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The Influence of Artificial Intelligence (AI) and Mobile Learning on Learning Outcomes in Higher Education: Did the Mediation of Self-Competence Matter?

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Abstract

Islamic Religious Education (PAI) has a significant impact on the development of students' character, morality, and overall learning outcomes. This study aims to investigate the effects of artificial intelligence (AI) and mobile learning on student learning outcomes, with a specific focus on the role of students' self-competence as a mediating factor. Employing a quantitative survey approach, the research included 208 students from the PAI Study Program at IAIN Ponorogo, using probability sampling techniques. Data was collected through Likert-scale questionnaires, and the research data was analyzed using PLS-SEM analysis. The results indicate a positive influence of AI and mobile learning on student learning outcomes, with self-competence playing a crucial role as a mediating factor. These findings highlight the importance of educators promoting self-regulation, self-efficacy, and motivation skills within online learning environments. The study emphasizes the potential of integrating AI and mobile learning to enhance the quality of education and recommends that educators continuously update their knowledge of technological advancements through training and collaboration. Strengthening these competencies can lead to a more interactive, personalized, and adaptive learning environment for students.

Keywords: Self Competence; Artificial Intelligence; Mobile Learning; Learning Outcomes; ChatGPT

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INTRODUCTION

Islamic Religious Education (PAI) holds considerable significance as a subject within numerous educational institutions under the purview of the Ministry of Education and Culture and the Ministry of Religion of the Republic of Indonesia (Abdullah, 2017). Moreover, PAI stands as a primary field of study for students pursuing a bachelor's degree in Islamic religious education, while also playing a pivotal role in molding students' character and morality (Aisyah et al., 2022). The resulting outcomes of PAI instruction are evaluated through the cognitive, affective, and psychomotor domains.

Within the cognitive domain, PAI learning outcomes encompass the mastery and application of PAI concepts, theories, and principles, thus equipping students with an in-depth comprehension of Islamic teachings. Conversely, within the affective domain, PAI learning outcomes pertain to students' attitudes, values, and emotions towards PAI, which ultimately shape their personality and moral compass in alignment with Islamic religious teachings. Finally, the psychomotor domain encompasses PAI learning outcomes associated with students' practical skills and actions in applying Islamic religious teachings in their everyday lives (Astiti et al., 2021).

By establishing a more coherent connection between these roles and specific learning outcomes within the cognitive, affective, and psychomotor domains, students can cultivate a more comprehensive understanding of Islamic religious teachings, subsequently integrating these values into their daily lives. This, in turn, can yield substantial benefits in terms of character development and moral formation, all within the framework of Islamic teachings.

Despite its significance, preliminary survey results indicate that inadequate learning methods contribute to subpar learning outcomes in PAI (Lamb et al., 2018). These methods often fail to accommodate the diverse learning styles of students, disregarding individual needs and cognitive preferences, thereby creating a disparity between the information delivered and the students' grasp of the subject matter (Guo et al., 2020). For instance, specific data pertaining to student learning outcomes reveals that a majority of students encounter difficulties in comprehending the concepts of Islam presented within the classroom. Furthermore, student feedback highlights a diminished level of motivation and engagement in the learning process, attributable to less interactive learning methods that fail to align with their preferred learning styles. The improper method of learning has a significant impact on student learning outcomes. The available data indicates that students tend to have low levels of understanding of Islamic religious teachings, as evidenced by their test scores and other evaluations. Moreover, the lack of student engagement in the learning process can prevent them from applying the teachings of Islam in their daily lives, which should be the primary goal of Islamic religious education. Therefore, it is crucial to update the teaching approach to better align with the students' learning characteristics and create a more effective learning environment.

The implementation of Artificial Intelligence (AI)-based learning media holds great promise in addressing the issue of poor learning outcomes in Islamic religious education. A recent study conducted by Astiti et al. (2021) demonstrates that AI-based learning media significantly enhances student learning outcomes. AI technology enables machines to simulate human cognitive processes, offering real-time assistance in learning and problem-solving (Zhang & Aslan, 2021). With the rapid advancement of information and communication technology, AI-based learning media emerges as an innovative alternative capable of enhancing the quality of learning and fostering students' skills.

Another study conducted by X. Chen et al. (2020) highlights the advantages of AI technology in education, with observations revealing that a substantial number of students (66.67%) actively employ AI to overcome learning challenges. This highlights the widespread adoption of AI technology among students and its potential to enhance student engagement and learning outcomes.

