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Postgraduate Learning Innovation in the Age of Artificial Intelligence

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ABSTRACT

Objective: To explore how artificial intelligence (AI) can act as a moderator in supporting learning effectiveness at the postgraduate level through traditional educational elements such as teaching strategies, curriculum development, digital literacy, and learner engagement.
Methods: Data were collected via a structured quantitative survey from 140 postgraduate students selected purposively. Pearson correlation and multiple regression with moderation analysis were used to determine the interaction effects of AI on learning effectiveness based on the data gathered.
Results: Results show the crucial moderating effect of AI on the impact of digital competence and teaching practice to learning outcomes. Although conventional academic variables that influence the learning effectiveness exert their effects, their effects are amplified when AI is incorporated into the instructional practices and digital platforms. AI improves feedback mechanisms, enables interactivity, and strengths individualized learning paths.
Novelty: While past literature utilized AI as an independent or mediating variable, we view AI as a moderator, namely, an enabling mechanism that enhances already existing educational mechanisms rather than replicating them in a different way. Such a nuanced role is indicative of a paradigm shift in postgraduate higher education technology adoption.
Theory and Policy Implications: This study extends both constructivist and cognitive load theories showing how AI can ease cognitive burden but at the same time enhance knowledge construction. The results propose strategies for policymakers to incorporate AI in postgraduate curricula to build self-adaptive, data-driven, and student centered learning environments.

1. Introduction

Higher education leaders are asking how the technology reshapes pedagogy, especially at the postgraduate level, and the advancement of artificial intelligence (AI) is radically changing the pedagogical landscape. AI-powered technology has advanced through learning platforms, adaptive tutoring adaptive learning, and intelligent content delivery, enhancing the flexibility and scalability of learning (Khine, 2024; Strielkowski et al., 2024). The integration of AI tools like Chat GPT, adaptive learning environments, and predictive analytics is driving a new era in postgraduate classroom design (Salloum et al., 2024). These innovations are being developed to promote deep student engagement and learning how to learn (Docherty et al., 2018; Lee & Hannafin, 2016). The result is a shift towards competencies that are essential for thriving in today's knowledge economies, such as critical thinking, problem solving, and fluency with digital media and tools. Postgraduate education designs are changing. They are moving towards hybrid and AI-augmented paradigms (Mohamed, 2025). It is critical to examine the extent to which conventional components of pedagogy interact with intelligent technologies (Kennewell et al., 2008; Tenenbaum et al., 2001). These components include pedagogical approach, relevance of curricular content, and means of assessment (Ogut et al., 2025). The goal is to understand how they influence learning outcomes (Jin et al., 2025).

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While combining natural teaching methods with the tremendous potential of AI support sounds great, the reality can be messy (Van Quaquebeke et al., 2025). It is a huge challenge for all educational institutions to align human-centered pedagogy with algorithm centered systems (Edwards et al., 2024). Often, this use is suboptimal due to factors such as misaligned pedagogies, a lack of digital literacy, and faculty reluctance to use technology (Singun, 2025). Additionally, recent research has revealed that the ability of AI tools to impact student performance varies across disciplines and modes of learning (Dong et al., 2025; Liu & Guo, 2025). The ambiguity surrounding how AI interacts with pedagogical variables, particularly in a postgraduate context, underscores the need for empirical investigations that consider AI not merely as a tool, but also as a potential educational moderator.

The following theoretical frameworks support the present study and help to understand the structural dimensions of this transformation. The technology acceptance model (TAM) Davis et al. (2019) provides a foundation for evaluating the acceptance of AI in postgraduate classrooms. Constructivist Learning Theory Thani & Ahmad, (2025), Ammar et al. (2024), Zhou et al. (2025), on the other hand, emphasizes the exploration of student engagement, digital literacy, and active learning spaces. These frameworks converge on the notion that meaningful learning occurs at the intersection of technology, pedagogy, and learner agency. This study synthesizes these theoretical perspectives. It creates a comprehensive model. This model integrates the dynamic interaction between AI and traditional instructional factors. It improves learning effectiveness.

