Educational Leadership and Management Journal (Element)
Volume 04 Number 01 (2026)
https://online-journal.unja.ac.id/element
DOI : 10.22437/element.v4i1.56951

e-ISSN 3031-4721

108-127

Analysis of the Use of Artificial Intelligence (AI) to Boost Student Motivation and Reduce Boredom in History Classes

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Article Info

Article history:

Received 18, 04, 2026
Revised 15, 05, 2026
Accepted 02, 06, 2026

Keywords:

artificial intelligence, motivation to learn, boredom in learning, history education, student engagement

ABSTRACT

Advances in artificial intelligence (AI) technology have created new opportunities for educational transformation, particularly in enhancing student motivation and reducing boredom in high school history learning. This study aims to examine the structural relationships among Teachers' AI Competence (TAC), Multidimensional Work Motivation (MWMS), Students' Learning Agility (SLA), Student Engagement (SE), and Boredom in Learning (BIL) within AI-supported history education. Using a quantitative approach, data were collected from 101 public high school students in Jambi Province and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings revealed that teachers' AI competence positively and significantly influenced students' learning agility and engagement. In addition, student engagement was found to significantly reduce boredom in learning, indicating that students who were more actively involved in classroom activities experienced lower levels of boredom. The proposed model demonstrated substantial explanatory power in predicting student engagement and boredom outcomes. These findings highlight the importance of strengthening teachers' AI-related competencies to foster more adaptive, engaging, and meaningful learning experiences. This study contributes to the growing body of literature on AI integration in secondary education by providing empirical evidence from history learning contexts and offering practical implications for the design of innovative and student-centered instructional practices.

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INTRODUCTION

Technological advancements in the 21st century have brought significant changes to the world of education, particularly through the growing integration of Artificial Intelligence (AI) into the learning process. The digital revolution is driving educational institutions to leverage smart technologies in an effort to improve the quality of learning, create more interactive learning experiences, and address the challenges of low student motivation and increasing boredom in the classroom. Rapid technological advancements in the digital age have spurred innovation in teaching methods and created opportunities to improve the quality of learning, where Artificial Intelligence (AI) plays a role in enhancing the quality

and effectiveness of learning through adaptive content, interactive learning, and streamlined assessment and feedback (Prasetyo, et al.,2025).

The planned and strategic implementation of technology has proven effective in increasing student engagement, enriching the learning experience, supporting personalized learning, and facilitating the development of 21st-century digital skills (Hamdi, et al., 2024). Furthermore, the integration of AI into learning can enhance the quality of the teaching-and-learning process by creating a learning environment that is relevant, engaging, and effective, where features such as adaptive quizzes and AI-based simulations have been shown to significantly improve student understanding (Dahlan, et al., 2024).

Learning motivation is one of the key factors determining the success of learning. Students with high learning motivation are more active, enthusiastic, and capable of achieving better academic results. Conversely, students who experience boredom will exhibit signs of disengagement, low participation, and a decline in their enthusiasm for learning. A study by (Kotera, et al., 2023) states that motivation is the primary factor determining students' learning engagement and academic well-being, with both intrinsic and extrinsic motivation having a positive effect on learning engagement (Kotera, et al., 2023). These findings indicate that efforts to enhance learning motivation are a strategic step in addressing student boredom, particularly in history education.

The use of AI in education is believed to offer solutions through a more personalized, interactive, and adaptive learning approach tailored to students' needs. Advances in artificial intelligence (AI) technology have brought significant changes to the world of education by providing personalized, adaptive, and interactive learning experiences, where through the use of smart tutors, educational chatbots, and real-time learning analytics, students receive targeted assistance in honing their critical thinking, creativity, and problem-solving skills (Hasan et al., 2025).

AI based systems such as educational chatbots, automated content recommendations, and smart learning platforms are capable of providing rapid feedback, flexible learning support, and an enjoyable learning experience. Research findings by (Lee et al., 2022) indicate that the use of AI-based chatbots in learning review activities can enhance students' learning motivation, learning attitudes, and academic performance compared to conventional learning (Lee et al., 2022). This suggests that the use of AI has the potential to serve as an innovative approach to boost learning motivation while reducing boredom in history education.