Therefore, the integration of AI-based learning media offers innovative solutions to improve learning outcomes in Islamic religious education. This technology can provide personalized learning support, promote student engagement, and offer real-time problem-solving capabilities. As AI-based learning media gains greater acceptance among students, it holds tremendous potential to revolutionize the learning paradigm and cultivate a more effective and conducive learning environment.

Recent research findings depict the increasing use of artificial intelligence (AI) in diverse fields, including Islamic religious education (PAI), which requires high-level cognitive abilities involving the acquisition, analysis, and synthesis of information. The introduction of ChatGPT has set a new standard in this evolving model, offering significant opportunities for education (İpek et al., 2023). The study's results demonstrate that the utilization of ChatGPT, particularly versions 3.5 and 4, can enhance writing quality by increasing word count through uniqueness and promoting sentence length diversity. However, a more explicit definition of the gap in integrating AI into Islamic religious education is needed. One specific aspect that has not been studied yet is how AI technology can be utilized to enhance the understanding and application of Islamic religious teachings in students' daily lives, specifically in the context of PAI. While previous research by İpek et al. (2023) and Karaköse et al. (2023) focused on improving general writing and critical thinking skills, this recent study specifically highlights the integration of AI in Islamic religious education.

A clearer articulation of this gap will highlight the unique contribution of research in exploring the potential of AI to support Islamic religious learning. As a result, educators should think creatively about how AI technology can effectively strengthen the understanding of Islamic religious values and promote their application in students' daily lives. It is important for all stakeholders to collaborate and take collective action to ensure that the integration of AI into Islamic religious education has a significant positive impact and contributes to a more inclusive and innovative future of education (Athanassopoulos et al., 2023).

AI also functions as a virtual mentor, providing guidance in the development of self-competence, motivation, and time management (L. Chen et al., 2020; X. Chen et al., 2020). This support can lead to more optimal learning outcomes. Moreover, AI can analyze and assess individual self-competence, allowing for tailored and effective learning approaches (X. Chen et al., 2020; Hwang et al., 2020). The mediation of self-competence in mobile learning enables personalized education that aligns with individual interests, needs, and abilities (Y.-H. Chen, 2021; Martzoukou et al., 2020). Mobile learning can also enhance motivation and self-confidence through features that offer rewards and community support (Burns et al., 2018).

In order for students to improve their learning outcomes, it is crucial for them to develop self-competence, which involves recognizing and optimizing their potential across cognitive, affective, and psychomotor aspects (Cheung et al., 2018). This competency is essential for effectively utilizing AI-based learning media and mobile learning. Therefore, the integration of AI and mobile learning in PAI education can significantly contribute to enhancing student learning outcomes and overall educational quality.

METHOD

Research Design and Participants

In this study, a quantitative approach with a survey research method was applied, following the approach used by Apriliani et al., 2023; Putra et al., 2022;

Widayanto et al., 2021. The research design was explanatory and correlational, enabling the exploration of relationships between variables in conceptual models. The analysis method utilized was Partial Least Squares Structural Equation Modeling (PLS-SEM), a multivariate statistical technique employed to analyze the relationships between latent or measurable variables in structural models.

The data collection process commenced with the development of a survey questionnaire designed to gather information on various relevant variables, including the utilization of artificial intelligence technology and mobile learning, student self-competence, and student learning outcomes. The survey questionnaire was distributed to 208 PAI students from the Class of 2021 at IAIN Ponorogo, employing a random sampling technique. Subsequently, the data collected through the survey questionnaire underwent analysis using the PLS-SEM method. PLS-SEM facilitated a holistic evaluation of the model, encompassing the identification of causal relationships and correlations between variables. The data was processed using appropriate statistical software to ensure accurate results.

The sample formula utilized was the Slovin formula, employing a significance level of 5% with a population size of 433 participants. The study sample consisted of 208 participants, which was deemed sufficient to minimize sampling errors and yield accurate estimates of the population. Table 1 presents the characteristics of the research sample for PAI students.