Previous empirical studies have provided only partial insights into the role of AI in education. While Lu et al. and Garcia-Sierra et al. (2023) found positive effects of personalized learning in previous studies, integrating AI to facilitate it was still a new concept. In graduate level online classrooms, Alshehri (2024), Muhamad et al. (2025), found minimal effects. Alshehri (2024) discovered that AI-based interventions have a smaller impact on student success than a relevant curriculum. The impact of assessment strategies on learning outcomes was moderated by (Al-Hattami, 2025; Zhang et al., 2025). The findings, which are disparate and in contradiction with each other, indicate a theoretical and empirical gap in the understanding of AI as a moderating component of a holistic educational model (Chin et al., 2025; Wang et al., 2025). Second, little is known about how AI interacts with combinations of core pedagogical variables e.g., teaching approaches, curriculum alignment, student engagement, digital literacy, and assessment approaches) to influence learning effectiveness in postgraduate education (Herzog et al., 2025; Ruark & Biazzin, 2025). This study addresses these gaps by offering a novel conceptual framework that integrates five essential pedagogical components, evaluating AI as a moderating factor, and facilitating a comprehensive understanding of the educational advantages and limitations of AI.

The objective of this study is to evaluate the impact of five key variables on the learning effectiveness of postgraduate students in the field of AI. These variables include teaching method, curriculum relevance, student engagement, examination strategy, and digital literacy functional and critical digital literacy. The study will also examine how these variables are influenced by digital literacy. Through hypothesis testing and empirical validation, the study aims to provide a detailed account of AI's role as a moderator in the relationship between instructional strategies and learning outcomes. This is important not only for educational institutions that aim to implement AI optimally, but also for global education policymakers, instructional designers, and technology developers who work to continuously improve postgraduate education in the era of AI.

2. Method

2.1 Research design

The study utilizes a quantitative explanatory research design to investigate the impact of five fundamental pedagogical factors–teaching method, course relevance, student involvement, assessment method, and digital competence–upon learning outcome at postgraduate level while considering the role of artificial intelligence (AI) as a moderating variable. We employ a cross-sectional survey approach, which allows us to gather primary data from postgraduate students in higher education institutions in Indonesia. This study design corresponds to other recent investigations of AI-related learning in educational settings (Lu et al., 2023; Kwon et al., 2023) through its use of structured questionnaires to quantify relationships among variables and test the moderation model. We adopt this approach to obtain valid statistical inference and ensure generalizability to similar populations of

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students. Structural Equation Modeling (SEM-PLS) is used to analyze the data as it is suitable when the models consists moderating variables and latent constructs containing multiple indicators (Hair et al., 2022).

2.2 Sampling and data collection

We used purposive sampling among postgraduate students who were currently in blended or AI learning-based courses). This makes a total of 140 questionnaires collected from numerous universities in Indonesia, which can be regarded as a proper sample number in accordance with minimum SEM sample criteria (Kock & Hadaya, 2018). A structured questionnaire was prepared in Google Forms and distributed through institutional mailing lists between April and May 2025. Criteria for inclusion A criteria for inclusion were being a current student at postgraduate level and having some experience using AI assisted platforms (Chat GPT, AI driven LMS, adaptive quizzes). Data collection aligned with ethical approaches to conducting research, and all participants gave voluntary and anonymously informed informed consent.

2.3 Instrumentation of variables

As such, all constructs were measured using multi-item five-point Likert scales (1 = strongly disagree to 5 = strongly agree) in an attempt to provide quantifiable and reliable measures of pedagogical and technological perceptions within the study. All measurement items were based on validated instruments, used in previous peer-reviewed Scopus-indexed studies (Prof. Abstract constructs like teaching methodology and assessment strategy were based on existing pedagogical frameworks (Han & Ellis, 2019; Nicol & Macfarlane-Dick, 2006); while digital literacy and AI integration were adapted from research on educational technology (Ng, 2012; Zawacki-Richter et al., 2019). For each variable we used 3 to 5 indicators, their meanings were reviewed by academic specialists. Cronbach's alpha was employed to assess the internal consistency of all items, with all values being above the acceptable threshold of 0.70 (Hair et al., 2022), hence, supporting construct reliability. Such structuring and instrumenting of data allowed for rigorous statistical analysis and hypothesis testing.

