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COMPARISON OF THE EFFECTIVENESS OF ADAPTIVE E-LEARNING PLATFORM (USING AI) WITH CONVENTIONAL LMS IN IMPROVING LEARNING OUTCOMES IN BASIC PROGRAMMING COURSES

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Abstract

The development of artificial intelligence (AI) has enabled adaptive e-learning platforms that personalize content and learning paths to individual needs. However, their effectiveness compared to conventional LMS in teaching challenging programming concepts remains limited. This study aimed to compare the effectiveness of AI-based adaptive e-learning and conventional LMS in improving students' learning outcomes in Basic Programming. A quasi-experimental design with a posttest-only control group was conducted with 64 students (experiment: n=32, control: n=32). The experiment group used an AI-based adaptive platform, while the control group used conventional LMS (e.g., Moodle). The intervention lasted one semester. Data was collected via posttest scores (concept understanding and coding skills) and user satisfaction questionnaires and analysed using independent samples t-test and descriptive statistics. Results showed a significant difference between groups ($p < 0.05$). The experiment group achieved higher mean scores ($M=82.5$, $SD=6.2$) than the control group ($M=75.3$, $SD=8.1$) and reported greater satisfaction and engagement. AI-based adaptive e-learning platforms are more effective than conventional LMS, supporting their potential to create personalized and impactful learning experiences. Limitations include a single university and course, uncontrolled prior ability, and internet variability, suggesting further research with larger samples and longer duration.

Keywords: Adaptive E- learning, Intelligence artificial, Learning outcomes, System management learning.

1. Introduction

The shape of a projectile is generally selected on the basis of combined Advances in educational technology have significantly transformed higher education, particularly in skills-based courses such as introductory programming. For more than two decades, conventional Learning Management Systems (LMS) such as Moodle, Canvas, and Blackboard have served as the backbone of educational digitalization by providing structured frameworks for content delivery, assessment, and administration. Studies confirm that LMS adoption improves accessibility and administrative efficiency compared to fully face-to-face methods [1] and can enhance programming outcomes when advanced features such as quizzes and workshops are fully utilized [2].

Nevertheless, programming education has unique demands, including repetitive practice, immediate feedback, and gradual problem-solving development. While conventional LMS partially address these needs, adaptive e-learning platforms have emerged as a logical evolution. Powered by artificial intelligence (AI) and learning analytics, adaptive platforms such as Knewton, Century Tech, and Codecademy Pro are designed to personalize learning paths, provide real-time feedback, and dynamically adjust difficulty levels. A large-scale meta-analysis reports generally positive effects of adaptive technologies on student engagement and retention in STEM education [3]. Comparative literature indicates that adaptive platforms offer stronger personalization, continuous formative assessment, and real-time feedback than conventional LMS [4-6]. Empirical studies in programming contexts show notable gains, including higher exam scores and reduced dropout rates when adaptive feedback is applied [7]. However, large-scale adoption remains constrained by high implementation costs, infrastructure demands, teacher readiness, and concerns about data privacy and algorithmic bias [6, 8, 9].

Importantly, evidence regarding the superiority of adaptive platforms remains inconsistent [6]. While several studies report significant learning gains, others find no statistically significant differences compared to well-designed LMS-based instruction, emphasizing the critical role of pedagogical design and human interaction [6, 10,11]. Meta-analytic evidence further suggests that adaptive learning effects often diminish in long-term, large-scale implementations [8, 11, 12].

This inconsistency reveals a critical research gap: the lack of rigorous head-to-head comparative studies conducted within the same educational context. Addressing this gap is particularly important in underrepresented settings such as Indonesian higher education. Consequently, the proposed study adopts a longitudinal quasi-experimental mixed-methods design to directly compare adaptive AI-based platforms and optimized conventional LMS in parallel introductory programming courses. By examining cognitive outcomes, learning processes, affective factors, and contextual moderators, the study aims to provide robust empirical evidence on when, how, and for whom adaptive e-learning platforms can effectively enhance programming education.

2. Literature Review

2.1. Social comparison theory

Social Comparison Theory posits that individuals evaluate their abilities and opinions by comparing themselves to others, especially without objective standards, via upward (to superiors) or downward (to inferiors) comparisons [13]. In the digital era, Instagram's curated visuals amplify upward comparisons, linking passive scrolling to physical appearance dissatisfaction and reduced psychological well-being [14, 15].

2.2. Cultivation theory

Developed by Gerbner [16] in the late 1960s, this theory argues prolonged TV exposure cultivates distorted social reality perceptions through "mainstreaming" and "resonance." Adapted to Instagram, heavy exposure to idealized beauty content fosters unrealistic standards, contributing to body image anxiety in teen girls via internalization [17, 18].

