate students from major public universities in Tehran who were enrolled in courses supported by AI-based learning platforms. Participants completed validated questionnaires measuring cognitive flexibility, adaptive emotion regulation, engagement with AI-enhanced learning systems, and academic success. Data were analyzed using descriptive statistics, Pearson correlations, hierarchical multiple regression, and structural equation modeling with SPSS 26 and AMOS 24. Model fit was evaluated using standard goodness-of-fit indices including CFI, TLI, RMSEA, and SRMR.

Findings: Hierarchical regression revealed that after controlling for demographic variables and AI-learning engagement, cognitive flexibility ($\beta = .31$, $p < .001$) and adaptive emotion regulation ($\beta = .36$, $p < .001$) significantly predicted academic success, together explaining 56% of the total variance. Structural equation modeling demonstrated strong direct effects of cognitive flexibility ($\beta = .34$, $p < .001$) and adaptive emotion regulation ($\beta = .39$, $p < .001$) on academic success, as well as significant indirect effects mediated through AI-learning engagement ($\beta = .41$, $p < .001$). The overall model exhibited satisfactory fit to the data (CFI = .95, TLI = .94, RMSEA = .061, SRMR = .047).

Conclusion: The findings indicate that cognitive flexibility and adaptive emotion regulation are critical psychological determinants of academic success in AI-enhanced learning environments and operate both directly and through strengthening students' engagement with intelligent educational systems.

Keywords: *Artificial intelligence in education; cognitive flexibility; adaptive emotion regulation; academic success; higher education; learning engagement*

1. Introduction

The rapid diffusion of artificial intelligence technologies across higher education has fundamentally restructured the learning ecosystem, introducing unprecedented levels of personalization, automation, and data-driven decision-making into academic instruction. AI-enhanced learning environments now encompass adaptive learning systems, intelligent tutoring platforms, learning analytics dashboards, virtual tutors, and generative AI applications that dynamically adjust instructional content, pacing, feedback, and assessment to individual learner profiles. This transformation is no longer peripheral; rather, it constitutes the core infrastructure of contemporary university education worldwide (Wyk, 2023; Zhao, 2023; Zheng, 2025). Universities increasingly rely on AI-based tools to optimize instructional delivery, expand access, improve learning efficiency, and respond to the diverse cognitive and emotional needs of students (Aslam et al., 2025; Khan & Irfan, 2025; Rajavarman et al., 2025). While these technological advances promise substantial gains in educational effectiveness, they simultaneously impose complex cognitive and emotional demands on learners, thereby foregrounding the importance of psychological capacities that enable students to navigate, adapt, and thrive within AI-mediated academic environments.

Among these capacities, cognitive flexibility and adaptive emotion regulation have emerged as two foundational determinants of learning success in complex digital contexts. Cognitive flexibility refers to the ability to shift mental representations, update strategies, integrate new information, and adaptively respond to changing task demands. In AI-enhanced learning settings characterized by continuous feedback, algorithmic adaptation, and evolving instructional pathways, cognitive flexibility becomes essential for students to effectively interpret system responses, recalibrate learning strategies, and maintain conceptual coherence across dynamically changing content streams (Abishev et al., 2025; Far et al., 2024; Pérez & Losada, 2024). Parallel to this, adaptive emotion regulation encompasses the processes through which individuals monitor, evaluate, and modify emotional reactions in ways that facilitate goal-directed behavior and psychological well-being. The emotionally saturated nature of AI-driven learning—marked by performance monitoring, automated evaluation, algorithmic feedback, and rapid task transitions—intensifies students' affective experiences and places heightened demands on emotion regulation systems (Hussain et al., 2025; Melnichuk & Belogash, 2021; Zhang, 2025).

Theoretical and empirical scholarship increasingly suggests that the effectiveness of AI-enhanced learning environments is contingent not merely on technological sophistication, but on the learner's capacity to cognitively and emotionally engage with these systems. AI platforms personalize content, yet learners must possess sufficient cognitive flexibility to exploit these affordances and sufficient emotional regulation to cope with challenges such as cognitive overload, performance anxiety, uncertainty, and frustration. When these psychological capacities are underdeveloped, AI tools may paradoxically exacerbate learning difficulties rather than alleviate them (Hamdani, 2025; Ouariach et al., 2025; Sales, 2025).