Table 1. Participant demographics

			Compare Means			
Characteristic	**Population**	**Sample**	**T-value**	**df**	**T-table**	**Sig (<0.05)**
Gender						
Male	102	71	51.889	70	1.667	0.000
Female	331	137	161.723	136	1.656	0.000
Class Section						
PAI.A	32	15	26.437	14	1.761	0.000
PAI.B	31	15	24.320	14	1.761	0.000
PAI.C	33	16	22.154	15	1.753	0.000
PAI.D	34	16	24.167	15	1.753	0.000
PAI.E	30	14	39.674	13	1.771	0.000
PAI.F	29	14	78.966	13	1.771	0.000
PAI.G	29	14	76.541	13	1.771	0.000
PAI.H	31	15	41.881	14	1.761	0.000
PAI.I	34	16	36.373	15	1.753	0.000
PAI.J	31	15	143.429	14	1.761	0.000
PAI.K	32	15	127.155	14	1.761	0.000
PAI.L	31	15	83.446	14	1.761	0.000
PAI.M	28	14	96.468	13	1.771	0.000
PAI.N	28	14	164.836	13	1.771	0.000
Academic levels						
Academic levels 4	207	110	76.191	109	1.659	0.000
Academic levels 6	226	98	135.586	97	1.661	0.000

By employing this methodology, it becomes possible to explore the connections among the variables delineated in our theoretical framework and gain a deeper comprehension of the intricacy inherent in the observed phenomena within the realm of learning. Consequently, the research techniques utilized enable us to generate pertinent and dependable outcomes, thereby addressing our research inquiries effectively.

Data Collection

An instrument consisting of four variables was utilized in the process of data collection. The mediator variable is self-competence (Z), the dependent variable is learning outcomes (Y), and the independent variables are artificial intelligence (X1) and mobile learning (X2). The Likert scale used in this study encompasses five possible responses, ranging from strongly disagree (1) to strongly agree (5) (Daryono et al., 2020; Widyastuti et al., 2023). The data collection was conducted using a survey method through Google Forms. The research instrument variables are presented in Table 2.

Table 2. The Construct of the Research Variables

No.	Variable	Indicator	Construct	References
1	Artificial Intelligence (AI)	Relevance	AI1	(Baidoo-anu & Ansah, 2023; Chassignol et al., 2018; X. Chen et al., 2020; Zawacki-Richter et al., 2019; Zhang & Aslan, 2021)
			AI2	
		Affordability	AI3	
		Interactivity	AI4	
		Innovation	AI5	
			AI6	
2	Mobile Learning	Material compatibility	ML1	(Crompton & Burke, 2018; García-Martínez et al., 2019; Golenhofen et al., 2020; Noh & Lee, 2013; Silitonga et al., 2021; Yu et al., 2022)
			ML2	
		Completeness of material	ML3	
		User Interactivity	ML4	
			ML5	
		Independence	ML6	
			ML7	
			ML8	
3	Self-Competence	Self-understanding	SC1	(Burns et al., 2018; X. Chen et al., 2020; Cheung et al., 2018; Martzoukou et al., 2020; Ohannessian et al., 2019; Spante et al., 2018)
			SC2	
		Self-confidence	SC3	
			SC4	
		Self-management	SC5	
			SC6	
		Self-socialization	SC7	
4	Learning Outcomes	Comprehension of the material	LO1	(Azevedo et al., 2021; Guo et al., 2020; Lamb et al., 2018; Saarinen et al., 2021; Supena et al., 2021)
			LO2	
			LO3	
		Critical thinking skills	LO4	
			LO5	
			LO6	

No.	Variable	Indicator	Construct	References
		Improved collaborative skills	LO7	
		Environmental awareness	LO8	

Data Analysis

The statistical analysis of this study employs the PLS-SEM measurement technique. The outer model testing stage is crucial in determining the validity and reliability of indicators and constructs. It is necessary to have a reflective construct AVE (>0.50) and an indicator loading factor (λ0.70) (Daryono et al., 2024; Fauzan et al., 2023; Supriyanto et al., 2022). Reliability estimates are calculated using Cronbach Alpha, Rho_A, and CR values (>0.70). The goodness of fit model testing stage assesses the model's predictive capacity and feasibility. In order to assess the model's prediction capability on the blindfolding output, the condition of predictive relevance must be met (Daryono et al., 2023; Hariyanto et al., 2022). The inner model testing stage evaluates the importance of direct impacts (H-DIR$_{1-5}$) and indirect impacts (mediating role of H-IND$_{1-2}$).

Ethical Consideration

In this study, various ethical considerations were considered to ensure the protection of participants and the integrity of the research process. Confidentiality and anonymity were strictly maintained, with personal identities removed and data coded. The study design also considered the welfare of participants, without involving procedures that were physically or psychologically harmful. The study protocol was reviewed and approved by the Human Subjects Research Ethics Committee at IAIN Ponorogo, ensuring compliance with institutional ethical guidelines. This study primarily used a survey method, which has low risk. This study also adhered to the ethical principles outlined in the authors' Duties on Publication Ethics, including maintaining the highest standards of integrity, transparency, and accountability throughout the research process. By integrating these ethical considerations, this study ensured the protection of participants' rights, maintained the integrity of the research process, and complied with the ethical standards required for publication.