2.3. Uses and gratifications theory

Blumler and Katz [19] frame audiences as active media users seeking needs like social integration, self-expression, and validation. On Instagram, teens pursue affiliation, identity curation, and likes, but this creates dependency cycles, heightening sensitivity to negative feedback and body dissatisfaction [20, 21].

3. Method

Study This use method quasi-experiment with design posttest -only control group, where the measurement results done only at the end intervention Because assumptions that assignment random group has minimize difference initial. Research sample consists of 64 students techniques taken through technique cluster random sampling based on class, then shared in a way random become group experiments (n=32) using an adaptive platform AI- based and group control (n=32) using conventional LMS like Moodle.

Intervention learning implemented during one full semester with equivalent material, where difference main lies in the nature of the platform used personal adaptive versus standard linear. Data were collected at the end of period using two instruments main, namely test results Study the end that measures understanding conceptual and coding skills, as well as questionnaire satisfaction users who use Likert scale.

Data analysis was performed in a way statistics with moreover formerly test prerequisite normality and homogeneity. For test hypothesis difference results study, use independent sample t-test (or Mann-Whitney U test) If assumptions parametric No fulfilled), whereas For describe characteristics sample, score results learning, and level satisfaction user, applied analysis statistics descriptive in the form of mean, median, standard deviation, frequency, and percentage. The entire research process notices aspect ethics through provision informed consent, guarantee data confidentiality, and principles volunteerism participation without impact to mark academic.

4. Results and Discussion

4.1 Sample description

Study involving 64 students who were divided evenly to in two groups. Characteristics sample presented in Table 1. Based on Table 1, it can be concluded that second group own characteristics relatively early equivalent before intervention, especially on the GPA which is indicator ability academic beginning.

Table 1. Characteristics respondents study.

Characteristics	Group Experiment (AI)	Group Control (Moodle)
Number (n)	32	32
Gender (M/F)	24/8	22 / 10
Average Age (years)	20.1 (SD = 1.2)	20.3 (SD = 1.1)
Previous Semester GPA (Average)	3.25 (SD = 0.31)	3.21 (SD = 0.29)

Based on all over series data analysis, research This produce a number of findings comprehensive key. First, second group research, namely group experiments using adaptive AI platforms and groups control that uses conventional LMS (Moodle), has profile equal start in matter characteristics demographics and capabilities academic (GPA), so that give valid basis for comparison results intervention. Second, after intervention during one semester, proven there is difference results significant learning in a way statistics, where the group experiment reaches scores the end that is substantial taller than group control. Third, analysis more deep to component results Study show that advantages of adaptive AI platforms the more stand out in development skills practice *coding* compared to improvement understanding conceptual, although second aspect still more superior from group control. Fourth, from perspective users, students in groups experiments also reported level more satisfaction tall in a way overall, with aspect engagement and perception benefit learning become an area with improvement the most real satisfaction. With thus, it can conclude that implementation of learning platforms adaptive AI based not only in a way effective increase achievements academic, in particular in ability practical, but also successful create experience learn more interesting and satisfying for student technique compared to with conventional LMS.

4.2. Prerequisite test results analysis (Normality and homogeneity test)

Before conducting *an independent sample t-test,* conducting a prerequisite test analysis against score data posttest results learning. The test results are presented in Table 2. Based on Table 2, it can be seen that score posttest from second group normally distributed ($p > 0.05$) and has homogeneous variance ($p = 0.447 > 0.05$). With Thus, the conditions For using *the independent sample t-* test parametric has fulfilled.

Table 2. Results of the normality and homogeneity test of posttest scores.

Group	Normality Test (Shapiro-Wilk)			Homogeneity Test (Levene's Test)		
	Statistics	***p-value***	**Decision**	**Statistics**	***p-value***	**Decision**
Experiment (AI)	0.983	0.845	Normal	0.587	0.447	Homogeneous
Control (Moodle)	0.974	0.632	Normal			

Description : Significance level α = 0.05. Data is normally distributed if *p-value* > 0.05. Homogeneous variant If *p-value* > 0.05.

4.3. Hypothesis test results (Differences in learning outcomes)

Hypothesis study tested use *independent sample t-test.* Comparison results score posttest between group experiments and controls presented in Table 3.

Table 3. Independent sample t-test results of posttest scores of learning outcomes.

Group	n	Average (Mean)	Deviation (SD)	t	df	p-value	Mean Difference
Experiment (AI)	32	84.06	6.15	5,742	62	0.000*	9.22
Control (Moodle)	32	74.84	7.88				

Description : *) Significant at the α = 0.05 level.