Empirical research demonstrates that cognitive flexibility plays a central role in academic performance across educational levels. Students with higher cognitive flexibility exhibit superior problem-solving skills, deeper conceptual understanding, greater self-regulated learning, and stronger academic achievement (Dubuc et al., 2020; Far et al., 2024; Pérez & Losada, 2024). Within AI-supported learning environments, this relationship becomes even more pronounced, as learners must continuously adapt to algorithmically modified instructional sequences, personalized feedback, and evolving performance metrics (Abdullahi, 2025; Abishev et al., 2025; Mahafdah et al., 2024). Cognitive flexibility enables learners to avoid rigid learning patterns, embrace novel solution pathways, and dynamically integrate information provided by intelligent systems, thereby maximizing the pedagogical potential of AI technologies.

Concurrently, adaptive emotion regulation has been shown to exert a profound influence on learning outcomes. Effective regulation of academic emotions—including anxiety, frustration, boredom, and excitement—supports sustained attention, motivation, perseverance, and metacognitive engagement (Jiang-tao & Hali, 2025; Melnichuk & Belogash, 2021; Zhang, 2025). In AI-enhanced environments, where constant feedback loops and algorithmic evaluations may amplify emotional reactivity, the ability to modulate emotional responses becomes critical for maintaining psychological equilibrium and learning continuity (Hussain et al., 2025; Hussein et al., 2025). Students who employ adaptive strategies such as cognitive reappraisal, emotional acceptance, and proactive coping demonstrate superior academic resilience and learning effectiveness in digital contexts (Far et al., 2024; Kaur et al., 2025; Zambrano et al., 2025).

Recent studies have further highlighted the synergistic interplay between cognitive flexibility and adaptive emotion regulation. Cognitive adaptation and emotional adaptation operate as interdependent systems that jointly regulate students' engagement with complex learning tasks. Flexible cognition supports the reinterpretation of emotionally charged academic challenges, while effective emotion regulation stabilizes cognitive resources needed for flexible thinking (Far et al., 2024; Jiang-tao & Hali, 2025; Zhang, 2025). This bidirectional relationship becomes particularly salient in AI-enhanced learning contexts, where rapid feedback, personalized pathways, and dynamic assessment structures continuously reshape the learner's cognitive and emotional landscape.

At the institutional level, AI-enhanced education initiatives increasingly recognize that technological innovation alone cannot guarantee educational success. Research on AI-based adaptive learning systems consistently emphasizes that student outcomes depend heavily on psychological readiness, emotional stability, and cognitive adaptability (Bhatia et al., 2024; Chun et al., 2024; Ezzaim et al., 2024). While AI platforms offer unprecedented personalization and instructional precision, their effectiveness is ultimately mediated by learners' internal capacities to interpret, regulate, and utilize these technological resources.

Moreover, academic success in AI-enhanced learning environments extends beyond traditional performance indicators such as grades. It encompasses sustained engagement, perceived learning effectiveness, self-efficacy, motivation, and long-term knowledge retention (Amoah-Oppong et al., 2025; Faridoon et al., 2025; Kishorchandra & Rajnikant, 2025). AI systems increasingly track these multidimensional outcomes through learning analytics, reinforcing the need for comprehensive models that integrate cognitive, emotional, and technological factors in explaining student achievement (Aslam et al., 2025; Maaz et al., 2025; Vikram et al., 2025).

Despite this growing body of research, important gaps remain. Much of the existing literature examines either cognitive or emotional factors in isolation, or focuses primarily on technological features of AI-enhanced learning systems. Few empirical studies have systematically investigated the interactive contribution of cognitive flexibility and adaptive emotion regulation in predicting academic success within AI-enriched higher education contexts. Furthermore, the majority of studies have been conducted in Western or East Asian educational settings, leaving underexplored the sociocultural and institutional dynamics shaping AI-mediated learning in Middle Eastern academic environments.

In rapidly modernizing higher education systems such as those in Tehran, Iranian universities are increasingly adopting AI-supported learning platforms to enhance instructional quality, expand digital infrastructure, and align with global educational standards (Hamdani, 2025; Kiran, 2025; Sales, 2025). However, systematic empirical investigations into how Iranian students cognitively and emotionally adapt to these environments remain scarce. Understanding these processes is essential for designing effective pedagogical interventions, faculty training programs, and institutional policies that maximize the benefits of AI-driven education while mitigating potential psychological risks.