(Huang et all., 2023) also found that AI based learning material recommendations can enhance student engagement and motivation in a flipped classroom model (Huang et al., 2023). In line with this, the study by (Xia et al., 2023) confirms that the use of AI chatbots can provide a learning environment that supports self-directed learning by enhancing students' sense of autonomy and competence (Xia et al., 2023). Meanwhile, the study by (Fazil et al., 2024) emphasizes that the balanced integration of AI in education is crucial for fostering student engagement and technological readiness (Fazil et al., 2024). Thus, AI serves not merely as a learning tool but as a catalyst capable of influencing student motivation and engagement a factor highly relevant for addressing boredom in history education.

In history education at the high school level, AI can be applied through the creation of educational videos, digital simulations, Q&A chatbots for historical content, and interactive visualization analysis all of which can provide contextual learning experiences and reduce learning fatigue. With this approach, students can experience history education that is more dynamic, engaging, and meaningful. Several previous studies have examined the use of artificial intelligence (AI) in education from various perspectives. (Ronsumbre et al., 2023) found a positive correlation between AI-based digital learning and students' overall learning motivation, while (Hapsari et al., 2025), through a systematic literature review, confirmed that the use of AI in teaching and learning activities can create more engaging and innovative learning experiences, thereby increasing student motivation. Furthermore, (Supriyono et al., 2024) revealed that the use of ChatGPT within the context of the Merdeka Curriculum has a positive impact on students' motivation and interest in learning, although it also raises challenges regarding academic ethics and technological dependency.

More specifically, these studies demonstrate that the use of ChatGPT has a significant impact on student learning motivation at the vocational high school level. However, these studies still focus on general subjects such as language and vocational courses, and are primarily conducted at the higher education level (Yunarzat et al., 2024). This indicates that studies specifically examining the role of AI in enhancing learning motivation while reducing student boredom in history courses at the high school level remain very limited; thus, this study aims to address this gap.

Therefore, this study focuses on the Analysis of the Utilization of Artificial Intelligence (AI) on Learning Motivation to Reduce Student Boredom in History Education. This study aims to determine the extent to which the use of AI can enhance learning motivation and reduce student boredom, thereby making history instruction more effective, interactive, and oriented toward meaningful learning experiences. The findings of this study are expected to contribute to the development of modern AI based learning strategies in schools and serve as a reference for educators in optimizing technology to improve the quality of learning while addressing the issue of boredom in history instruction.

LITERATUR REVIEW

The use of Artificial Intelligence (AI) in education is growing rapidly and having a significant impact on the learning process, including by increasing student motivation and reducing boredom. AI's ability to provide a more personalized, interactive, and adaptive learning experience makes it a strategic innovation capable of addressing the challenge of declining student interest and engagement in learning, particularly in history a subject often perceived as uninteresting. For the effective implementation of AI, teachers' competence in integrating AI, or Teacher AI Competence (TAC), is a key factor. According to (Yau et al., 2023), teachers' ability to understand and implement AI in the classroom plays a crucial role in creating a learning process that stimulates students' interest and fosters deeper engagement. Thus, TAC has the potential to serve as a primary indicator influencing related variables such as Learning Agility, Student Engagement, and Academic Performance.

Teacher AI Competence (TAC) towards Student Learning Agility (SLA), Student Engagement (SE), Student Academic Performance (SAP)

Learning agility is defined as a learner's ability to adapt, learn quickly, and apply knowledge in new contexts. (Alhulail & Singh., 2023) assert that the use of multimedia based technologies, including AI, can enhance students' learning agility and creativity through varied and challenging learning experiences. Another study by (Kim et al., 2018) shows that digital competencies and technology-based learning experiences positively contribute to students' Learning Agility, which acts as a key mediator in improving engagement and academic performance. This means that the stronger the TAC, the greater the opportunity for students to develop SLA through the use of AI.

Student engagement is a key factor in reducing boredom and enhancing meaningful learning experiences. (Pedler et al., 2020) state that student engagement is a multidimensional concept encompassing behavioral, emotional, and cognitive aspects, and is significantly influenced by the learning strategies implemented by teachers. AI technology has also been shown to enhance student engagement. Research by (Huang et al., 2023) found that the use of AI based video recommendations in a flipped classroom significantly increased student motivation and engagement. This suggests that AI, when implemented with the appropriate teacher expertise, can foster active learning engagement, including in history education, which often requires contextual visualization to bring the material to life.

