

Artificial Intelligence Enabled Adaptive Pedagogy in Physical Education for Multidomain Learning

1st Mohamad Da'i¹, 2nd Rohmad Apriyanto², 3rd Benny Widya Priadana³,
4th Olivia Dwi Cahyani⁴
{dai@unugiri.ac.id¹, rohmadaapriyanto87@unugiri.ac.id², benny.wp@unugiri.ac.id³,
olivia@unugiri.ac.id⁴}

Universitas Nahdlatul Ulama Sunan Giri^{1,2,3,4}

Abstract. This study examined the relationship between artificial intelligence enabled adaptive pedagogy and perceived multidomain learning in physical education. A quantitative cross-sectional correlational design involved 196 undergraduate Physical Education students. Data were collected using a 43-item questionnaire measuring five adaptive pedagogy dimensions and cognitive, affective, and psychomotor learning domains. Descriptive statistics, Pearson correlation, and linear regression were applied. Artificial intelligence enabled adaptive pedagogy showed a strong positive relationship with perceived multidomain learning, $r = .666$, $p < .001$, and explained 44.3% of its variance. Learning personalization emerged as the strongest unique statistical correlate, $\beta = .296$, $p = .003$. These findings indicate that personalization, adaptive feedback, task adjustment, learning analytics, and learner autonomy can support perceived multidomain learning across cognitive, affective, and psychomotor domains. The study highlights the pedagogical significance of AI for responsive and data-informed physical education.

Keywords: artificial intelligence; adaptive pedagogy; physical education; perceived multidomain learning; learning personalization.

1. Introduction

Artificial intelligence has become an increasingly important component of contemporary educational systems because it can support learner modeling, automated assessment, instructional recommendations, and data-informed decision making. AI applications in education have expanded from basic automation toward systems that analyze learner characteristics and provide learning support according to individual needs [1]. This development requires a pedagogical orientation that places learning objectives, learner agency, and instructional quality above technological novelty [2]. Recent conceptual perspectives describe AI in education through successive paradigms that move from system directed instruction toward learner-centered and collaborative forms of intelligent support [3]. Systematic evidence also shows that AI creates substantial opportunities for personalization, feedback, prediction, and learning analytics, while raising persistent concerns related to pedagogical alignment, teacher competence, transparency, and educational effectiveness [4]. These conditions establish a strong rationale for examining AI as a pedagogical mechanism rather than as an isolated digital tool.

Physical education provides a distinctive setting for AI integration because learning simultaneously involves conceptual knowledge, affective engagement, physical competence, and observable movement performance. AI has been applied in physical education to support personalized instruction, movement analysis, fitness evaluation, learning assessment, and

instructional decision making [5]. A recent systematic review confirms that AI applications in physical education have grown across intelligent tutoring, motion recognition, personalized learning, prediction, and feedback systems [6]. Digital innovation in physical education has also expanded beyond conventional learning platforms. Da'i and Apriyanto demonstrated the potential of digital comics as a learning medium for enhancing elementary athletic learning [7]. Dai et al. developed a mixed reality approach for pencak silat learning to support differentiated and technology-integrated instruction [8]. Broader evidence indicates that the effective use of AI in physical education depends on teachers' ability to connect technological functions with curriculum design, pedagogical adaptation, and learner characteristics [9]. These findings indicate a transition from digital media use toward more adaptive and responsive instructional environments.

Adaptive pedagogy provides a relevant conceptual framework for organizing these technological capabilities into a coherent learning process. AI enabled adaptive learning systems can analyze learner data and modify content, learning pathways, feedback, and task demands according to individual performance and progression [10]. Reviews of adaptive learning supported by AI identify personalization, learner profiling, prediction, recommendation, and dynamic adjustment as central mechanisms for improving the responsiveness of learning environments [11]. These mechanisms are highly relevant to physical education because students differ in prior knowledge, motor competence, confidence, physical capacity, and learning pace. AI can provide immediate information after task performance, identify errors, and generate targeted recommendations for subsequent learning activities. Recent research on AI-based real-time feedback in physical education has shown the practical relevance of responsive feedback for supporting instructional processes [12]. Intelligent evaluation and feedback systems also provide opportunities to use performance information for instructional adjustment and continuous learning monitoring [13]. AI enabled adaptive pedagogy can therefore be operationalized through learning personalization, adaptive real-time feedback, adjustment of task difficulty, learning analytics for decision making, and support for learner autonomy.

The value of adaptive pedagogy in physical education should be evaluated through outcomes that represent the multidimensional character of learning. Physical education does not focus exclusively on physical performance. Quality physical education contributes to learning and development across cognitive, behavioral, social, emotional, and physical dimensions [14]. Pedagogical approaches that support physical literacy also emphasize the integration of knowledge, motivation, confidence, and physical competence [15]. Physical literacy research has consistently conceptualized learning as an interaction between cognitive understanding, affective disposition, and embodied competence [16]. These principles support a multidomain framework in which cognitive learning includes knowledge of movement concepts, biomechanical principles, analysis, and instructional understanding. Affective learning includes motivation, confidence, discipline, responsibility, and engagement. Psychomotor learning includes movement competence, technical execution, coordination, demonstration, and practical performance. Evidence from physical education research also shows that instructional design can influence achievement motivation and students' willingness to participate actively in learning [17]. Meta-analytic evidence further confirms that pedagogical interventions can produce measurable effects on motivation when instructional content and learning experiences are structured appropriately [18].