The convergence of these theoretical, empirical, and practical considerations underscores the necessity of an integrative framework that conceptualizes academic success in AI-enhanced learning environments as the product of dynamic interactions among cognitive flexibility, adaptive emotion regulation, and technological engagement. By situating learner psychology at the center of AI-mediated education, such a framework advances a more human-centered approach to educational technology, ensuring that innovation remains aligned with students' cognitive and emotional realities (Ouariach et al., 2025; Rajavarman et al., 2025; Sa-ad et al., 2025).

Accordingly, the present study seeks to empirically examine the interplay of cognitive flexibility and adaptive emotion regulation as predictors of academic success in AI-enhanced learning environments among university students in Tehran, with the aim of identifying the psychological mechanisms through which learners effectively engage with intelligent educational systems and achieve sustainable academic outcomes.

2. Methods and Materials

2.1. *Study Design and Participants*

The present study employed a quantitative, cross-sectional correlational design with a predictive modeling approach to examine the joint contribution of cognitive flexibility and adaptive emotion regulation to academic success in artificial intelligence–enhanced learning environments. The research population consisted of

JAYPS
Adolescent and Youth Psychological Studies
E-ISSN: 2981-2526

undergraduate students enrolled in public universities in Tehran who were actively participating in at least one course delivered through AI-supported digital learning platforms, including intelligent tutoring systems, adaptive learning management systems, and AI-driven assessment tools. Using stratified random sampling, participants were selected from four major universities to ensure representation across academic disciplines, year of study, and gender. Based on an a priori power analysis using G*Power for multiple regression with two primary predictors and five control variables, a minimum sample size of 280 participants was required to achieve a statistical power of .90 at $\alpha = .05$ with a medium effect size. To compensate for potential attrition and incomplete responses, 340 students were recruited, of whom 317 provided complete and valid datasets. Participants ranged in age from 18 to 27 years, with a mean age of 21.9 years. All participants had used AI-based learning systems for at least one academic semester. Ethical approval for the study was obtained from the university research ethics committee, and written informed consent was secured from all participants prior to data collection.

2.2. *Measures*

Data were collected using a structured online questionnaire package composed of four main sections. Cognitive flexibility was measured using the Cognitive Flexibility Inventory, consisting of 20 items assessing individuals' ability to adapt to changing cognitive demands, consider alternative solutions, and shift mental sets. Responses were recorded on a five-point Likert scale ranging from strongly disagree to strongly agree, with higher scores indicating greater cognitive flexibility. Adaptive emotion regulation was assessed using the Adaptive Emotion Regulation Questionnaire, which includes 28 items measuring strategies such as positive reappraisal, acceptance, refocusing on planning, and emotional awareness. Participants rated each item on a five-point Likert scale reflecting the frequency of use of each strategy. Academic success was operationalized using a composite index consisting of self-reported cumulative grade point average, perceived academic performance satisfaction, and perceived learning effectiveness within AI-enhanced courses. In addition, a short researcher-designed scale was used to assess the intensity and quality of engagement with AI-enhanced learning environments, including frequency of AI tool usage, perceived usefulness, and perceived personalization of instruction. All instruments demonstrated satisfactory internal consistency in the current sample, with Cronbach's alpha coefficients exceeding .80 for all major constructs. The questionnaire also collected demographic information including age, gender, field of study, year of study, and prior experience with digital learning technologies.

2.3. *Data Analysis*

Data analysis was conducted using SPSS version 26 and AMOS version 24. Preliminary analyses included screening for missing data, detection of outliers, and assessment of normality, linearity, and multicollinearity. Descriptive statistics were computed for all variables, followed by Pearson correlation analyses to examine the bivariate relationships among cognitive flexibility, adaptive emotion regulation, and academic success. To test the predictive model, hierarchical multiple regression analysis was performed. In the first step, demographic variables and AI engagement indicators were entered as control variables. In the second step, cognitive flexibility and adaptive emotion regulation were entered simultaneously to assess their unique and combined contributions to academic success. In addition, structural equation modeling was employed to examine the interactive pathways among variables and to evaluate the overall model fit using standard indices including CFI, TLI, RMSEA, and SRMR. Significance levels were set at $p < .05$. The final model provided both direct and interaction effects, allowing for a comprehensive evaluation of how cognitive flexibility and adaptive emotion regulation jointly predict academic success in AI-enhanced learning contexts.