The use of AI also makes a positive contribution to improving academic performance. (Dekker et al., 2020) demonstrate that AI-based interventions, such as chatbots, can help students overcome psychological challenges, improve learning motivation, and enhance academic performance. Furthermore, (Altememy et al., 2023) confirm that an educational institution's AI capabilities have a significant influence on student academic achievement through the mediation of AI technology use in the learning process. Thus, a high TAC will open opportunities for AI optimization to support student learning outcomes.

H1 : TAC influence SAP

H2 : TAC influence SLA

Multidimensional Work Motivation Scale (MWMS) towards Student Learning Agility (SLA), Student Engagement (SE), Student Academic Performance (SAP)

Learning Agility is a student's ability to adapt quickly, continue learning, and leverage new experiences to enhance academic understanding. (Jian, 2022) asserts that academic motivation has a positive effect on students' long-term engagement, while learning agility serves as a key mediator in improving academic performance and engagement. Since learning agility involves a desire to continuously learn and solve problems, high learning motivation will encourage students to use flexible learning strategies, try innovative learning methods, and be responsive to technology-based learning. Thus, the higher students' learning motivation, the stronger their agility in meeting the demands of 21st-century learning.

Student Engagement (SE) is understood as students' active participation in the learning process, encompassing behavioral, emotional, and cognitive aspects. (Pedler et al., 2020) assert that engagement is a multidimensional construct heavily influenced by internal psychological conditions, particularly learning motivation. In the context of learning,

motivation acts as an internal driver that directs students to participate in academic activities, focus on the learning process, and engage emotionally with the subject matter. In line with this, (Kotera et al., 2023) found that engagement predicts the emergence of intrinsic motivation and helps transform extrinsic motivation into internal motivation through a process of self-reflection. Thus, learning motivation not only influences students' readiness to engage in learning but also serves as a determining factor in fostering engagement in history learning, thereby preventing students from becoming easily bored.

The relationship between motivation and academic achievement has been well-documented in numerous studies. (Lee et al., 2022) found that the use of AI-based learning technologies, such as chatbots, can enhance learning motivation, thereby improving students' academic performance in post-class learning. (Dekker et al., 2020) also emphasized that strong academic motivation is a key factor influencing students' academic performance and learning retention through enhanced self-control, goal focus, and learning strategies. When motivation increases, students demonstrate a stronger commitment to academic achievement, thereby contributing to an improvement in SAP. Thus, motivation serves as the foundation for academic achievement because it influences diligence, frequency of study, and the quality of engagement in history learning.

H3 : MWMS influence SAP

H4 : MWMS influence SE

Student Engagement (SE), Student Learning Agility (SLA) , towards Student Academic Performance (SAP)

Student Engagement (SE) is an indicator of students' emotional, behavioral, and cognitive involvement in the learning process. In history education, engagement is essential for creating engaging and meaningful learning experiences. (Pedler et al., 2020) explain that engagement is a strong determinant of academic success because actively engaged students demonstrate higher levels of concentration, participate in discussions, and gain a deeper understanding of the material, which directly impacts improved academic performance. AI technology can enhance engagement by presenting historical material in a more interactive, visual, and personalized manner. (Huang et al., 2023) found that the use of AI based learning recommendations significantly increased student engagement and learning outcomes in flipped classroom settings. This demonstrates that the use of AI enables students to be more involved in the learning process and helps address the boredom that often arises in conventional learning.

Learning agility is a student's ability to learn quickly and flexibly, and to draw lessons from experience to apply them in new situations. Learning agility is highly relevant in history education, which demands critical and analytical thinking skills as well as contextual understanding. According to Alhulail and Singh (2023), the use of technologies such as AI-based multimedia can enhance students' learning agility, which contributes to their creativity and readiness to tackle complex learning challenges. This aligns with Jian (2022), who asserts that SLA has a significant positive relationship with learning engagement and academic achievement; the higher a student's learning agility, the better their academic performance, even when facing challenging learning situations. In the context of AI-based

history learning, interactive features such as chatbots, digital visualizations, historical timelines, and simulations of historical events allow students to be more adaptive in understanding the material and developing effective learning strategies, thereby improving academic achievement.