Table 2. Variables, Indicators, and Sources

Variable	Code	Indicator Example	No. of Items	Source(s)
Teaching Methodology (X1)	TM	TM1: Lecturers use varied strategies in class	5	Han & Ellis (2019); Wang et al. (2022)
		TM2: Class sessions are interactive and student-centered		
		TM3: Use of problem-based learning is encouraged		
		TM4: Materials are explained clearly and systematically		
		TM5: Lecturers integrate real-world examples		
Curriculum Relevance (X2)	CR	CR1: Course content aligns with current industry needs	4	Alghamdi et al. (2023)
		CR2: The curriculum supports practical skill development		
		CR3: The learning material is up-to-date		
		CR4: Learning objectives are clearly defined		
Student Engagement (X3)	SE	SE1: I actively participate in discussions	5	Fredricks et al. (2019); Bond et al. (2020)

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Variable	Code	Indicator Example	No. of Items	Source(s)
		SE2: I feel emotionally invested in my courses		
		SE3: I put extra effort into my assignments		
		SE4: I regularly collaborate with peers		
		SE5: I feel motivated to attend classes		
Assessment Strategy (X4)	AS	AS1: Feedback from lecturers is constructive	4	Nicol & Macfarlane-Dick (2006); Kwon et al. (2023)
		AS2: Assessments reflect real-world tasks		
		AS3: Assessment criteria are communicated clearly		
		AS4: Various assessment formats are used (e.g., oral, project)		
Digital Literacy (X5)	DL	DL1: I can evaluate the credibility of online sources	5	Ng (2012); Tang et al. (2022)
		DL2: I use digital tools for collaborative learning		
		DL3: I am confident using AI-based applications		
		DL4: I can solve problems using digital technologies		
		DL5: I adapt quickly to new digital platforms		
Learning Effectiveness (Y)	LE	LE1: I achieve learning objectives effectively	6	García-Peñalvo et al. (2020); Sun et al. (2024)
		LE2: I can apply knowledge in practical settings		
		LE3: I feel my critical thinking has improved		
		LE4: I retain knowledge over the long term		
		LE5: I can synthesize and evaluate complex ideas		
		LE6: I am satisfied with my academic performance		
AI Integration (Moderator)	AI	AI1: AI tools support my learning process	5	Zawacki-Richter et al. (2019); Lu et al. (2023)
		AI2: I find AI useful in understanding complex material		
		AI3: AI platforms enhance my productivity		
		AI4: I rely on AI systems to support academic tasks		
		AI5: I believe AI has improved my learning outcomes		

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2.4 Data analysis

The Statistical Package for the Social Sciences (SPSS) version 27 was used to analyze the collected data and assess the direct and interaction effects between the research variables. First, descriptive statistics were conducted to examine the general distribution, central tendencies, and demographics of the respondents. A reliability test was then carried out to assess the reliability of each construct. This assessment was based on the established threshold level of construct reliability and internal consistency, which is expected to exceed 0.70, as outlined in [46]. Inter-item and item-total correlations were determined to assess the validity of the measurement. Multiple linear regression analysis was used to test the hypotheses (H1–H10), with interaction terms added when AI (artificial intelligence) acts as a moderator. The moderation test of hierarchical regression was used, and the increase in CFI was evaluated to determine the model fit by comparing models before and after the interaction variables were included. All tests were conducted at a significance level of $p < 0.05$, and multicollinearity was evaluated via the Variance Inflation Factor (VIF) to maintain model stability.

3. Results

3.1 Descriptive statistics

Descriptive statistics for the key constructs in the study are shown in Table 3 based on 140 respondents. Of the variables, Digital literacy (DL) had the highest mean score (4.21 (SD = 0.51)), suggesting that respondents largely consider themselves to be digitally competent. Third, positively perceived instructional strategies such as Teaching Methodology (TM) and Learning Effectiveness (LE_Y) came out next to 4.15 and 4.12 mean scores. Meanwhile, Curriculum Relevance (CR) and Assessment Strategy (AS), also showed to have a moderate-to-high satisfaction distribution with mean values above 4.00. On the other hand, Student Engagement (SE) presented the lowest mean (3.95, SD = 0.63) which can indicate possible difficulties in maintaining active engagement or interest, even though the other instructional aspects seem to be performing relatively well. In general the variables displays constant distributions as indicated by their standard deviations ranging narrowly between 0.51 and 0.63, with the minimum and maximum values falling within a range of expectations.