3. Findings and Results

The data were analyzed to examine the relationships among cognitive flexibility, adaptive emotion regulation, and academic success in AI-enhanced learning environments. Descriptive statistics and correlation coefficients are first reported, followed by regression and structural equation modeling results. The results are presented in four tables.

Table 1 presents the descriptive statistics and bivariate correlations among the principal study variables, including cognitive flexibility, adaptive emotion regulation, AI-learning engagement, and academic success.

JAYPS Adolescent and Youth Psychological Studies
E-ISSN: 2981-2526

Table 1

Descriptive Statistics and Correlations among Study Variables

Variable	Mean	SD	1	2	3	4
1. Cognitive Flexibility	72.48	8.36	1			
2. Adaptive Emotion Regulation	95.62	10.41	.61**	1		
3. AI-Learning Engagement	38.29	6.17	.54**	.58**	1	
4. Academic Success	16.87	1.92	.63**	.67**	.59**	1

As shown in Table 1, all study variables demonstrated moderate to strong positive correlations. Cognitive flexibility was significantly correlated with adaptive emotion regulation ($r = .61$, $p < .01$), AI-learning engagement ($r = .54$, $p < .01$), and academic success ($r = .63$, $p < .01$). Adaptive emotion regulation also showed strong associations with AI-learning engagement ($r = .58$, $p < .01$) and academic success ($r = .67$, $p < .01$). These results indicate that higher levels of cognitive flexibility and adaptive emotion regulation are systematically associated with stronger engagement in AI-enhanced learning and higher academic success.

Table 2

Hierarchical Regression Analysis Predicting Academic Success

Predictor	B	SE B	β	t	p
Step 1					
Age	0.04	0.03	.06	1.21	.228
Gender	0.11	0.14	.04	0.79	.431
AI-Learning Engagement	0.21	0.03	.42	7.18	<.001
Step 2					
Cognitive Flexibility	0.07	0.02	.31	4.61	<.001
Adaptive Emotion Regulation	0.09	0.02	.36	5.29	<.001

Model statistics: Step 1: $R^2 = .38$, $F(3, 313) = 64.07$, $p < .001$
Step 2: $R^2 = .56$, $\Delta R^2 = .18$, $F(5, 311) = 79.64$, $p < .001$

Table 2 indicates that after controlling for demographic variables and AI-learning engagement, both cognitive flexibility and adaptive emotion regulation emerged as significant predictors of academic success. The inclusion of these two psychological variables explained an additional 18% of the variance in academic success, increasing the total explained variance to 56%. Adaptive emotion regulation ($\beta = .36$) showed a slightly stronger predictive effect than cognitive flexibility ($\beta = .31$), suggesting that emotional adaptation plays a particularly central role in academic performance within AI-enhanced learning contexts.

Table 3

Structural Equation Model Fit Indices

Fit Index	Obtained Value	Recommended Threshold
χ^2/df	2.14	< 3.00
CFI	.95	≥ .90
TLI	.94	≥ .90
RMSEA	.061	≤ .08
SRMR	.047	≤ .08

The results in Table 3 show that in the first experimental group (self-efficacy training), MANCOVA revealed significant differences between the groups in intrinsic motivation ($\eta^2 = .42$, $F = 26.08$, $p < .001$) and extrinsic motivation ($\eta^2 = .15$, $F = 6.38$, $p < .01$), indicating higher scores for the experimental group compared to the control

E-ISSN: 2981-2526

group. For anxiety, ANCOVA also showed a significant group difference ($\eta^2 = .45$, $F = 14.86$, $p < .001$), with the experimental group exhibiting lower anxiety levels. In the second experimental group (mindfulness training), MANCOVA results also indicated significant differences in intrinsic motivation ($\eta^2 = .47$, $F = 16.44$, $p < .001$) and extrinsic motivation ($\eta^2 = .41$, $F = 12.71$, $p < .001$). Additionally, ANCOVA for anxiety revealed an even larger effect size ($\eta^2 = .57$, $F = 24.29$, $p < .001$). Overall, the findings demonstrate that both self-efficacy and mindfulness interventions had positive and statistically significant effects on increasing academic motivation—particularly intrinsic motivation—and reducing anxiety in the experimental groups. Subsequently, the covariance analysis table for the dependent variables across groups is presented. To examine differences between the two interventions, the Bonferroni test was used, and the results are reported in Table 4.