A critical research gap remains between technological innovation and integrated pedagogical evidence. Studies on AI in education have identified persistent gaps between technological development, educational theory, and empirically demonstrated learning effects

[19]. Research in physical education has often examined specific applications such as movement analysis, intelligent evaluation, fitness prediction, generative AI, or technology acceptance. This fragmented orientation makes it difficult to determine whether AI functions collectively as an adaptive pedagogical system. Evidence from K-12 education also indicates that AI offers substantial instructional affordances, but its educational value depends on contextual suitability, teacher mediation, ethical use, and alignment with learner needs [20]. Recent research on generative AI in sport and physical education has expanded discussion on instructional planning, content generation, and learning support, yet the field still requires stronger empirical evidence connecting AI-based adaptation with multidomain learning outcomes [21]. Limited research has examined personalization, adaptive feedback, task difficulty adjustment, learning analytics, and learner autonomy as interconnected dimensions of one adaptive pedagogical construct and related them simultaneously to cognitive, affective, and psychomotor learning.

This study addresses this gap by examining artificial intelligence enabled adaptive pedagogy in physical education and its relationship with multidomain learning among university students in physical education. The study conceptualizes AI enabled adaptive pedagogy through five dimensions, namely learning personalization, adaptive real-time feedback, adjustment of task difficulty, learning analytics for instructional decision making, and learner autonomy. Multidomain learning is examined through cognitive, affective, and psychomotor domains. The study aims to describe the level of AI enabled adaptive pedagogy and multidomain learning, examine the relationship between both constructs, and determine the extent to which adaptive pedagogy is associated with multidomain learning. The novelty of this study lies in integrating several adaptive AI functions into a unified pedagogical construct and linking that construct to three learning domains that represent the core educational characteristics of physical education. This framework provides an empirical basis for designing physical education environments that are more personalized, responsive, data-informed, and aligned with multidomain learning.

2. Method

Study Design

This study employed a quantitative cross-sectional correlational design to examine the relationship between artificial intelligence enabled adaptive pedagogy and perceived multidomain learning in physical education. Artificial intelligence enabled adaptive pedagogy was positioned as the predictor construct, while perceived multidomain learning was treated as the outcome construct. The design enabled the simultaneous assessment of students' learning experiences and perceived multidomain learning outcomes without manipulating instructional conditions.

Participants

The participants were 196 undergraduate students enrolled in the Physical Education, Health, and Recreation program. The sample comprised 149 male students, 76.0%, and 47 female students, 24.0%. A total of 134 students, 68.4%, were in the fourth semester and 62 students, 31.6%, were in the sixth semester. Previous experience using artificial intelligence applications was reported by 131 students, 66.8%. All complete responses were included in the analysis.

Instrument

Data were collected using a structured 43-item questionnaire developed to measure artificial intelligence enabled adaptive pedagogy and perceived multidomain learning. The adaptive pedagogy construct consisted of 25 items covering learning personalization, adaptive real-time feedback, task difficulty adjustment, learning analytics for decision making, and

learner autonomy support. These dimensions represent key applications of AI for personalized instruction, intelligent guidance, evaluation, and adaptive recommendation in physical education [22], [23], [24], [25], [26].

Perceived multidomain learning consisted of 18 items representing cognitive, affective, and psychomotor domains, with six items in each domain. All items were rated using a five-point Likert scale ranging from 1, Strongly Disagree, to 5, Strongly Agree. Higher scores indicated stronger perceptions of AI enabled adaptive pedagogy and perceived multidomain learning. The complete construct structure is presented in Table 1.

Table 1. Structure of the Research Instrument

Construct	Dimension	Item Code	Number of Items
Artificial Intelligence Enabled Adaptive Pedagogy	Learning Personalization	X1–X5	5
Artificial Intelligence Enabled Adaptive Pedagogy	Adaptive Real-Time Feedback	X6–X10	5
Artificial Intelligence Enabled Adaptive Pedagogy	Task Difficulty Adjustment	X11–X15	5
Artificial Intelligence Enabled Adaptive Pedagogy	Learning Analytics for Decision Making	X16–X20	5
Artificial Intelligence Enabled Adaptive Pedagogy	Learner Autonomy Support	X21–X25	5
Perceived Multidomain Learning	Cognitive Domain	Y1–Y6	6
Perceived Multidomain Learning	Affective Domain	Y7–Y12	6
Perceived Multidomain Learning	Psychomotor Domain	Y13–Y18	6

Content validity was assessed through expert judgment based on item relevance, language clarity, and item construction. The expert ratings ranged from 3 to 4 on a four-point scale, and the instrument was judged suitable for use without revision. Internal consistency was subsequently assessed using Cronbach's alpha and corrected item-total correlations.

Data Collection and Ethical Considerations

Participants received information about the study objectives, voluntary participation, confidentiality, and the academic use of the collected data before completing the questionnaire. Participation did not affect academic assessment, and respondents could discontinue participation at any stage. Participants first completed demographic information and previous AI experience, followed by the 25 adaptive pedagogy items and 18 perceived multidomain learning items. Data screening confirmed that all 196 responses contained complete values across the 43 analytical items.