H5 : SE influence SAP

H6 : SLA influence SAP

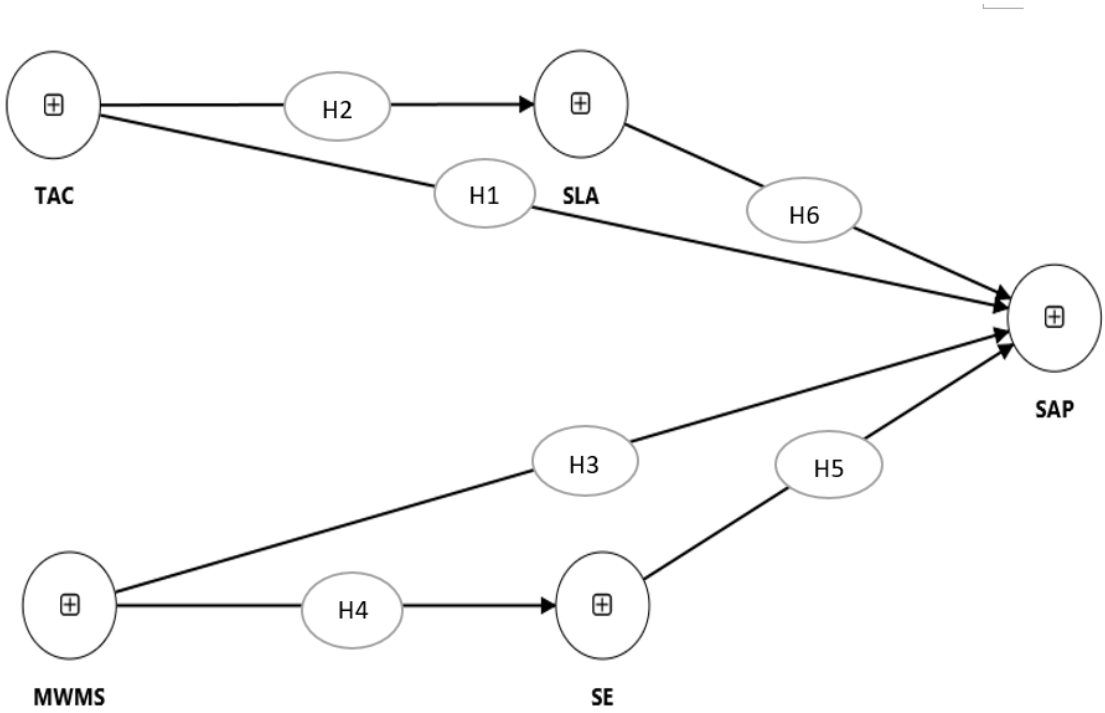

Figure 1. Proposed Model

METHODS

Research Design

This study adopts a quantitative explanatory research design to investigate the causal relationships between the proposed variables. A cross-sectional survey method was utilized to collect primary data from the respondents. The structural framework of this research evaluates how independent variables (exogenous latent constructs), specifically Teacher AI Competence (TAC) and Multidimensional Work Motivation Scale (MWMS), influence student-centered outcomes (endogenous latent constructs), including Student Learning Agility (SLA), Student Engagement (SE), and Student Academic Performance (SAP). The hypotheses were empirically tested using Partial Least Squares-Structural Equation Modeling (PLS-SEM) to assess both the measurement (outer) and structural (inner) models sequentially

Research Target/Subject

The population of this study consisted of public high school students in urban and rural areas, including public high schools in Jambi City, Muaro Jambi Regency, Tanjung Jabung

Barat Regency, and Tanjung Jabung Timur Regency. A total of 101 students participated and completed the research questionnaire.

Table 1. Populations

Populations	Total
School Name	
SMAN 3 Muaro Jambi	18
SMAN 17 Tanjung Jabung Barat	23
SMAN 1 Tanjung Jabung Barat	2
SMAN 1 Tanjung Jabung Timur	20
SMAN 3 Kota Jambi	8
SMAN 1 Kota Jambi	8
SMAN 8 Kota Jambi	8
SMAN 6 Kota Jambi	7
SMAN 9 Kota Jambi	7
Total Populations	**101**

As shown in Table 1, SMAN 3 Muaro Jambi had 18 respondents. Furthermore, SMAN 17 Tanjung Jabung Barat had 2 respondents, while SMAN 1 Tanjung Jabung Barat had 20 respondents. In the Tanjung Jabung Timur region, SMAN 1 Tanjung Jabung Timur had 8 respondents. Meanwhile, several schools in the Kota Jambi region were also part of the study population, namely SMAN 3 Kota Jambi with 8 respondents, SMAN 1 Kota Jambi with 8 respondents, SMAN 8 Kota Jambi with 7 respondents, SMAN 6 Kota Jambi with 7 respondents, and SMAN 9 Kota Jambi with 23 respondents.