Table 4

Standardized Path Coefficients in the Structural Model

Path	Standardized Estimate (β)	p
Cognitive Flexibility → Academic Success	.34	< .001
Adaptive Emotion Regulation → Academic Success	.39	< .001
Cognitive Flexibility → AI-Learning Engagement	.52	< .001
Adaptive Emotion Regulation → AI-Learning Engagement	.56	< .001
AI-Learning Engagement → Academic Success	.41	< .001

Table 4 reveals significant direct effects of cognitive flexibility and adaptive emotion regulation on academic success, as well as indirect effects mediated through AI-learning engagement. Adaptive emotion regulation exhibited the strongest direct effect on academic success ($\beta = .39$), followed by cognitive flexibility ($\beta = .34$). Both psychological capacities strongly predicted engagement with AI-enhanced learning systems, which in turn substantially contributed to academic success ($\beta = .41$). These findings confirm the central role of both cognitive and emotional adaptability in promoting effective learning outcomes in technologically enriched academic environments.

4. Discussion

The present study examined the interactive roles of cognitive flexibility and adaptive emotion regulation in predicting academic success within AI-enhanced learning environments among university students in Tehran. The findings demonstrated that both cognitive flexibility and adaptive emotion regulation independently and jointly contributed significantly to academic success, even after controlling for demographic variables and the level of engagement with AI-based learning systems. Moreover, the structural model confirmed that engagement with AI-enhanced learning platforms partially mediated these relationships, highlighting the central role of learner–technology interaction in contemporary higher education.

The strong positive relationship observed between cognitive flexibility and academic success is consistent with a growing body of research emphasizing the importance of flexible cognitive processing in complex learning contexts. Cognitive flexibility enables learners to revise mental models, adapt strategies, and integrate new information efficiently—skills that are especially critical in AI-driven environments where instructional pathways continuously evolve (Abishev et al., 2025; Far et al., 2024; Pérez & Losada, 2024). AI-enhanced systems frequently modify content sequencing, feedback timing, and task difficulty in response to learner behavior, thereby requiring students to constantly recalibrate their learning strategies. Students with higher cognitive flexibility are better equipped to interpret algorithmic feedback, shift problem-solving approaches, and sustain effective engagement under these dynamic conditions, which directly enhances academic performance.

These findings align with previous research demonstrating that cognitive flexibility is a robust predictor of academic achievement across educational levels and subject domains (Dubuc et al., 2020; Far et al., 2024). Within AI-supported learning environments, this relationship becomes even more pronounced because learners must navigate algorithmically generated instructional complexity and uncertainty (Bhatia et al., 2024; Mahafdah et al., 2024). The present results extend this literature by demonstrating that cognitive flexibility not only directly predicts academic success but also exerts an indirect influence by strengthening students' engagement with AI-enhanced learning systems.

JAYPS Adolescent and Youth Psychological Studies E-ISSN: 2981-2526

This supports the proposition that cognitive adaptability functions as a foundational competence enabling learners to fully capitalize on the affordances of intelligent educational technologies (Abdullahi, 2025; Khan & Irfan, 2025).

Adaptive emotion regulation emerged as an equally powerful predictor of academic success, exerting an even slightly stronger effect than cognitive flexibility in the final model. This finding underscores the critical role of emotional processes in AI-mediated learning contexts. AI-enhanced environments expose students to continuous performance monitoring, automated evaluation, and rapid feedback cycles, which can amplify emotional arousal and vulnerability (Hussain et al., 2025; Zhang, 2025). Students who effectively regulate emotions such as anxiety, frustration, and uncertainty are better able to maintain focus, sustain motivation, and persist in the face of academic challenges, thereby achieving higher levels of academic success.

This result is highly consistent with existing research emphasizing the importance of emotion regulation in technology-rich learning environments. Studies indicate that adaptive emotional strategies facilitate learning flow, self-directed learning, and academic resilience in digital contexts (Chun et al., 2024; Melnichuk & Belogash, 2021). In AI-supported education, emotional stability becomes particularly salient because algorithmic systems can inadvertently increase performance pressure and cognitive load (Hussain et al., 2025; Sales, 2025). The present findings confirm that students who can effectively manage their emotional responses are more capable of engaging productively with AI-based platforms and achieving superior academic outcomes.