Statistical Analysis

Descriptive statistics included frequency, percentage, mean, standard deviation, minimum, and maximum values. Internal consistency was assessed using Cronbach's alpha and corrected item-total correlations. Distributional assumptions were examined using the Shapiro-Wilk test, skewness, and kurtosis.

Pearson correlation was used to examine the association between artificial intelligence enabled adaptive pedagogy and perceived multidomain learning. Simple linear regression assessed the association between the overall adaptive pedagogy score and perceived multidomain learning. Multiple linear regression examined the unique associations of the five adaptive pedagogy dimensions with perceived multidomain learning, with variance inflation

factors used to assess multicollinearity. Statistical significance was set at $p < .05$ using two-tailed tests.

3. Results

Participant Characteristics

The analysis included 196 undergraduate students from the Physical Education, Health, and Recreation program. Male students represented 76.0% of the sample, while female students represented 24.0%. Most participants were fourth-semester students, 68.4%, and 66.8% reported previous experience using artificial intelligence applications. All 196 cases contained complete responses across the 43 analytical items, resulting in no missing data for the primary analyses.

Table 2. Characteristics of Participants.

Characteristic	Category	n	%
Gender	Male	149	76
	Female	47	24
Semester	Fourth semester	134	68.4
	Sixth semester	62	31.6
Previous AI experience	Yes	131	66.8
	No	65	33.2

Descriptive Statistics and Internal Consistency

Table 3 presents the descriptive statistics and internal consistency of the study constructs. The overall score for artificial intelligence enabled adaptive pedagogy was relatively high, $M = 3.923$, $SD = 0.489$. Learning Personalization showed the highest mean among the five adaptive pedagogy dimensions, $M = 3.969$, followed by Task Difficulty Adjustment, $M = 3.921$, Learner Autonomy Support, $M = 3.918$, Adaptive real-time feedback, $M = 3.911$, and Learning Analytics, $M = 3.896$. The narrow range of dimension means indicates relatively consistent perceptions across the adaptive learning components.

Perceived multidomain learning also showed a relatively high overall score, $M = 3.939$, $SD = 0.387$. The Cognitive Domain recorded the highest mean, $M = 3.963$, followed by the Psychomotor Domain, $M = 3.932$, and the Affective Domain, $M = 3.923$. Internal consistency was strong for the overall adaptive pedagogy scale, $\alpha = .941$, and perceived multidomain learning scale, $\alpha = .868$. Reliability coefficients across the specific dimensions ranged from .620 to .783.

Table 3. Descriptive Statistics and Internal Consistency of Study Constructs

Construct and Dimension	M	SD	Min	Max	Cronbach's alpha
Artificial Intelligence Enabled Adaptive Pedagogy	3.923	0.489	2.48	4.92	0.941
Learning Personalization	3.969	0.533	2.20	5.00	0.760
Adaptive Real-Time Feedback	3.911	0.531	2.60	5.00	0.740
Task Difficulty Adjustment	3.921	0.528	2.60	5.00	0.727
Learning Analytics	3.896	0.561	2.00	5.00	0.783
Learner Autonomy Support	3.918	0.564	2.40	5.00	0.781
Perceived Multidomain Learning	3.939	0.387	2.83	4.83	0.868
Cognitive Domain	3.963	0.397	2.67	4.83	0.620
Affective Domain	3.923	0.450	2.50	5.00	0.714
Psychomotor Domain	3.932	0.438	2.67	5.00	0.666

Correlations Between Adaptive Pedagogy and Perceived Multidomain Learning

The overall artificial intelligence enabled adaptive pedagogy score was positively and significantly correlated with perceived multidomain learning, $r = .666$, $p < .001$. This coefficient indicates a moderate-to-strong positive relationship, suggesting that higher levels of adaptive pedagogy were associated with higher perceived cognitive, affective, and psychomotor learning outcomes.

All five adaptive pedagogy dimensions showed significant positive correlations with the three perceived learning domains: cognitive, affective, and psychomotor, with coefficients ranging from $r = .454$ to $r = .612$, all $p < .001$. Learning Personalization demonstrated the strongest correlation with the Psychomotor Domain, $r = .612$. Learner Autonomy Support showed the strongest relationship with the Affective Domain, $r = .576$, while Learning Personalization also displayed a substantial relationship with the Cognitive Domain, $r = .571$.

Table 4. Correlations Between Adaptive Pedagogy Dimensions and Perceived Multidomain Learning

Adaptive Pedagogy Dimension	Cognitive	Affective	Psychomotor
Learning Personalization	0.571	0.541	0.612
Adaptive Real-Time Feedback	0.537	0.548	0.548
Task Difficulty Adjustment	0.484	0.454	0.523
Learning Analytics	0.551	0.514	0.555
Learner Autonomy Support	0.558	0.576	0.552

Note. All correlations were statistically significant at $p < .001$.

Figure 1 illustrates the relationship between Artificial Intelligence Enabled Adaptive Pedagogy and Perceived Multidomain Learning. The distribution of individual observations shows a clear positive linear pattern. Higher adaptive pedagogy scores were associated with higher perceived multidomain learning scores. This visual pattern is consistent with the Pearson correlation analysis, which demonstrated a significant positive relationship between the two constructs, $r = .666$, $p < .001$.