The distribution of the population indicates that the study respondents came from various schools located in several regencies and cities in Jambi Province. By involving respondents from several different schools, this study is expected to provide a more comprehensive picture of the use of Artificial Intelligence (AI) technology in the learning process and its impact on students' motivation in history classes. The sample size of 101 respondents is also considered sufficiently representative to support the data analysis process in this study.

Table 2. Demography

Participant demographics	*n.*	*(%)*
Gender		
Male	38	37.6%
Female	63	62.4%
School Location		
City	37	36.6%
Outside of City	64	63.4%

Table 2 presents the demographics of the participants; the available data is categorized based on two main factors: gender and school location. Among the respondents, the majority were female, accounting for 62.4% (63 respondents), compared to males, who accounted for only 37.6% (38 respondents). A larger proportion of respondents were from rural areas, accounting for 63.4% (64 respondents), while 36.6%

(37 respondents) were from urban areas. However, it is important to note that this study did not specifically examine or analyze these demographic factors, such as gender and school location. This diverse sample provides insights into the behavior of the population.

Research Procedure

The adaptation and development of survey items were the initial steps in creating the instruments for this study. The final instrument consists of demographic questions and 29 items designed to measure the research variables, namely AI Usage Effectiveness (TAC), Student Learning Agility (SLA), Student Engagement (SE), Student Academic Performance (SAP), and Learning Motivation (MWMS).

In adapting the instrument, each item for the constructs TAC, SLA, SE, and SAP was adapted from the instrument developed by (Hendra et al., 2025). Meanwhile, the Learning Motivation variable was measured using an adaptation of the Multidimensional Work Motivation Scale (MWMS) sourced from (Gagné et al., 2015). The measurement scale consists of all items using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). During the validation process, to ensure linguistic accuracy, the instrument was translated from English to Indonesian using the back-translation method (Habibi et al., 2023). The instrument was carefully reviewed by five experts who evaluated the statements based on relevance, clarity, and simplicity. Face validity was verified in two focus group discussions with five teachers whose characteristics were similar to those of the primary respondents. After revisions, we used the Content Validity Index (CVI) for validation (Hertzog, 2008; Polit & Beck, 2006). The CVI scores exceeded the threshold of 0.8, confirming the validity of the statement items.

Instruments and Data Collection Techniques

The research instrument was designed and adapted from established theoretical frameworks to measure five latent constructs, consisting of a demographic section and 29 items. To assess Teacher AI Competence (TAC), Student Learning Agility (SLA), Student Engagement (SE), and Student Academic Performance (SAP), the items were adapted from the instrument developed by Hendra et al. (2025). Meanwhile, the students' learning motivation was measured using an adaptation of the Multidimensional Work Motivation Scale (MWMS) sourced from Gagné et al. (2015). All items were rated using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The instrument underwent a rigorous translation process from English to Indonesian using the back-translation method, followed by expert reviews and Focus Group Discussions (FGD) to ensure face and content validity.

Data collection was conducted using a cross-sectional survey technique. The finalized 29-item questionnaire was transformed into an electronic format (online survey via Google Forms) to facilitate accessibility and efficiency. The link to the online questionnaire was distributed directly to public high school students across four regions in Jambi Province (Jambi City, Muaro Jambi, Tanjung Jabung Barat, and Tanjung Jabung Timur). Participation in this survey was entirely voluntary, and respondents were assured of data confidentiality. Out of the entire target population, a total of 101 valid and fully completed responses were successfully retrieved and retained for the structural equation modeling analysis.