Table 3. descriptive statistics of research variables

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Teaching Methodology (TM)	140	4.12	0.56	2.60	5.00
Curriculum Relevance (CR)	140	4.08	0.60	2.40	5.00
Student Engagement (SE)	140	3.95	0.63	2.20	5.00
Assessment Strategy (AS)	140	4.05	0.58	2.80	5.00
Digital Literacy (DL)	140	4.21	0.51	2.80	5.00
Learning Effectiveness (LE_Y)	140	4.15	0.55	2.60	5.00
AI Integration (Moderator M)	140	4.10	0.52	2.80	5.00

3.2 Validity and reliability test

The detail of the validity and reliability test results for all measurement constructs is shown in table 4. Internal consistency was observed for all constructs, with Cronbach′s Alpha coefficients higher than 0.70 in all cases (from 0.802 (Curriculum Relevance) to 0.853 (Learning Effectiveness), as recommended by Hair et al. (2019). Finally, the Composite Reliability (CR) values of the variables ranged from 0.825 to 0.872, which are well above the satisfactory thresholds of 0.70 [49]. Additionally, our Average Variance Extracted (AVE) values (all ≥ 0.50) varied between.566 and.610, affirming appropriate convergent validity (Fornell & Larcker, 1981). The greatest AVE values were reported across Digital Literacy and Learning Effectiveness indicating that much of the variance associated with these constructs is accounted for by the associated indicators. Together, these results provide strong evidence for the reliability and construct validity of the measurement model, suggesting an adequate degree of conceptual equivalence among the instruments used in the present study.

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Table 4. validity and reliability of constructs

Variable	Number of Items	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Teaching Methodology	5	0.826	0.842	0.566
Curriculum Relevance	4	0.802	0.825	0.582
Student Engagement	5	0.838	0.856	0.593
Assessment Strategy	4	0.817	0.832	0.568
Digital Literacy	5	0.844	0.861	0.610
Learning Effectiveness	6	0.853	0.872	0.601
AI Integration	5	0.830	0.848	0.587

3.3 Pearson correlation matrix

Table 5 presents the Pearson correlation matrix, indicating the strength and direction of the relationships among the study variables. All correlation coefficients are positive and statistically significant at the 0.01 level ($p < 0.01$), suggesting strong interconnections among constructs. Teaching Methodology (TM) shows moderate correlations with all other variables, particularly with Learning Effectiveness ($r = 0.546$) and Curriculum Relevance ($r = 0.522$). Digital Literacy (DL) demonstrates consistent associations across variables, with the highest correlation to Learning Effectiveness ($r = 0.548$). Similarly, AI Integration (AII_M) is positively correlated with all constructs, especially with Learning Effectiveness ($r = 0.537$) and Digital Literacy ($r = 0.534$), highlighting its growing role in educational enhancement. The strong correlation between Student Engagement and Curriculum Relevance ($r = 0.534$) further emphasizes the role of contextualized learning materials in promoting active participation. Overall, the results indicate significant mutual reinforcement among instructional strategies, digital competencies, and learning outcomes, providing a robust foundation for further analysis of direct and mediated effects in the structural model.

Table 5. pearson correlation matrix

Variable	TM	CR	SE	AS	DL	Y	AI
Teaching Methodology (TM)	1.00						
Curriculum Relevance (CR)	0.522	1.00					
Student Engagement (SE)	0.487	0.534	1.00				
Assessment Strategy (AS)	0.501	0.469	0.455	1.00			
Digital Literacy (DL)	0.498	0.511	0.524	0.508	1.00		
Learning Effectiveness (LE_Y)	0.546	0.532	0.519	0.535	0.548	1.00	
AI Integration (AII_M)	0.498	0.512	0.509	0.517	0.534	0.537	1.00

3.4 Classical assumption tests

The classical assumption test results to verify the regression model are listed in Table 6. For the normality test, the Kolmogorov-Smirnov test obtained a significance value of 0.117 or > 0.05 which states that the residuals are

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normal. The Variance Inflation Factor (VIF) (1.23 to 2.02), was also used to assess multicollinearity and all VIF values were far lower than 10 (the cutoff), indicating no multicollinearity between independent variables. Results: From the Glejser test of heteroscedasticity, significance values of all variables were found to be more than 0.05 thus indicating that the data is homoscedatic or confirms constant variance. Finally, Durbin-Watson statistic = 1.976 less than 1.5 to 2.5 signaled no autocorrelation in the residual. Taken together, these results corroborate that the data was in accordance with classical linear regression assumptions, thus having enabled the subsequent hypothesis tests to be accurate and robust.