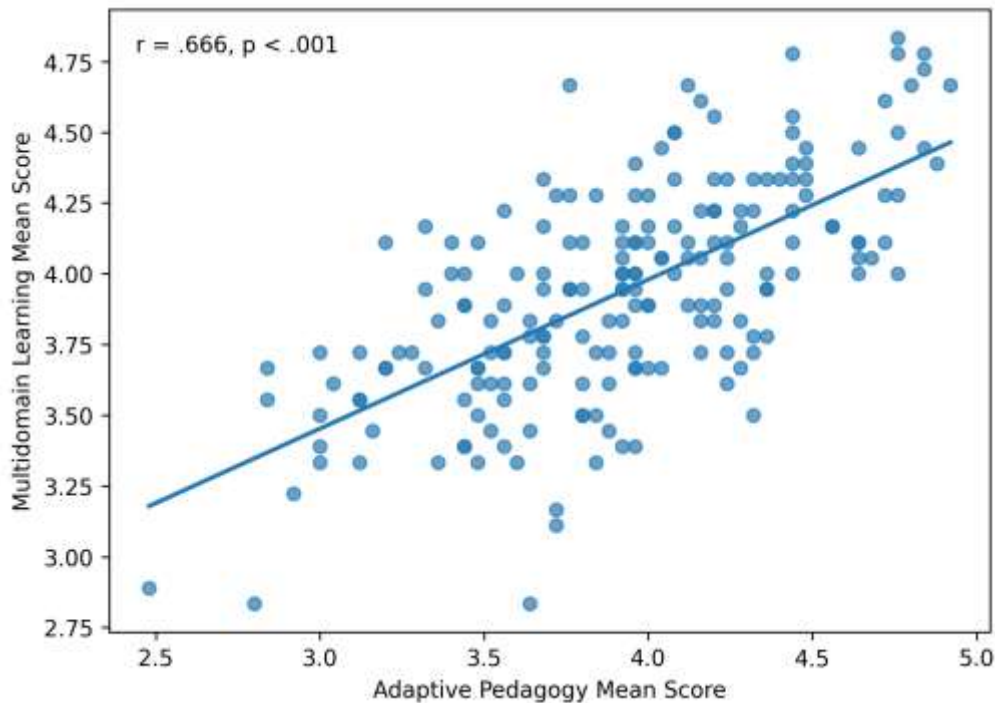


Fig. 1. Relationship between Artificial Intelligence Enabled Adaptive Pedagogy and Perceived Multidomain Learning

The correlation pattern indicates that no single adaptive function was restricted to one learning domain. Each component was associated with cognitive, affective, and psychomotor outcomes. Learning Personalization showed particularly consistent associations across all three domains, while Task Difficulty Adjustment produced comparatively lower, although still significant, coefficients.

Overall Association With Perceived Multidomain Learning

The simple linear regression model was significant, with artificial intelligence enabled adaptive pedagogy explaining variance in perceived multidomain learning, $F(1, 194) = 154.30$, $p < .001$. The model explained 44.3% of the variance in perceived multidomain learning, $R^2 = .443$, adjusted $R^2 = .440$. A one-point increase in adaptive pedagogy was associated with a 0.527-point increase in perceived multidomain learning, $B = 0.527$, $SE = 0.042$, $\beta = .666$, $t = 12.423$, $p < .001$.

Table 5. Simple Linear Regression of AI Enabled Adaptive Pedagogy and Perceived Multidomain Learning

Predictor	B	SE	beta	t	p	95% CI
Constant	1.873	0.168		11.175	< .001	1.542, 2.203
AI Enabled Adaptive Pedagogy	0.527	0.042	0.666	12.423	< .001	0.443, 0.610

Model statistics: $R^2 = .443$, Adjusted $R^2 = .440$, $F(1, 194) = 154.30$, $p < .001$.

The regression assumptions were adequately supported. The overall adaptive pedagogy score showed no significant departure from normality, $W = .990$, $p = .208$, and perceived multidomain learning also showed an approximately normal distribution, $W = .992$, $p = .327$. Regression residuals were normally distributed, $W = .996$, $p = .932$. The Breusch-Pagan test did not indicate heteroscedasticity, $p = .676$.

Associations of Adaptive Pedagogy Dimensions With Perceived Multidomain Learning

A multiple regression model was conducted to examine the unique associations of the five adaptive pedagogy dimensions. The combined model was statistically significant, $F(5, 190) = 31.68$, $p < .001$, explaining 45.5% of the variance in perceived multidomain learning, $R^2 = .455$, adjusted $R^2 = .440$.

Learning Personalization emerged as the only statistically significant unique predictor after controlling for the other adaptive pedagogy dimensions, $B = 0.215$, $\beta = .296$, $p = .003$. Learner Autonomy Support showed a positive coefficient, $\beta = .194$, but did not reach the .05 significance threshold, $p = .077$. Variance inflation factors ranged from 2.69 to 4.16, indicating that multicollinearity remained within an interpretable range.

Table 6. Multiple Regression of Adaptive Pedagogy Dimensions and Perceived Multidomain Learning

Predictor	B	SE	beta	p	VIF
Learning Personalization	0.215	0.071	0.296	0.003	3.32
Adaptive Real-Time Feedback	0.086	0.076	0.118	0.258	3.75
Task Difficulty Adjustment	0.027	0.065	0.036	0.681	2.69
Learning Analytics	0.063	0.075	0.092	0.397	4.08
Learner Autonomy Support	0.133	0.075	0.194	0.077	4.16

Model statistics: $R^2 = .455$, Adjusted $R^2 = .440$, $F(5, 190) = 31.68$, $p < .001$.