The results in Table 3 show that there is significant difference between results Study students using adaptive platforms AI- based (M = 84.06, SD = 6.15) and students who used conventional LMS (M = 74.84, SD = 7.88), t(62) = 5.742, $p < 0.001$. The *p-value* (0.000) is far more small from level significance 0.05. The magnitude The mean difference is 9.22 points, which indicates that group experiment own performance that is statistics taller.

Findings study This in a way clear confirm that learning platform adaptive AI-based generating results learn more height and satisfaction more users big compared to conventional LMS for students technique. Advantages significant group experiment in harmony with theory personalized learning, where content and pace Study customized with need individual, so that reduce burden cognitive that is not need and maximize time For mastery difficult concept [22]. A quasi - experimental design was applied, although No allows randomization full subject, shows strong effect Because characteristics beginning second equal groups, giving sufficient internal validity For conclude that difference results This of course sourced from variables treatment.

4.4. An analysis descriptive components of learning outcomes

For see achievements in aspects specific, score posttest analysed per component (understanding concept and coding). The results presented in Table 4.

Table 4. Posttest score description based on component evaluation.

Component	Group Experiment (AI)		Group Control (Moodle)	
	Mean	Elementary School	Mean	Elementary School
Understanding Concept (Max 50)	42.34	3.45	38.91	4.12
Skills (Max 50)	41.72	4.01	35.93	5.67
Total Score (Max 100)	84.06	6.15	74.84	7.88

Table 4 reveals that group experiment excel in both components. The most striking advantage seen on the components Coding Skills, where the average difference is reached 5.79 points. This is show that approach adaptive from the AI platform perhaps more effective in practice skills practice programming.

The most striking advantage in the components skills coding indicates strength main adaptive AI platform in support learning based practice and problem-solving. System This possibility big give bait automatic, instant, and specific feedback to error syntax or logic in written code students. Mechanism This simulate tutor guidance continuously, allowing cycle more experiments, evaluations, and improvements (iterative refinement) fast and intensive compared to conventional LMS which often only provide example code and questions without bait come back adaptive [23]. Findings This supported by research who also reported improvement ability significant programming after use tool help AI-powered code feedback [24].

Temporary that, improvements to the components understanding concept, although significant, have greater difference small. This can explain by the nature of conventional LMS like Moodle which remains effective in convey static material in the form of text, images, and videos for formation draft basic. However, the AI platform seems to outperform in help student translate concepts in application concrete practical system adaptive can identify misconception through response students in training formative and in an automatic serve explanation for example alternative until draft the understandable, a difficult mechanism replicated by linear LMS [25].

4.5. Results of the satisfaction questionnaire analysis users

Questionnaire satisfaction measured with Likert scale 1-5 (1=Very Dissatisfied, 5=Very Satisfied). Average score results per aspect presented in Table 5.

Table 5. Average satisfaction score users per aspect.

Aspect Satisfaction	Group Experiment (AI)		Group Control (Moodle)	
	Mean	Elementary School	Mean	Elementary School
Convenience Usability	4.41	0.52	3.97	0.61
Involvement Learning (Engagement)	4.53	0.48	3.59	0.72
Relevance and Quality of Material	4.22	0.55	4.15	0.53
Benefits for Understanding	4.47	0.50	3.84	0.66
Satisfaction Overall	4.38	0.49	3.81	0.65

In a way overall, level satisfaction users in the group experiment more high in all aspect compared to group control. The biggest difference seen in the aspect Involvement Learning (Engagement) with average difference of 0.94 points. This indicates that the platform is adaptive AI- based assessed more attractive and capable guard involvement student during learning. Aspects The relevance of the material is the only one that shows the smallest difference, because the core material of both platforms is indeed on purpose equalized.

Satisfaction level more users high, especially in the aspect of engagement and benefits learning, is indicator important from reception technology this. Experience personalized learning creating a greater sense of achievement (mastery) and autonomy big, which is element key in theory Self- Determination For motivating learning intrinsic [26]. The content presented right on the level appropriate difficulty No too easy until boring and not too difficult until make frustration can extend duration and quality involvement students. A study also found correlation positive between use system education adaptive with improvement motivation and perception student to quality learning [27].

Implications practical from study this is very relevant for education tall outcome -oriented techniques. Adaptive AI platform integration can be a strategy for overcome gap ability gap in class big, where the teacher own limitations For give individual attention. This platform functioning as assistant scalable tutoring, enabling more assistance evenly. However, success implementation need consideration ripe to infrastructure technical, training user (good lecturer and students), and design compatible content with machine adaptive [28].