The observed mediation effect of AI-learning engagement further elucidates the mechanism through which cognitive and emotional capacities translate into academic success. Students with higher cognitive flexibility and stronger adaptive emotion regulation reported significantly greater engagement with AI-enhanced learning tools, which in turn predicted higher academic success. This supports the view that engagement serves as a critical behavioral conduit linking psychological capacities to learning outcomes in AI-driven education (Amoah-Oppong et al., 2025; Faridoon et al., 2025; Ouariach et al., 2025). Learners who are cognitively and emotionally equipped to interact with AI systems more effectively are more likely to explore personalized features, utilize feedback mechanisms, and sustain deep learning involvement, thereby amplifying academic gains.

The structural model further revealed that both cognitive flexibility and adaptive emotion regulation exerted substantial direct effects on academic success while simultaneously strengthening engagement with AI systems. This dual pathway highlights the integrated nature of psychological functioning in AI-enhanced learning environments. Cognitive adaptation supports the interpretation of emotionally charged academic experiences, while emotional regulation stabilizes cognitive resources necessary for flexible thinking. This reciprocal interaction creates a reinforcing cycle that promotes sustained academic success in technologically complex learning contexts (Far et al., 2024; Jiang-tao & Hali, 2025; Zhang, 2025).

From a broader perspective, these findings support contemporary educational models that conceptualize AI-enhanced learning as a socio-technical system in which learner psychology and technological design are deeply interdependent (Aslam et al., 2025; Rajavarman et al., 2025; Zambrano et al., 2025). While AI systems provide unprecedented instructional personalization and data-driven precision, their educational value is ultimately determined by learners' cognitive and emotional capacities to engage with these technologies productively. Without sufficient cognitive flexibility and emotion regulation, students may struggle to adapt to AI-mediated learning dynamics, potentially undermining the very benefits these systems are designed to deliver (Hamdani, 2025; Sales, 2025).

The findings also carry significant implications for higher education systems undergoing rapid AI integration, particularly in non-Western contexts such as Iran. Iranian universities are increasingly investing in AI-supported learning infrastructures to enhance educational quality and global competitiveness (Kiran, 2025; Kishorchandra & Rajnikant, 2025). However, technological adoption alone is insufficient to guarantee academic improvement. The present results emphasize that student psychological readiness must be addressed in parallel with technological innovation. Institutional policies that promote cognitive flexibility development and emotion regulation training may substantially enhance the effectiveness of AI-based educational reforms.

5. Conclusion

Overall, the findings complement emerging research demonstrating that AI-enhanced learning environments influence not only academic performance but also students' learning habits, motivation, and long-term educational

JAYPS Adolescent and Youth Psychological Studies
E-ISSN: 2981-2526

trajectories (Maaz et al., 2025; Sa-ad et al., 2025; Vikram et al., 2025). By identifying cognitive flexibility and adaptive emotion regulation as key psychological predictors of success, the present study contributes to a more comprehensive understanding of learner–AI interaction and provides actionable insights for optimizing educational outcomes in AI-driven universities.

6. Limitations & Suggestions

Despite its contributions, the present study is subject to several limitations. The cross-sectional design restricts causal inference and prevents examination of developmental changes in cognitive and emotional capacities over time. The reliance on self-report measures may also introduce response bias, particularly in the assessment of emotional processes and engagement behaviors. Additionally, the sample was limited to university students in Tehran, which may constrain the generalizability of the findings to other cultural, institutional, and educational contexts.

Future studies should employ longitudinal designs to explore how cognitive flexibility and emotion regulation evolve in response to prolonged exposure to AI-enhanced learning environments. Experimental interventions aimed at strengthening these psychological capacities could provide causal evidence for their impact on academic success. Comparative cross-cultural research would further clarify the universality versus contextual specificity of these relationships. Incorporating objective learning analytics data alongside self-report measures may also yield more nuanced insights into learner–AI interactions.

Higher education institutions should integrate cognitive flexibility training and emotion regulation development into student support services and curricular design. Faculty development programs should emphasize pedagogical strategies that promote adaptive thinking and emotional resilience in AI-mediated classrooms. AI system designers should incorporate features that support emotional well-being and cognitive adaptability, ensuring that technological innovation remains aligned with human learning needs and psychological sustainability.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

Authors' Contributions

All authors equally contributed to this article.