RESULTS AND DISCUSSION

Construct Validity: Evaluation of the Structural Model (Inner Model)

Evaluating measurement models is of utmost importance in ensuring that the indicators used to measure latent constructs or variables are precise and consistent with the research objectives. The primary aim of model evaluation is to assess construct validity. This can be achieved by examining the relationship between the indicator and the measured construct, thereby ensuring that the indicator accurately represents the intended element of the construct. Researchers can determine which indicators to include in the study and which to exclude by analyzing factors such as factor loadings, reliability, and discriminant validity. The convergent validity measurement employs a factor loading value threshold of 0.70. According to Table 3, the overall loading factor values for each sub-variable exceed 0.70 (ranging from 0.703 for self-understanding to 0.780 for independence).

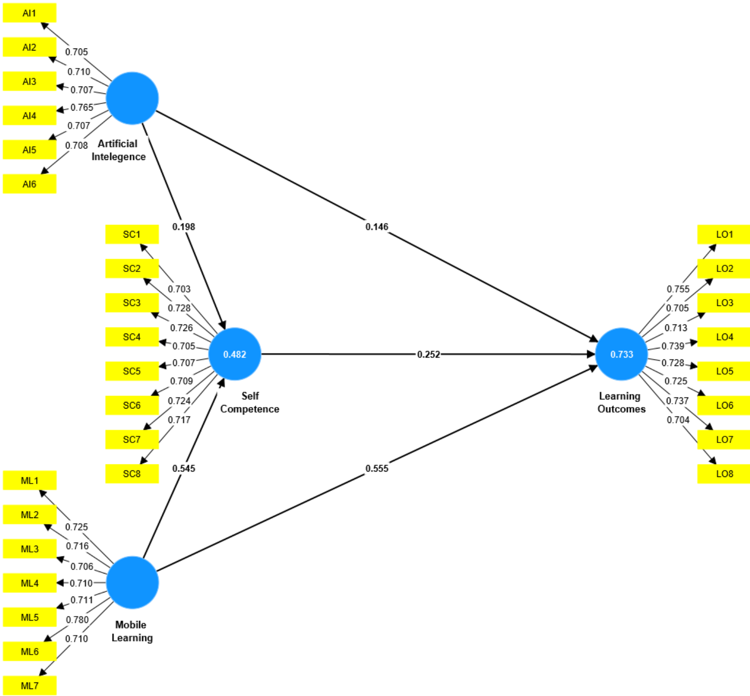

Figure 1. Evaluation of the Measurement Model

The result implies that the degree of correlation between sub-variables and the underlying variables is between 70.30% and 78.00%. Furthermore, the Average Extracted Variance (AVE) values for each variable surpass 0.50 (ranging from 0.511 for self-competence (Z) to 0.627 for learning outcomes (Y)). Therefore, it can be inferred that both the sub-variables and variables within the research model instrument meet the requirements for convergent validity. Looking at the loading factor coefficient values, the most influential statement item in assessing student learning outcomes is independence, with a coefficient of 0.780 (ML6). This indicates that the independence construct can account for 78.00% of the variance in learning outcomes. Conversely, the weakest item is the self-understanding construct, with a coefficient of 0.703 (SC1, or 70.30%).

Table 3. Outer Model: Convergent Validity and Reliability

No.	Variable	Indicator	Convergent Validity		Consistency Reliability		
			FL (λ>0.70)	AVE (>0.50)	CA (α>0.70)	rho_A (φ>0.70)	CR (δ>0.70)
1	Artificial Intelligence (AI)	AI1	0.705	0.515	0.812	0.814	0.864
		AI2	0.71				
		AI3	0.707				
		AI4	0.765				
		AI5	0.707				
		AI6	0.708				
2	Mobile Learning	ML1	0.725	0.523	0.848	0.849	0.885
		ML2	0.716				
		ML3	0.706				
		ML4	0.71				

No.	Variable	Indicator	Convergent Validity		Consistency Reliability		
			FL (λ>0.70)	AVE (>0.50)	CA (α>0.70)	rho_A (φ>0.70)	CR (δ>0.70)
		ML5	0.711				
		ML6	0.78				
		ML7	0.71				
		ML8	0.725				
3	Self-Competence	SC1	0.703	0.511	0.864	0.863	0.893
		SC2	0.728				
		SC3	0.726				
		SC4	0.705				
		SC5	0.707				
		SC6	0.709				
		SC7	0.724				
4	Learning Outcomes	LO1	0.755	0.527	0.872	0.873	0.899
		LO2	0.705				
		LO3	0.713				
		LO4	0.739				
		LO5	0.728				
		LO6	0.725				
		LO7	0.737				
		LO8	0.704				