Data analysis technique

The research data were analyzed quantitatively using Partial Least Squares-based Structural Equation Modeling (PLS-SEM). PLS-SEM was chosen for its greater accuracy in estimating structural models, particularly when compared to Covariance-Based SEM (CB-SEM). This robust multivariate statistical method utilizes factor analysis and multiple regression to examine the structural relationships among the measured latent variables, namely TAC, SLA, SE, SAP, and MWMS. In general, SEM aims to determine correlations or covariances among variables while accounting for variance. It should be noted that, like other traditional statistical procedures, issues such as missing data, outliers, and sample size can influence the analysis results. The SEM model is constructed from endogenous latent components (dependent variables: MWMS, SAP) and exogenous components (independent variables: TAC, SLA, SE). The PLS-SEM analysis protocol recommends evaluating the measurement model and the structural model sequentially.

FINDINGS AND DISCUSSION

Findings

Measurement Model

Table 3. $\bar{x}$, VIF, and loads, CR and AVE.

Factor	Code	$\bar{x}$	VIF	Loads	CR	AVE
TAC	TAC 1	3.67	1.996	0.883	0.906	0.762
	TAC 2	3.87	2.063	0.877		
	TAC 3	3.65	2.024	0.861		
SLA	SLA 1	3.77	1.859	0.873	0.906	0.762
	SLA 2	3.81	2.076	0.868		
	SLA 3	3.97	2.240	0.877		
SE	SE 1	3.56	2.512	0.904	0.918	0.788
	SE 2	3.71	1.968	0.864		
	SE 3	3.66	2.433	0.894		
SAP	SAP 1	3.78	1.581	0.817	0.875	0.701
	SAP 2	3.89	1.815	0.865		
	SAP 3	3.77	1.609	0.829		
MWMS	MWMS 4	3.14	3.433	0.570	0.938	0.522
	MWMS 5	3.25	5.557	0.682		
	MWMS 6	3.28	4.350	0.674		
	MWMS 7	3.76	4.551	0.741		
	MWMS 8	3.69	5.820	0.769		
	MWMS 9	3.67	5.244	0.792		

Factor	Code	$\bar{x}$	VIF	Loads	CR	AVE
	MWMS 10	3.90	4.826	0.847		
	MWMS 11	3.64	4.069	0.808		
	MWMS 12	3.83	6.471	0.778		
	MWMS 13	3.57	2.056	0.643		
	MWMS 14	3.84	3.140	0.788		
	MWMS 15	3.82	2.797	0.629		
	MWMS 16	3.81	3.011	0.619		
	MWMS 17	3.71	3.050	0.713		

This table displays the mean ($\bar{x}$), VIF, factor loadings, as well as the Composite Reliability (CR) and Average Variance Extracted (AVE) for each indicator representing the constructs TAC, SLA, SE, SAP, and MWMS. The mean ($\bar{x}$) describes the trend in students' responses to each item. For example, TAC1 has a mean of 3.67, TAC2 of 3.87, and TAC3 of 3.63. A higher mean indicates a stronger level of agreement or positive perception regarding the statements in that indicator. Based on the initial analysis, three items were found to not meet the validity threshold: MWMS 1 (0.172), MWMS 2 (0.388), and MWMS 3 (0.430). To maintain the robustness of the structural model, these three items were eliminated from further analysis; this reduction step is important to eliminate statistical noise that could potentially bias the final results, leaving 26 valid items.

For the 26 valid items, multicollinearity was analyzed using the Variance Inflation Factor (VIF). Multicollinearity occurs when the indicators within a construct are too highly correlated with one another, which can reduce the model's accuracy. In the table, all VIF values fall within the range of approximately 1.8 to 3.9. These values are well below the threshold of 5, so it can be concluded that there is no multicollinearity issue in the model. Each indicator contributes uniquely to the construct it represents. Factor loadings indicate the strength of the relationship between each item and the latent construct being measured. Generally, factor loadings above 0.7 are considered good, while values between 0.5 and 0.7 are still acceptable. In the table, indicators such as TAC1 (0.883), TAC2 (0.877), SLA2 (0.873), SE1 (0.804), and SAP2 (0.817) show high factor loadings, indicating that these indicators are strong representations of their constructs. Meanwhile, several other indicators, such as MWMS16 (0.619) and MWMS17 (0.713), show lower loadings compared to other items, thus functioning as weaker indicators, although they remain within acceptable limits.