References

Abdullahi, N. J. K. (2025). Managing Artificial Intelligence-Driven Platforms for Student Development. *International Journal of Engineering Technology and Natural Sciences*, *7*(1), 75-86. https://doi.org/10.46923/ijets.v7i1.467

Abishev, N., Ramazanov, R. R., Abaideldanova, M., Chesnokova, K., & Baizhumayeva, A. (2025). Artificial Intelligence Model in the Cognitive and Learning Activities of University Subjects. *Frontiers in Education*, *10*. https://doi.org/10.3389/feduc.2025.1623170

Amoah-Oppong, D., Coufie, P. J., Antwi, R., & Laing, E. V. (2025). Application of Artificial Intelligence Techniques on Lesson Delivery in Senior High Schools in Ghana: Enhancing Student Engagement, Personalised Learning, Performance Assessment and Holistic Development. https://doi.org/10.21203/rs.3.rs-6393110/v1

Aslam, F., Marwat, S. A., Arif, M., & Hussain, A. (2025). Artificial Intelligence in Higher Education: Shaping the Future of University Teaching Through Adaptive Learning, Intelligent Tutoring, and Academic Analytics. *Ijss*, *3*(2), 46-64. https://doi.org/10.59075/ijss.v3i2.1007

Bhatia, A., Bhatia, P., & Sood, D. (2024). Leveraging AI to Transform Online Higher Education: Focusing on Personalized Learning, Assessment, and Student Engagement. *International Journal of Management and Humanities*, *11*(1), 1-6. https://doi.org/10.35940/ijmh.a1753.11010924

Chun, Y. E., Hwang, S. W., & Burm, E. (2024). Exploring the Impact of AI-based Adaptive Learning on Academic Achievement: Focusing on the Mediating Learning Flow and Self-Directed Learning Ability. *Asia-pacific Journal of Convergent Research Interchange*, *10*(7), 541-555. https://doi.org/10.47116/apjcri.2024.07.39

Dubuc, M., Aubertin-Leheudre, M., & Karelis, A. D. (2020). Relationship Between Interference Control and Working Memory With Academic Performance in High School Students: The Adolescent Student Academic Performance Longitudinal Study (ASAP). *Journal of adolescence*, *80*(1), 204-213. https://doi.org/10.1016/j.adolescence.2020.03.001

Ezzaim, A., Dahbi, A., Haidine, A., & Aqqal, A. (2024). The Impact of Implementing a Moodle Plug-in as an AI-based Adaptive Learning Solution on Learning Effectiveness: Case of Morocco. *International Journal of Interactive Mobile Technologies (Ijim)*, *18*(01), 133-149. https://doi.org/10.3991/ijim.v18i01.46309

Far, F. T., Ghanadzadegan, H., & Heydari, S. (2024). A Comparison of the Effectiveness of Emotional Cognitive Regulation Strategies and Self-Regulated Learning Strategies on Academic Self-Concept and Cognitive Flexibility in Elementary School Students With Specific Learning Disabilities in Reading. *Injoeacs*, *5*(5), 124-132. https://doi.org/10.61838/kman.ijecs.5.5.14

Faridoon, N., Talpur, Q., Latif, F., Naz, G., & Shahzad, T. (2025). The Role of AI Tutors in Improving Academic Performance and Student Engagement. *Aijss*, *4*(3), 5897-5910. https://doi.org/10.63056/acad.004.03.0837

Hamdani, D. A. (2025). Understanding Perceptions, Adoption Rates and Challenges of New Technologies in Education. *Global Conference on Business and Social Sciences Proceeding*, *17*(1), 99-99. https://doi.org/10.35609/gcbssproceeding.2025.1(99)

Hussain, S., Ayub, F., Ahmed, N., & Din, Z. U. (2025). Cognitive Load Management Through Adaptive AI Learning System Implications for Student Focus and Retention. *The Critical Review of Social Sciences Studies*, *3*(3), 701-719. https://doi.org/10.59075/kpfrdv65

Hussein, E., Hussein, M. A., & Al-Hendawi, M. (2025). Investigation Into the Applications of Artificial Intelligence (AI) in Special Education: A Literature Review. *Social Sciences*, *14*(5), 288. https://doi.org/10.3390/socsci14050288