A variable is deemed dependable when its CA, Rho_A, and CR values are greater than 0.70. The table below presents the SmartPLS output, which indicates that all variables have CA values ranging from 0.812 to 0.872, rho_A values ranging from 0.814 to 0.873, and CR values ranging from 0.864 to 0.899. Therefore, it can be concluded that the instrument exhibits good reliability in measuring student learning outcomes, as its internal consistency in these three aspects exceeds 0.70.

The Fornell-Larcker test is a technique utilized in partial least squares structural equation modeling (PLS-SEM) to assess the discriminant validity of constructs within a model. This test aims to ensure that the different constructs in the model can be distinguished from one another. It achieves this by comparing the amount of variance explained by each construct to the variance explained by the remaining constructs in the model. If a construct explains more variation than another, it demonstrates excellent discriminant validity.

The Fornell-Larcker value is determined by examining the correlation between the latent variable itself and the correlation variables of other latent variables. Referring to Table 4, the correlation value between Artificial Intelligence (X1) and Artificial Intelligence is 0.718, which surpasses the correlation values of Self-Competence (Z) with other variables (Learning Outcomes → 0.664, Mobile Learning → 0.676, and Self-Competence → 0.567). Therefore, it can be concluded that there is a significant correlation between Artificial Intelligence and other variables.

Table 4. Discriminant Validity: The Fornell Larcker

Variable	X1	Y	X2	Z
Artificial Intelligence X1	**0.718**			
Learning Outcomes Y	0.664	**0.726**		
Mobile Learning X2	0.676	0.724	**0.723**	
Self-Competence Z	0.567	0.711	0.679	**0.715**

Structural Reliability: Evaluation of the Structural Model (Inner Model)

The primary objective of structural evaluation in PLS-SEM testing is to assess the reliability of the given model in a more academic manner. This entails determining the model's efficacy in predicting endogenous variables and explaining variations in real-world data. By examining the correlations between different variables, researchers aim to enhance their understanding of the underlying dynamics and identify the elements contributing to the observed phenomena. Ultimately, the overall goal of structural evaluation is to advance knowledge within the research context.

Table 5. Measurement of Structural Model: R2 dan F2

Variable	R2		F2	
	Value	Decision	Value	Decision
Learning Outcomes	0.733	Large	-	-
Mobile Learning	-	-	0.477	Large
Artificial Intelligence	-	-	0.042	Small
Self-Competence	0.482	Moderate	0.123	Small
Learning Outcomes	0.733	Large	-	-

The PLS-SEM model's capacity to elucidate the variability in the observed endogenous variables (constructs) is summarized by the R^2 (Coefficient of Determination). The extent to which the model can account for variation in the construct increases as the R^2 score rises. R^2 enables the comparison of different PLS-SEM models. By means of R^2 values, researchers can evaluate the efficacy of various models in explaining the variation in observed components. Based on the aforementioned table, the R^2 coefficient for the learning outcomes variable was determined to be 0.733. This implies that artificial intelligence, mobile learning, and self-competence collectively account for 73.30% of the influence on the learning outcomes variable, with the remaining 26.70% being affected by external variables not included in the model.

One of the metrics used in PLS-SEM to assess the impact of latent variables on the observed construct is known as "effect size," or f^2. Specifically, f^2 evaluates the predictive capability of a latent variable on a specific model component. To be more precise, the formula for f^2 is derived from the square of the latent variable's regression loading on a given construct, divided by the residual error (error variance) of that construct. The findings provide insights into the degree to which the variability in the observed construct can be explained by the latent variable. f^2 helps determine the significance of the latent variables' contribution to the observable construct. Comparing the contributions of multiple latent variables to a single construct is made possible by f^2, aiding in the identification and determination of the latent factors that have the strongest impact. According to the effect size output, mobile learning (f^2 =

0.477) falls into the strong category as the variable with the greatest influence on learning outcomes, while artificial intelligence (f^2 = 0.042) is classified as having a small effect size and therefore the least impact on learning outcomes.

Path Analysis and Hypothesis Testing

Analyzing the relationship between variables in a proposed model serves as a fundamental objective in hypothesis testing. This entails scrutinizing the significance and magnitude of correlations among the variables within the model. To achieve this, researchers employ direct effect evaluation to determine the extent to which empirical findings align with the theoretical framework of the model. Furthermore, the test examines the significance of the mediation effect within the research model. Gaining a comprehensive understanding of the mechanisms underlying variable interactions and the potential mediating or moderating role of specific variables in relationships is of utmost importance.