Taken together, the results show three central findings. Artificial intelligence enabled adaptive pedagogy and perceived multidomain learning were both rated relatively high. All adaptive pedagogy dimensions were positively associated with cognitive, affective, and psychomotor learning. The overall adaptive pedagogy construct explained a substantial proportion of perceived multidomain learning variance, while learning personalization emerged as the strongest unique dimension when the five adaptive functions were considered simultaneously.

4. Discussion

The present study identified a strong positive association between artificial intelligence enabled adaptive pedagogy and perceived multidomain learning, $r = .666$, $p < .001$, with the overall model explaining 44.3% of the variance in perceived multidomain learning. This result supports recent evidence that AI is transforming physical education through intelligent analysis, responsive instructional support, and data-informed decision making [27]. Interactive visual analysis has demonstrated the capacity of AI to strengthen university physical education systems [28], while integration of AI with the Internet of Things has expanded opportunities for intelligent sports practice teaching [29]. Real-time AI methods also provide increasingly sophisticated mechanisms for monitoring and interpreting performance data [30]. Comparable developments are evident in intelligent college sports training systems [31], personalized digital training and feedback platforms [32], AI-supported evaluation of teaching methods [33], and machine-learning-based prediction of sports achievement [34]. These studies mainly

demonstrate technological capability. The present findings extend this evidence by showing that AI becomes educationally meaningful when its functions operate within an integrated adaptive pedagogical structure. We argue that the observed association does not arise from AI availability alone. Its pedagogical value depends on how personalization, feedback, task adaptation, analytics, and learner autonomy are coordinated to respond to individual learning conditions.

Learning personalization was the strongest unique statistical correlate of perceived multidomain learning, $\beta = .296$, $p = .003$, when the five adaptive pedagogy dimensions were examined simultaneously. This finding gives personalization a central pedagogical position within AI enabled physical education. AI-generated training has demonstrated the feasibility of tailoring exercise experiences to individual learners [35], while AI-delivered physical activity interventions indicate that intelligent systems can support populations with distinct learning and developmental characteristics [36]. Machine learning also enables physical education researchers and teachers to analyze behavioral patterns that are difficult to capture through conventional observation alone [37]. The present results extend these studies because personalization was associated with an integrated outcome encompassing cognitive, affective, and psychomotor learning rather than a single performance indicator. We interpret this result through the heterogeneous nature of physical education. Students enter learning situations with different prior knowledge, movement competence, confidence, physical capacity, and rates of skill acquisition. A uniform instructional pathway cannot respond equally to these differences. Personalization allows task demands and learning information to remain aligned with individual progression. The absence of unique statistical significance for several other dimensions should not be interpreted as evidence that those dimensions are unimportant. Their significant bivariate relationships with perceived multidomain learning suggest that they may operate as interconnected components of the same adaptive process rather than as independent instructional mechanisms.

The relatively balanced cognitive, affective, and psychomotor scores provide further evidence that AI enabled adaptive pedagogy should be evaluated through the multidimensional character of physical education. AI applications have already been developed to support risk identification and emergency responses during physical education activities [38], [39], illustrating that intelligent systems can interact with observable physical behavior in real learning environments. Generative AI has expanded this role into sport education, instructional design, assessment, and learning support. ChatGPT has been examined as an instructional resource in sport-related higher education [40], and physical education scholarship has identified practical applications for planning, instruction, and assessment [41]. Structured guidance for using generative AI in physical education lesson planning has also emerged [42], while research on ChatGPT in sport education identifies both instructional opportunities and implementation constraints [43]. Recent conceptual work further positions generative AI as a mechanism for integrating physical education and health learning [44]. We argue that these technological functions can influence different learning domains through distinct but connected pathways. Adaptive information supports cognitive processing, individualized challenge may strengthen confidence and engagement, and repeated corrective feedback may facilitate psychomotor refinement. This interpretation explains why AI enabled adaptive pedagogy should not be evaluated exclusively through knowledge acquisition or technical performance. Its educational relevance lies in its capacity to support multidomain development within the same learning environment.

The findings also reinforce the position of teachers as central agents in AI enabled adaptive pedagogy. Earlier reviews of AI in higher education identified a strong technological orientation and questioned the limited visibility of educators in AI research [45]. Current scholarship on

generative AI calls for stronger pedagogical design, explicit learning objectives, and responsible integration of intelligent systems [46]. Reviews of empirical AI applications in online higher education similarly show considerable variation in pedagogical functions and educational evidence [47]. Historical analysis demonstrates that AI in education has progressively shifted from isolated technological applications toward broader learning and instructional ecosystems [48], while recent evidence confirms rapid expansion of AI across teaching and learning in higher education [49]. Physical education creates an additional requirement because teachers must interpret AI-generated information in relation to movement quality, individual differences, interaction, safety, and instructional context. Qualitative evidence from physical education teachers confirms that AI adoption is shaped by individual, behavioral, and environmental factors [50]. We therefore argue for a teacher-mediated model of adaptive AI rather than algorithmic substitution. AI should identify patterns, generate feedback, and support adaptation. Teachers should retain responsibility for interpreting data, selecting pedagogically appropriate responses, and determining whether algorithmic recommendations fit the learner and instructional context. This human-guided configuration provides a stronger basis for responsible AI integration in physical education.