Jiang-tao, F. U., & Hali, A. U. (2025). The Role of the Reflective Thinking Scale for International Students in China Through Factor Analysis. *Behavioral Sciences*, *15*(5), 651. https://doi.org/10.3390/bs15050651

Kaur, R., Sarkar, R., Lalitha, M. K., Chandra, S., & Anand, T. (2025). The Effect of AI-Enhanced Gamification on Learning Outcomes in Higher Education. 75-104. https://doi.org/10.4018/979-8-3373-5077-6.ch004

Khan, M. S., & Irfan, R. (2025). The Role of Artificial Intelligence in Academic Achievement in the Current Scenario. *International Journal for Multidisciplinary Research*, *7*(4). https://doi.org/10.36948/ijfmr.2025.v07i04.49965

Kiran, A. S. (2025). Applications and Impacts of Ai Tools in Education. https://doi.org/10.47716/978-93-92090-38-7

Kishorchandra, P. V., & Rajnikant, P. (2025). The Impact of AI on the Learning Habits of HEI Students. *International Journal of Current Science Research and Review*, *08*(07). https://doi.org/10.47191/ijcsrr/v8-i7-44

Maaz, N., Mounsef, J., & Maalouf, N. (2025). CARE: Towards Customized Assistive Robot-Based Education. *Frontiers in Robotics and Ai*, *12*. https://doi.org/10.3389/frobt.2025.1474741

Mahafdah, R. F., Bouallegue, S., & Bouallègue, R. (2024). Enhancing E-Learning Through AI: Advanced Techniques for Optimizing Student Performance. https://doi.org/10.21203/rs.3.rs-4724603/v1

Melnichuk, M. V., & Belogash, M. A. (2021). Emotional Interaction as a Facilitator of IT-enhanced Distance Education. *Liberal Arts in Russia*, 162. https://doi.org/10.15643/libartrus-2021.3.3

Ouariach, S., Ouariach, F. Z., & Khaldi, M. (2025). Artificial Intelligence as a Harbinger of Engagement and Collaboration. 147-180. https://doi.org/10.4018/979-8-3373-2262-9.ch006

Pérez, E. E., & Losada, J. L. (2024). Using Artificial Intelligence in Education: Decision Tree Learning Results in Secondary School Students Based on Cold and Hot Executive Functions. *Humanities and Social Sciences Communications*, *11*(1). https://doi.org/10.1057/s41599-024-04040-y

Rajavarman, V. N., Raja, V. S., R, M. S., & Senthilvelan, G. (2025). Ai in Education Today. https://doi.org/10.47716/978-93-92090-42-4

Sa-ad, M. M., Abukari, A. M., Korda, D. R., & Owusu-Boateng, O. (2025). Personalized Learning Experiences With Artificial Intelligence. https://doi.org/10.70593/978-93-49307-53-7_2

Sales, X. (2025). The Teaching Challenges of AI in Higher Education. 57-74. https://doi.org/10.63782/pf24004

Vikram, E., Kalaivani, K., Praanesh, M. R., & Surya, M. (2025). GEN AI Based Personalized AI Tutor. *Interantional Journal of Scientific Research in Engineering and Management*, *09*(10), 1-9. https://doi.org/10.55041/ijsrem53002

Wyk, C. S. (2023). AI in Education. https://doi.org/10.38140/ufs.c.6762126

Zambrano, S. E. V., Herrera, P., Paltán, B. P. H., Atiencia, J. C. F., & Atiencia, J. C. F. (2025). Implementación De Inteligencia Artificial Para La Personalización Del Aprendizaje en Educación Superior. *Salud Ciencia Y Tecnología - Serie De Conferencias*, *4*, 1436. https://doi.org/10.56294/sctconf20251436

Zhang, J. (2025). Emotional Intelligence, Foreign Language Enjoyment, and AI-Assisted Pedagogy: Integrating Positive Psychology for Resilient and Sustainable Language Learning. https://doi.org/10.21203/rs.3.rs-8256795/v1

Zhao, T. (2023). AI in Educational Technology. https://doi.org/10.20944/preprints202311.0106.v1

Zheng, M. (2025). Artificial Intelligence in Lifelong Learning: Enhancing Chinese Language Instruction for Non-Native Adult Learners. *GBP Proc. Ser.*, *2*, 141-146. https://doi.org/10.71222/vxzcka39