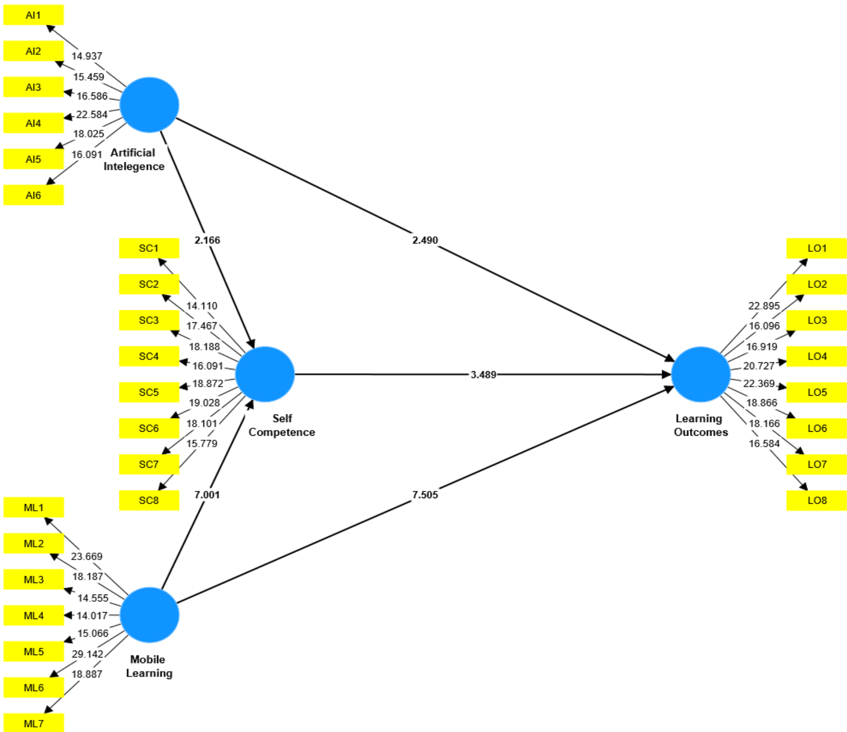

Figure 2. Evaluation of Structural Model

If the T-statistic value of a hypothesis exceeds 1.96, it can be accepted based on the substantial criterion. Additionally, if the B-value coefficient indicates the direction of the positive or negative influence, the hypothesis can be accepted with either a positive or negative influence. According to the table below, the hypothesis H1 (Artificial Intelligence (X1) → Learning Outcomes (Y)) obtained β-values of 0.146 and P-values of 0.013 (0.05). This indicates that the artificial intelligence variable (X1) has a positive and significant effect on learning outcomes (Y). In other words, an increase in the artificial intelligence variable (X1) will also lead to a significant increase in the learning outcomes variable. Moreover, hypotheses H2 to H5 demonstrate a positive and significant effect on the influence of the entrepreneurial interest variable. Among these hypotheses, the Mobile Learning and Learning Outcomes variables obtained the highest β-value score of 0.555, indicating their prominent contribution to influencing learning outcomes.

Table 6. Results of Path Coefficients: Direct Effects

Hypothesis	Path Analysis	β-Values (+/-)	Sample Mean	SDV	T-Statistics (>1,96)	P-Values (<0,05)	Decision
H-DIR$_1$	AI → LO	0.146	0.148	0.059	2.49	0.013	Accepted
H-DIR$_2$	AI → SC	0.198	0.204	0.091	2.166	0.030	Accepted
H-DIR$_3$	ML → LO	0.555	0.553	0.074	7.505	0.000	Accepted
H-DIR$_4$	ML → SC	0.545	0.546	0.078	7.001	0.000	Accepted
H-DIR$_5$	SC → LO	0.252	0.252	0.072	3.489	0.000	Accepted

The Mediating Role of Self-Competence on the Artificial Intelligence and Mobile Learning on Learning Outcomes

Based on Table 7, it can be concluded from the H-IND1 hypothesis that there is a positive but insignificant influence (β-values = 0.05) between artificial intelligence (X1) factors and learning outcomes (Y), as evidenced by the non-significant T statistic (1.908 > 1.96) and P value (0.056 < 0.05) of the mediating effect of the self-competence (Z) variable. Therefore, H-IND1 states that there is no significant positive influence of self-competence in mediating the impact of artificial intelligence on learning outcomes.