Table 6. classical assumption tests

Test	Result	Criteria	Decision
Normality (Kolmogorov-Smirnov)	Sig = 0.117	Sig > 0.05	Normal distribution
Multicollinearity (VIF)	VIF = 1.23–2.02	VIF < 10	No multicollinearity
Heteroscedasticity (Glejser)	Sig > 0.05 for all variables	Sig > 0.05	Homoscedastic
Autocorrelation (Durbin-Watson)	DW = 1.976	1.5 < DW < 2.5	No autocorrelation

3.5 Multiple linear regression (Main Effects)

In the multiple linear regression analysis conducted via Table 7, it is determined that all five predictor and independent variables Teaching Methodology (β = 0.201, p = 0.001), Curriculum Relevance (β = 0.179, p = 0.003), Student Engagement (β = 0.155, p = 0.011), Assessment Strategy (β = 0.188, p = 0.002) and Digital Literacy (β = 0.212, p = 0.001) are statistically significant positive predictors of academic performance. Of these, Digital Literacy has the largest standardized coefficient, indicating that it has the greatest influence. The model (R^2 = 0.534) explains approximately 53.4% of the variance in academic performance, and overall model fit is significant (F = 23.615, $p < 0.001$). These findings show that the specific instructional and digital factors selected together help explain students outcomes meaningfully, consistent with the theoretical premise that multiple educational strategies enhance learning effectiveness in the context of higher education.

Table 7. multiple linear regression results

Predictor Variable	β	t-value	Sig.
Teaching Methodology (TM)	0.201	3.412	0.001
Curriculum Relevance (CR)	0.179	3.029	0.003
Student Engagement (SE)	0.155	2.565	0.011
Assessment Strategy (AS)	0.188	3.208	0.002
Digital Literacy (DL)	0.212	3.501	0.001
R^2 = 0.534, F = 23.615, $p < 0.001$			

3.6 Moderation analysis using interaction terms

As shown in Table 8, the moderation analysis using interaction terms indicates that the integration of Artificial Intelligence (AI) has a substantial impact on the relationship between each of the five independent variables and academic performance. Specifically, the interaction terms for teaching methodology (β = 0.142, p = 0.033), curriculum relevance (β = 0.115, p = 0.044), student engagement (β = 0.124, p = 0.028), assessment strategy (β = 0.138, p = 0.014), and digital literacy (β = 0.147, p = 0.009) all demonstrate statistically significant moderation effects. Including these interaction terms increases the model's explanatory power, raising the R^2 to 0.613 and producing a significant R^2 change (ΔR^2) of 0.079 (F Change = 7.218, $p < 0.001$). These findings suggest that integrating AI enhances the strength of the relationships between pedagogical variables and academic performance, indicating its catalytic role in modern educational environments.

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Table 8. Moderation regression results

Interaction Term	β	t-value	Sig.	Interpretation
X_1 AI Integration	0.142	2.154	0.033	Significant moderation
X_2 AI Integration	0.115	2.031	0.044	Significant moderation
X_3 AI Integration	0.124	2.225	0.028	Significant moderation
X_4 AI Integration	0.138	2.489	0.014	Significant moderation
X_5 AI Integration	0.147	2.643	0.009	Significant moderation
$R^2 = 0.613$, $\triangle R^2 = 0.079$, F Change = 7.218, $p < 0.001$				

4. Discussion

The discussion in this paper centers on the key findings of a study. These findings highlight the pivotal role that teaching methodologies, curriculum adaptation to context, student engagement, assessment techniques, and digital literacy play in facilitating effective learning for postgraduate students. The results emphasize that effective learning is tied not only to instructional design but also to digital competence among learners and their interaction with learning environments. Biggs and Tang (2011) argue that effective teaching in higher education is based on constructive alignment between teaching methods and intended learning outcomes. These results once again demonstrate the importance of teaching in achieving academic success, consistent with prior studies.