This study contributes an integrated empirical perspective by linking five adaptive AI functions with cognitive, affective, and psychomotor learning. Its interpretation remains bounded by the cross-sectional design, reliance on self-reported measures, and sample of university physical education students. The statistical relationships cannot establish causal effects, and perceived multidomain outcomes cannot replace direct assessment of knowledge, affective development, or motor performance. Future studies should employ experimental and longitudinal designs, objective movement measurements, performance assessments, learning analytics, and repeated observations. Established physical education models also indicate that intervention effects depend on implementation characteristics, participant profiles, and pedagogical design [51]. Research on physical literacy further demonstrates the importance of assessing multidimensional competence and professional pedagogical capacity [52]. We contend that the next stage of research should move from perception-based association toward direct testing of adaptive mechanisms. Experimental systems should determine whether personalization, real-time feedback, task adjustment, learning analytics, and learner autonomy produce measurable changes in cognitive achievement, affective development, and psychomotor performance. Such evidence would provide a stronger basis for developing AI enabled physical education as a pedagogically grounded adaptive learning system rather than a technology-centered instructional innovation.

5. Conclusion

Artificial intelligence enabled adaptive pedagogy demonstrated a strong positive relationship with perceived multidomain learning in physical education, with personalization emerging as the strongest unique statistical correlate and the overall model explaining 44.3% of the variance in perceived multidomain learning. These findings indicate that AI contributes most effectively when personalization, adaptive feedback, task adjustment, learning analytics, and learner autonomy are integrated into a coherent pedagogical system. The study highlights the significance of AI as a support mechanism for responsive, data-informed, and learner-centered physical education while maintaining the teacher's role in pedagogical interpretation and decision making. The findings provide an empirical basis for designing adaptive physical education environments that address multidomain learning rather than isolated performance outcomes. The cross-sectional design, reliance on self-reported data, and sample limited to university physical education students restrict causal interpretation and broader generalization.

Future research should use experimental or longitudinal designs and include direct measures of cognitive achievement, affective development, and psychomotor performance.

References

- [1] Chen, L., Chen, P., Lin, Z.: Artificial intelligence in education: A review. *IEEE Access*. 8, 75264–75278 (2020). <https://doi.org/10.1109/ACCESS.2020.2988510>
- [2] Hwang, G.J., Xie, H., Wah, B.W., Gašević, D.: Vision, challenges, roles and research issues of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence*. 1, 100001 (2020). <https://doi.org/10.1016/j.caeai.2020.100001>
- [3] Ouyang, F., Jiao, P.: Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*. 2, 100020 (2021). <https://doi.org/10.1016/j.caeai.2021.100020>
- [4] Chiu, T.K.F., Xia, Q., Zhou, X., Chai, C.S., Cheng, M.: Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*. 4, 100118 (2023). <https://doi.org/10.1016/j.caeai.2022.100118>
- [5] Lee, H.S., Lee, J.: Applying artificial intelligence in physical education and future perspectives. *Sustainability*. 13(1), 351 (2021). <https://doi.org/10.3390/su13010351>
- [6] Zhou, T., Wu, X., Wang, Y., Wang, Y., Zhang, S.: Application of artificial intelligence in physical education: A systematic review. *Education and Information Technologies*. 29(7), 8203–8220 (2024). <https://doi.org/10.1007/s10639-023-12128-2>
- [7] Da'i, M., Apriyanto, R.: Integrating digital comics into physical education: a new model for enhancing elementary athletic learning. *Edu Sportivo: Indonesian Journal of Physical Education*. 6(1), 77–92 (2025). [https://doi.org/10.25299/esijope.2025.vol6\(1\).18645](https://doi.org/10.25299/esijope.2025.vol6(1).18645)
- [8] Dai, M., Apriyanto, R., Kaito, I., Dwi Yusrowatin, C., Suningsih, S.: The Application of Mixed Reality Technology in The 5.0 Era Learning Pencak Silat to Support The Independent Curriculum. *JOSSAE Journal of Sport Science and Education*. 9(2), 121–131 (2024). <https://doi.org/10.26740/jossae.v9n2.p121-131>
- [9] Wang, Y., Wang, X.: Artificial intelligence in physical education: Comprehensive review and future teacher training strategies. *Frontiers in Public Health*. 12, 1484848 (2024). <https://doi.org/10.3389/fpubh.2024.1484848>
- [10] Kabudi, T., Pappas, I., Olsen, D.H.: AI enabled adaptive learning systems: A systematic mapping of the literature. *Computers and Education: Artificial Intelligence*. 2, 100017 (2021). <https://doi.org/10.1016/j.caeai.2021.100017>
- [11] Gligorea, I., Cioca, M., Oancea, R., Gorski, A.T.: Adaptive learning using artificial intelligence in e learning: A literature review. *Education Sciences*. 13(12), 1216 (2023). <https://doi.org/10.3390/educsci13121216>
- [12] Ma, J., Ma, L., Qi, S., Zhang, B., Ruan, W.: A practical study of artificial intelligence based real time feedback in online physical education teaching. *Smart Learning Environments*. 12, 52 (2025). <https://doi.org/10.1186/s40561-025-00411-3>
- [13] Wang, J., Chen, Y., Li, Y.: Evaluation and feedback system for physical education teaching effectiveness based on artificial intelligence. *International Journal of Computational Intelligence Systems*. 18, 303 (2025). <https://doi.org/10.1007/s44196-025-01046-5>
- [14] Dudley, D., Mackenzie, E., Van Bergen, P., Cairney, J.: What drives quality physical education? A systematic review and meta analysis of learning and development effects from physical education based interventions. *Frontiers in Psychology*. 13, 799330 (2022). <https://doi.org/10.3389/fpsyg.2022.799330>