Similarly, the results of testing the mediating effect of the self-competence (Z) variable in the H-IND2 hypothesis indicate a significant positive influence (β-values = 0.137) between the mobile learning factor (X2) and learning outcomes (Y), as demonstrated by the significant T statistic (2.897 > 1.96) and P value (0.004 < 0.05). Consequently, H-IND2 states that there is a significant positive influence of self-competence in mediating the impact of mobile learning on learning outcomes.

Table 7. Results of Path Coefficients: Indirect Effects

Hypothesis	Path Analysis	β-Values (+/-)	SDV	T-Statistics (>1,96)	P-values	Decision	Mediating Role
H-IND$_1$	AI → SC → LO	0.05	0.026	1.908	0.056	Rejected	No mediation
H-IND$_2$	ML → SC →LO	0.137	0.047	2.897	0.004	Accepted	Partial mediation

Discussion

The results of the evaluation conducted on the H1 hypothesis demonstrated that the statistical T value was 2.49, surpassing the threshold of 1.96, indicating statistical significance and thereby accepting the first hypothesis. This outcome signifies that artificial intelligence (AI) positively impacts the enhancement of student learning outcomes. This finding aligns with Zheng et al.'s (2023) research, which asserted that AI, when employed in conjunction with interactive technology, exerts a substantial influence on learning outcomes, offering students a more engaging and effective learning experience. The heightened level of interactivity facilitated by AI stands out as a primary indicator of its impact on learning outcomes. Through interactive AI systems, students actively engage in the learning process and receive immediate feedback, thereby augmenting their comprehension of the subject matter.

Moreover, Robert et al.'s (2024) research lends additional support to this explanation, contending that AI's capacity to tailor learning materials to the specific needs and comprehension levels of students enhances learning outcomes. By identifying students' needs and levels of understanding, AI ensures the provision of learning materials that are relevant to their circumstances. This sense of relevance motivates students to develop a stronger enthusiasm for learning as they recognize the value and applicability of the knowledge they acquire. Considering these factors collectively, it becomes evident that the utilization of AI in the education realm yields positive outcomes for students. The interactive nature and relevance of AI features contribute to a more stimulating, efficient, and effective learning experience. As a result, students can personalize their learning process to suit their individual needs, leading to the attainment of optimal learning outcomes.

However, it is imperative to acknowledge that while AI holds tremendous potential across various fields, including business process automation and educational services, its impact on the development of self-competence is not entirely significant. This assertion is in line with Perry (2023), who posits that AI tends to be objective, lacking the ability to empathize or account for human emotions. Consequently, while AI can offer logical suggestions or recommendations based on available data, it fails to provide the emotional support or motivation necessary for fostering self-competence. Additionally, Ahmad et al.'s (2023) research indicates that excessive reliance on AI can lead to a dependence on technology, diminishing individuals' capacity to rely on their own judgment and problem-solving skills. Consequently, individuals must continue to independently cultivate their competency abilities without excessively relying on AI technology.On the other hand, mobile learning, also known as mobile-based learning, has gained significant popularity in the field of education. The incorporation of mobile technology in the teaching and learning process has had a profound impact on student learning outcomes, particularly in enhancing learning autonomy and the customization of materials to suit individual needs. A study conducted by Widowati and Tyas (2024) indicates that mobile learning enables students to learn at any time and anywhere, based on their preferred time and location. This provides students with the opportunity to manage their study schedules, enhance their independence in time management, and prioritize their learning activities. Aligning with the research findings by Yang et al. (2021), mobile learning allows teachers to provide students with direct feedback on their learning progress. By receiving accurate and real-time information about students' learning achievements, teachers can offer appropriate guidance to support the development of students' learning autonomy and tailor learning materials to their individual needs.