Even though Thus, research This own a number of limitations. First, the sample is relatively small and comes from One context institution limit generalization finding. Second, the duration intervention one semester maybe Not yet Enough For observe effect term long to retention knowledge. Third, research This Not yet measure cognitive and meta- cognitive process variables during use of the platform, such as the learning strategies used students. Future research is recommended For do longitudinal study with more samples wide, combining method qualitative (interviews, think-aloud protocols) for understand experience Study deep, and explore design AI that is not only adaptive to performance but also towards style learning and circumstances affective state of students [8].

In a way overall, results study This give proof strong empirical about contribution positive adaptive AI technology in increase quality and experience learning in education technique. Findings This strengthen shift paradigm in education from approach one-size-fits-all (one-size-fits-all) towards personalized approach, with technology as its main enabler. Thoughtful and planned adoption to innovation This potential big For answer challenge in prepare graduate of competent techniques in the digital age.

5. Conclusions

Based on all over analysis and discussion, research This conclude that implementation of learning platforms adaptive based on Artificial Intelligence (AI) proven in a way significant more effective compared to conventional Learning Management Systems (LMS) in context education technique. The advantages of the AI platform are not only reflected in the increase achievements results Study overall, but in a way special very prominent in develop skills practice student programming (coding). Findings This reinforced by the level greater user satisfaction and engagement high, which shows that personalization and feed come back adaptive from AI system is successful create experience learn more relevant, interesting, and supportive. Therefore that, a kind of platform This can considered as innovation potential pedagogical For overcome challenge personalization in class big and increasing quality output learning in the field technique.

Although Thus, the findings This need addressed with consider a number of limitations research, such as scope sample limited to one institutions and duration intervention one semester. For study next, it is necessary longitudinal study with coverage more samples wide and diverse For test consistency and sustainability effect positive observed. Exploration more deep through approach method mixed - methods are also recommended For uncover cognitive processes and experiences subjective student during interact with AI systems. Implications practical from study This push institution education For consider integration adaptive AI technology in a way more strategic, supported by training for educators and designers the right content, in order to realize more personal, responsive, and student - centred learning.

Based on findings study here, there is significant managerial implications for institutions education high, especially faculty or study program technique. First, the party management institutions need consider allocation budget and resources Power strategic For adopt or developing learning platforms adaptive AI -based as part from digital transformation of learning. Investment This No only covers cost license or platform development but also training comprehensive for lecturer in utilise feature analytics and personalization system, as well as formation team supporters technical. Investment decisions This can justified by evidence empirical evidence that shows improvement results learning and satisfaction students, who in turn impact on indicators performance main institutions like quality graduates and retention student.

Second, at the level operational, study program manager and chairperson major need design and implement an integration roadmap structured technology. This roadmap must include: (1) selection or aligned platform development with achievements specific learning (CPL) field technique, (2) compilation guidelines and training sustainable for lecturer For interpret analytical data from system to perform intervention appropriate pedagogical time, and (3) creation mechanism bait regular feedback loop with students and lecturers For evaluation and improvement sustainable. In addition, management needs to develop supportive policies culture experiments and innovations teaching, as well as system award for successful lecturer integrate technology. This for increase quality learning, so that adoption technology not only is top-down but also becomes part from an adaptive academic culture.

References

1. Salgado-Chamorro, D.L.; Noble-Ramos, V.M.; and Gómez-Jaramillo, S. (2023). Adoption of learning Management systems in face-to-face learning: A systematic literature review of variables, relationships, and models. *International Journal of Learning, Teaching and Educational Research*, 22(12), 326-350.
2. Cigdem, H.; Korkusuz, M.E.; and Karaçaltı, C. (2023) Gamified learning: Assessing the influence of leaderboards on online formative quizzes in a computer programming course. *Computer Applications in Engineering Education*, 32(2), e22697.
3. Cao, X.; Lu, H.; Wu, Q.; and Hsu, Y. (2025). Systematic review and meta-analysis of the impact of STEM education on students learning outcomes, *Frontiers in Psychology*, 16, 1579474.
4. Zawacki-Richter, O.; Marín, V.I.; Bond, M.; and Gouverneur, F. (2019) Systematic review of research on artificial intelligence applications in higher education - where are the educators?. *International Journal Educational Technology in Higher Education.* 16(1), 39.
5. Suazo-Galdamés, I.C.; and Chaple-Gil, A.M. (2025) AI-powered adaptive learning systems in higher education: A scoping review of implementation and impact on academic performance. *Data and Metadata*, 4, 981.