- [15] Wong, M.Y.C.: The physical education pedagogical approaches in nurturing physical literacy among primary and secondary school students: A scoping review. *International Journal of Educational Research*. 116, 102080 (2022). <https://doi.org/10.1016/j.ijer.2022.102080>
- [16] Edwards, L.C., Bryant, A.S., Keegan, R.J., Morgan, K., Jones, A.M.: Definitions, foundations and associations of physical literacy: A systematic review. *Sports Medicine*. 47, 113–126 (2017). <https://doi.org/10.1007/s40279-016-0560-7>
- [17] Jaitner, D., Rinas, R., Becker, C., Niermann, C.: Supporting subject justification by educational psychology: A systematic review of achievement goal motivation in school physical education. *Frontiers in Education*. 4, 70 (2019). <https://doi.org/10.3389/educ.2019.00070>
- [18] Song, J., Shang, C., Chen, A.: Does content focused intervention enhance motivation in physical education? A meta analysis. *Quest*. 77(2), 150–174 (2025). <https://doi.org/10.1080/00336297.2024.2417790>
- [19] Chen, X., Xie, H., Zou, D., Hwang, G.J.: Application and theory gaps during the rise of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence*. 1, 100002 (2020). <https://doi.org/10.1016/j.caeai.2020.100002>
- [20] Crompton, H., Jones, M.V., Burke, D.: Affordances and challenges of artificial intelligence in K 12 education: A systematic review. *Journal of Research on Technology in Education*. 56(3), 248–268 (2024). <https://doi.org/10.1080/15391523.2022.2121344>
- [21] Lai, C.Y.: The role of ChatGPT in sport and physical education: A scoping review using the SWOT analysis framework. *Journal of Hospitality, Leisure, Sport & Tourism Education*. 38, 100602 (2026). <https://doi.org/10.1016/j.jhlste.2026.100602>
- [22] Eid, R.A.F.H., Zhao, Z.: Developing and validating a domain-specific instrument for measuring physical education teachers' acceptance of artificial intelligence: the AI-PEQ. *Frontiers in Education*. 11, 1888874 (2026). <https://doi.org/10.3389/educ.2026.1888874>
- [23] Li, Y., Li, X.: The artificial intelligence system for the generation of sports education guidance model and physical fitness evaluation under deep learning. *Frontiers in Public Health*. 10, 917053 (2022). <https://doi.org/10.3389/fpubh.2022.917053>
- [24] Song, X.: Physical education teaching mode assisted by artificial intelligence assistant under the guidance of high-order complex network. *Scientific Reports*. 14, 4104 (2024). <https://doi.org/10.1038/s41598-024-53964-7>
- [25] Jiang, X., Du, Y., Zheng, Y.: Evaluation of physical education teaching effect using Random Forest model under artificial intelligence. *Heliyon*. 10(1), e23576 (2024). <https://doi.org/10.1016/j.heliyon.2023.e23576>
- [26] Zhen, A., Wang, X.: The deep learning-based physical education course recommendation system under the internet of things. *Heliyon*. 10(19), e38907 (2024). <https://doi.org/10.1016/j.heliyon.2024.e38907>
- [27] Hu, Z., Liu, Z., Su, Y.: AI-driven smart transformation in physical education: Current trends and future research directions. *Applied Sciences*. 14(22), 10616 (2024). <https://doi.org/10.3390/app142210616>
- [28] He, Q., Chen, H., Mo, X.: Practical application of interactive AI technology based on visual analysis in professional system of physical education in universities. *Heliyon*. 10(3), e24627 (2024). <https://doi.org/10.1016/j.heliyon.2024.e24627>
- [29] Yu, H., Mi, Y.: Application model for innovative sports practice teaching in colleges using Internet of Things and artificial intelligence. *Electronics*. 12(4), 874 (2023). <https://doi.org/10.3390/electronics12040874>