Mobile learning has a significant impact on students' self-competence, particularly in terms of learning autonomy. Consistent with the research conducted by Bernacki et al. (2020), the flexibility and easy accessibility facilitated by mobile technology empower students to manage their study time, choose the content they wish to learn, and adapt the learning methods to align with their preferred learning styles. This fosters an increase in students' independence in managing their learning process, without being constrained by specific time and location requirements. This supportive role is further corroborated by the research of Aubusson et al. (2009). Through mobile learning, students can engage in collaborative learning with their teachers or peers. This collaborative interaction enables students to support one another and benefit from shared experiences and knowledge, thereby enhancing students' self-competence in social interactions and collaborative efforts to achieve learning goals. Furthermore, through such collaboration, students can expand their social networks and improve their ability to adapt to diverse learning environments. The self-competence exerts a significant influence on student learning outcomes, particularly in terms of self-understanding and self-confidence. The research conducted by Amerstorfer and Freiin von Münster-Kistner (2021) demonstrates that self-understanding entails students' ability to identify their strengths, weaknesses, and their interest and motivation to learn. A solid grasp of one's self enables students to pinpoint areas that require improvement and develop effective learning strategies that align with their individual characteristics. Consequently, this enhances the quality of learning and overall student academic performance. In accordance with Akbari's (2020) findings, self-confidence also plays a pivotal role in achieving optimal learning outcomes. Students with a heightened sense of self-assurance are more inclined to confront learning challenges with confidence and overcome obstacles that arise during the learning process. Additionally, strong self-confidence fosters motivation and perseverance in the face of learning difficulties, ultimately cultivating a positive and conducive learning environment.

While advancements in artificial intelligence (AI) technology have made notable contributions across various domains, there is insufficient empirical evidence to substantiate its efficacy in improving students' self-competence. Wei et al.'s (2022) research on self-competence, encompassing students' self-understanding and confidence, indicates that individual internal factors carry more influence than AI technology. The capacity to recognize one's strengths and weaknesses and foster confidence cannot be entirely supplanted by AI technology. The learning process, incorporating social interaction, self-reflection, and firsthand experience, remains paramount in developing students' self-competence. Consequently, an instructional approach that prioritizes students' psychological and emotional well-being remains pivotal in bolstering self-competence and holistic learning outcomes.

Nevertheless, mobile learning, or learning facilitated through mobile devices, has exhibited a significant impact on student learning outcomes by augmenting self-competence. This aligns with Kadel et al.'s (2021) research findings, which expound upon how the utilization of mobile learning technology empowers students to learn anytime and anywhere, thereby fostering motivation and self-directedness in learning. Mobile learning grants students’ independent access to a myriad of learning resources, subsequently enhancing their self-competence and comprehension of subject matter. Agustina et al.'s (2022) study unveiled that mobile learning also fosters the development of critical and analytical thinking skills required for problem-solving, a key aspect of self-competence. Through active and interactive engagement with mobile learning, students can more efficiently enhance their mastery of subject matter.

CONCLUSION

Research in the field of enhancing self-competence as a means to mitigate the impact of artificial intelligence (AI) and mobile learning on educational outcomes provides valuable insights for the realm of digital education. This study emphasizes the significance of cultivating self-regulation, self-efficacy, and motivation skills within the context of online learning. A comprehensive comprehension of how self-competence influences educational outcomes empowers educators to design learning strategies that are more efficacious, with a focus on both cognitive and emotional development. The integration of AI and mobile learning technologies presents opportunities to create adaptive, personalized, and responsive learning environments. These technologies have the potential to effectively address individualized learning needs, thereby fostering better engagement and comprehension. Consequently, this research facilitates the emergence of innovative learning methodologies that augment the overall quality of education and educational outcomes.

RECOMMENDATION

Based on the findings obtained from the aforementioned research, there are several recommendations and suggestions that can be put forward. Firstly, educational institutions should take a more proactive role in the development and implementation of artificial intelligence (AI) technology in the realm of learning. This can be achieved through the integration of interactive AI systems into the learning process, which can provide direct feedback to students and enhance their active participation. Moreover, there is potential to enhance the utilization of mobile learning to offer students more flexible access to education. Educational institutions can create mobile learning platforms that are highly interactive and user-friendly, thus facilitating independent learning among students.

The emphasis on fostering students' self-competence must also be strengthened within educational curricula. Learning experiences ought to be designed in a manner that encourages self-reflection, social interaction, and hands-on engagement, as this can facilitate students in gaining a better understanding of themselves and bolster their self-confidence. It is crucial to recognize that, while AI technology has beneficial effects on learning, excessive reliance on AI also entails risks. Therefore, individuals need to continuously develop their self-competence autonomously, without excessively depending on AI technology, with the aim of ensuring their independence and decision-making skills. Finally, further research is warranted to gain a deeper comprehension of the impact of artificial intelligence technology and mobile learning on students' learning outcomes across diverse educational settings. Future studies could also explore effective and sustainable ways to integrate such technology into educational curricula. By taking these measures, it is anticipated that education will become more adaptable, inclusive, and efficacious in preparing students to tackle future challenges.

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The authors have sufficiently contributed to the study. All authors have read and agreed to the published version of the manuscript.

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Conflict of interests
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