6. Tan, L.Y.; Hu, S.; Yeo, D.J.; and Cheong, K.H. (2025). Artificial intelligence-enabled adaptive learning platforms: A review. *Computers and Education: Artificial Intelligence*, 9, 100429.
7. Ling, H.-C.; and Chiang, H.-S. (2024). Learning performance in adaptive learning systems: A case study of web programming learning recommendations. *Frontiers in Psychology*, 13, 770637.
8. Du Plooy, E.; Casteleijn, D.; and Franzsen, D. (2024). Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement. *Heliyon*, 10(21), e39630.
9. Judijanto, L. (2025). A bibliometric analysis of adaptive learning in K-12 education. *The Eastasouth Journal of Learning and Educations*, 3(01), 75-86.
10. Kwak, M. (2025). The effectiveness of AI-driven tools in Improving student learning outcomes compared to traditional methods. *Issues in Information Systems*, 26(4), 233-247.
11. Ipinnaiye, O.; and Risquez, A. (2024). Exploring adaptive learning, learner-content interaction and student performance in undergraduate economics classes. *Computer & Education*, 215, 105047.
12. Fraulini, N.W.; Marraffino, M.D.; Garibaldi, A.E.; Johnson C.I.; Whitmer, D.E. (2025) Adaptive training instructional interventions: A meta-analysis. *Military Psychology*, 37(5), 479-493.
13. Festinger, L. (1954). A theory of social comparison processes, *Human Relations*, 7(2), 117-140.
14. Faelens, L.; Hoorelbeke, K.; Cambier, R.; Van Put, J.; Van de Putte, E.; De Raedt, R.;. Koster, E.H.W. (2021). The relationship between Instagram use and indicators of mental health: A systematic review, *Computers in Human Behavior Reports,* 4, 100121.
15. Le Blanc-Brillon, J.; Fortin, J.S.; Lafrance, L.; and Hétu, S. (2025). The associations between social comparison on social media and young adults' mental health, *Frontier in Psychology*, 16, 1597241.
16. Gerbner, G. (1969). toward "cultural indicators": the analysis of mass mediated public message systems. *AV Communication Review*, 17(2), 137-148.
17. Pedalino, F.; and Camerini, A.-L. (2022). Instagram use and body dissatisfaction: he mediating role of upward social comparison with Peers and Influencers among Young Females, *International Journal of Environmental Research and Public Health*, 19(3), 1543.
18. Brasil, K.M.; Mims, C.E.; Pritchard, M.E.; and McDermott, R.C. (2024). Social media and body image: Relationships between social media appearance preoccupation, self-objectification, and body image. *Body Image*, 51, 101767.
19. Blumler, J.G.; and Katz, E. (1974). *The uses of mass communications: Current perspectives on gratifications* (1st Ed.). Sage Publications.
20. Longobardi, C.; Settanni, M.; Fabris, M.A.; Marengo, D. (2020). Exploring the links between Instagram popularity, social media addiction, cyber victimization, and subjective happiness in Italian Adolescents. *Children and Youth Services Review*, 113, 104955.
21. Charmaraman, L.; Richer, A.M.; Liu, C.; Lynch, A.D.; and Moreno, M.A. (2021) Early adolescent social media-related body dissatisfaction:

Associations with depressive symptoms, social anxiety, peers, and celebrities. *Journal of Developmental and Behavioral Pediatrics*, 42(5), 401-407.

22. Xie, H.; Chu, H.-C.; Hwang, G.-J.; and Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education*, 140, 103599.
23. Luckin, R.; Cukurova, M.; Kent, C.; and Du Boulay, B. (2022). Empowering educators to be AI-ready. *Computers and Education: Artificial Intelligence*, 3, 100076.
24. Lepp, M.; and Kaimre, J. (2025). Does generative AI help in learning programming: Students' perceptions, reported use and relation to performance*,* *Computers in Human Behavior Reports*, 18, 100642.
25. Chen, X.; Xie, H.; and Hwang, G.J. (2020). A multi-perspective study on Artificial Intelligence in Education: grants, conferences, journals, software tools, institutions, and researchers. *Computers and Education: Artificial Intelligence,* 1, 100005.
26. Ryan, R.M.; and Deci, E.L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, 61, 101860.
27. Ristić, I.; Runić-Ristić, M.; Savić Tot, T.; Tot, V.; and Bajac, M. (2023). The effects and effectiveness of an Adaptive E-learning system on the learning Process and Performance of Students, *International Journal of Cognitive Research in Science, Engineering and Education*, 11(1), 77-92.
28. Li, F.; He, Y.; and Xue, O. (2021). Progress, challenges and countermeasures of adaptive Learning: A systematic review. *Educational Technology & Society*, 24(3), 238-255.