Student engagement in particular emerged as a key variable, consistent with the findings of Fredricks et al. (2019), who highlighted the importance of behavioral, emotional, and cognitive engagement in academic persistence and success. The favorable result of engagement implies that learning environments should trigger active participation, affective engagement, and cognitive engagement. The argument that engagement is both an indicator of and an antecedent to educational quality supports the adoption of learner-centered pedagogies for postgraduate education.

Additionally, the process's effectiveness is enhanced by the incorporation of artificial intelligence (AI) in a specific role: that of a contextual moderator, working in conjunction with existing systems, rather than as a mere mediator. Rather than merely transferring knowledge, AI provides greater personalization, adaptive feedback, and real-time learning analytics, aligning with the vision of Zawacki-Richter et al. (2019). AI does not change the relationship between teaching strategies and student behavior. Rather, it enhances individual and collective relationships by enabling and facilitating the customization and tuning of these interactions in real time. Likewise, Lu et al. (2023) believe that AI enhances the learner experience through adaptive pathways and the immediacy of support during complex academic activities.

Although academic prowess takes precedence over impact for some, the importance of the curriculum and its applicability to the real world remains. Alghamdi et al. (2023) found that student motivation and perceived value increase considerably when curricular content aligns with industry and global competencies. Postgraduate learners also experience purpose alignment when the curriculum design considers challenges that cross disciplines, sustainability, and digital transformation (e.g., Khan, 2021; MichMadrid, 2021). Therefore, relevance is no longer a static characteristic of curriculum design; it must be dynamic in response to societal and technological changes.

I have previously contended that the strategy used for assessment can also affect learning effectiveness, especially when it is formative and gives students the power to take control. In accordance with the assertions put forth by Nicol and Macfarlane-Dick in 2006, the process of evaluating learning can be metamorphosed into an assessment for learning by integrating feedback and introspection. Building on this perspective, Kwon et al. (2023) argue that assessment for learning can be achieved by incorporating feedback and reflection.

Lastly, digital literacy is a core competence that drives all other learning components. Ng (2012) conceptualizes digital literacy as a three-way interaction of the cognitive, technical, and socio-emotional domains. With AI-assisted education, digital literacy is necessary to interact meaningfully with intelligent systems and gain value from them. The assertion made by Tang et al. and Cohen (2022) is that if educational institutions are not adequately prepared in terms of digital readiness, the potential benefits of artificial intelligence (AI) in the educational sector might actually serve to amplify existing inequalities rather than mitigating them. Therefore, digital literacy should be regarded not only as a technical skill set provided by institutions, but also as a potentially influential tool in creating learning ecosystems that encourage critical skills for learning in the digital age.

5. Conclusion

This research is a meaningful contribution that highlights the importance of AI integration in unlocking postgraduate learning effectiveness through moderating influence on pedagogy elements of teaching methodology, curriculum relevance, student engagement, assessment, and digital literacy. The results of the analysis imply that AI is not serving merely as a mediating or an exogenous treatment but rather acts as a contextual lever that modulates the educational effectiveness of quality instructional strategies. The interaction between artificial intelligence and traditional school-related factors represents a paradigm shift in education, with digital enhancement complementing curricular embrace, enabling self-directed learners, assisting agile feedback mechanisms, and driving flexible conveying of content. It also supports the emerging consensus in the academic community that AI-powered learning environments facilitate personalized learning, better retention of knowledge and the ability to think critically. The findings also offer possibilities to help academic institutions that want to improve their postgraduate curricula through intelligent systems to create a more flexible, engaging, and results-oriented learning environment. Research opportunities include examining domain-specific applications of AI across different educational contexts, ethical, cultural, and cognitive dimensions to inform equitable and resilient learning environments.

Limitations

The limitations of this study occur in the sample size (though large) consist of only postgraduate students potentially less generalizable to other levels in academia) from a single institution (perhaps even less generalizable. Self-reported surveys could also introduce bias in measuring constructs such as digital literacy and learning engagement. Also, the cross sectional design of the data collection inhibits the determination of causal inferences between the variables. More longitudinal or experimental designs should be used in the future and include a wider range of educational institutions so that findings can be more externally valid.

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Author Contributions

Conceived the research work, provided input for the literature review, drafted and finalized the manuscript: Murtono. Mulyo Prayitno did data collection, analysis, and writing of the discussion and conclusion. Final version of the manuscript was approved by both the authors.

Conflicts of Interest

There is no competing interest regarding the publication of this article.

Data Availability Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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