- [30] Vec, V., Tomažič, S., Kos, A., Umek, A.: Trends in real-time artificial intelligence methods in sports: A systematic review. *Journal of Big Data*. 11, 148 (2024). <https://doi.org/10.1186/s40537-024-01026-0>
- [31] Wei, S., Wang, K., Li, X.: Design and implementation of college sports training system based on artificial intelligence. *International Journal of System Assurance Engineering and Management*. 13(Suppl 3), 971–977 (2022). <https://doi.org/10.1007/s13198-021-01149-0>
- [32] Wang, Y., Feng, X., Wu, Y., Zhang, X., Wu, J.: CoachXNet: An artificial intelligence and Internet of Things integrated platform for personalized training and feedback in digital sports. *International Journal of Computational Intelligence Systems*. 19(1), 49 (2026). <https://doi.org/10.1007/s44196-025-01146-2>
- [33] Li, S., Wang, C., Wang, Y.: Fuzzy evaluation model for physical education teaching methods in colleges and universities using artificial intelligence. *Scientific Reports*. 14, 4788 (2024). <https://doi.org/10.1038/s41598-024-53177-y>
- [34] Wang, G., Ren, T.: Design of sports achievement prediction system based on U-net convolutional neural network in the context of machine learning. *Heliyon*. 10(10), e30055 (2024). <https://doi.org/10.1016/j.heliyon.2024.e30055>
- [35] Masagca, R.C.: The AI coach: A 5-week AI-generated calisthenics training program on health-related physical fitness components of untrained collegiate students. *Journal of Human Sport and Exercise*. 20(1), 39–56 (2024). <https://doi.org/10.55860/13v7e679>
- [36] Aydemir, U.: ChatGPT-delivered physical activity intervention for children with autism spectrum disorder: Pre-post feasibility study. *JMIR Human Factors*. 12, e71119 (2025). <https://doi.org/10.2196/71119>
- [37] Leukel, C., Leuders, T., Ward, P.: Using machine learning to support behavioral data analysis in physical education. *Journal of Teaching in Physical Education*. 1–9 (2026). <https://doi.org/10.1123/jtpe.2025-0392>
- [38] Guangde, Z.: Physical education and emergency response system using deep learning: A step toward sustainable development of physical education environment. *Frontiers in Environmental Science*. 10, 974291 (2022). <https://doi.org/10.3389/fenvs.2022.974291>
- [39] Leilei, W., Rajendiran, S., Gayathri, K.: An emergency response system created to combat injuries during physical education training in a university using deep learning. *The Electronic Library*. 39(4), 505–525 (2021). <https://doi.org/10.1108/EL-07-2020-0175>
- [40] Keiper, M.C., Fried, G., Lupinek, J., Nordstrom, H.: Artificial intelligence in sport management education: Playing the AI game with ChatGPT. *Journal of Hospitality, Leisure, Sport & Tourism Education*. 33, 100456 (2023). <https://doi.org/10.1016/j.jhlste.2023.100456>
- [41] Albaloul, O., Marttinen, R., Killian, C.: Unlocking educational potential: How physical education teachers can thoughtfully benefit from using ChatGPT for planning, instruction, and assessment. *Journal of Physical Education, Recreation & Dance*. 95(7), 32–41 (2024). <https://doi.org/10.1080/07303084.2024.2378776>
- [42] Trendowski, T.: A checklist for using generative artificial intelligence to create lesson plans in K–12 physical education. *Journal of Physical Education, Recreation & Dance*. 96, 15–27 (2025). <https://doi.org/10.1080/07303084.2024.2437988>

- [43] Chang, S.H., Chen, S.Y., Chang, C.H.: Exploring opportunities and challenges toward ChatGPT for inclusion in sport education. *Journal of Hospitality, Leisure, Sport & Tourism Education*. 37, 100572 (2025). <https://doi.org/10.1016/j.jhlste.2025.100572>
- [44] Zhu, G., Dai, X., Jiang, S., Wang, Z., Liang, M., Pan, Y., Tao, Y.: Generative AI in physical education and health: A narrative review and conceptual framework for interdisciplinary thematic learning. *Frontiers in Public Health*. 14, 1842782 (2026). <https://doi.org/10.3389/fpubh.2026.1842782>
- [45] Zawacki-Richter, O., Marín, V.I., Bond, M., Gouverneur, F.: Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education*. 16, 39 (2019). <https://doi.org/10.1186/s41239-019-0171-0>
- [46] Chiu, T.K.F.: Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*. 6, 100197 (2024). <https://doi.org/10.1016/j.caeai.2023.100197>
- [47] Ouyang, F., Zheng, L., Jiao, P.: Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies*. 27, 7893–7925 (2022). <https://doi.org/10.1007/s10639-022-10925-9>
- [48] Guan, C., Mou, J., Jiang, Z.: Artificial intelligence innovation in education: A twenty-year data-driven historical analysis. *International Journal of Innovation Studies*. 4(4), 134–147 (2020). <https://doi.org/10.1016/j.ijis.2020.09.001>
- [49] Crompton, H., Burke, D.: Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*. 20, 22 (2023). <https://doi.org/10.1186/s41239-023-00392-8>
- [50] Yang, W., Chen, H., Rao, F.: A qualitative study of physical education teachers' perceptions of artificial intelligence and influencing factors based on social cognitive theory. *BMC Psychology*. 14, 530 (2026). <https://doi.org/10.1186/s40359-026-04295-x>
- [51] Yao, G., Zhang, J., Soh, K.G., Bai, X., Xiao, W., Anuar, M.A.M., Bao, L.: Effective implementation of the Sport Education Model in physical education: A meta-analysis of participant and intervention characteristics. *PLOS ONE*. 20(10), e0331228 (2025). <https://doi.org/10.1371/journal.pone.0331228>
- [52] Yin, H., Dev, R.D.O., Soh, K.G., Li, F., Lian, M.: Assessment and development of physical education teachers' physical literacy: A systematic review. *PLOS ONE*. 19(7), e0307505 (2024). <https://doi.org/10.1371/journal.pone.0307505>