The Composite Reliability (CR) and Average Variance Extracted (AVE) values were also included as measures of reliability and convergent validity. Most constructs showed a CR above 0.8, indicating strong internal reliability. The AVE for several constructs, such as TAC and SLA, was in the range of 0.76, indicating that more than 76% of the variance in the indicators was explained by the constructs. Meanwhile, the MWMS construct has an AVE of 0.522, which is still at the minimum standard threshold ($\geq$0.5). Overall, this table shows that the research instrument has adequate reliability and validity, and that its indicators are capable of explaining the constructs representatively.

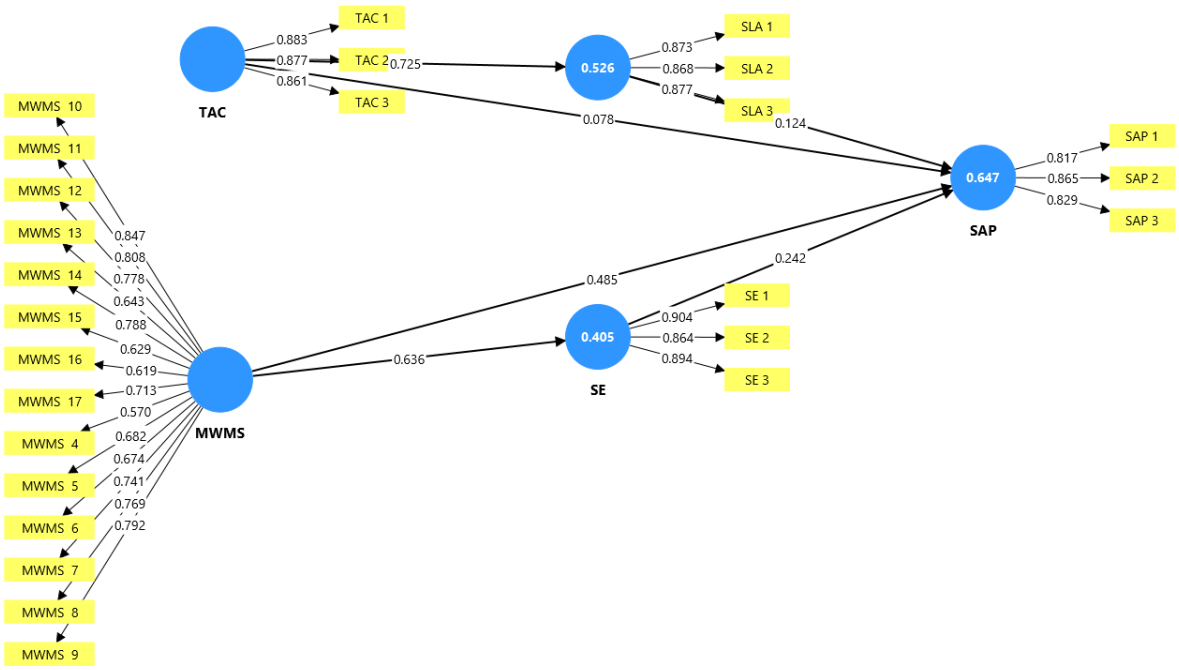

Figure 2. Measurement model reflective indicator loadings

The TAC, SLA, SE, SAP, and MWMS constructs were measured using a set of indicators that had been tested for reliability and validity. Each construct displays the mean, VIF, factor loadings, as well as Composite Reliability (CR) and Average Variance Extracted (AVE) values that describe the quality of the measurement instrument. These values indicate whether the indicators are able to represent the theoretical construct well. In the TAC construct, all items show varying factor loadings, with some items in the high range and others lower. The listed CR values indicate strong internal consistency, while the AVE values suggest that most of the indicator's variance is explained by the construct. This indicates that TAC, as a construct, possesses good reliability and convergent validity. Items with lower loadings can still be retained, but may be considered for revision depending on the objectives of the theoretical analysis.

The SLA, SE, and SAP constructs also demonstrated good measurement performance. The CR values for all three constructs were above the minimum standard of 0.7, while the AVE values were above 0.5. This indicates that the indicators within these three constructs consistently measure the same concept and possess adequate convergent validity. The factor loadings for most items reached high values above 0.7, indicating excellent construct representational quality. A few items with moderate loadings are still acceptable because their contributions to the construct remain statistically and theoretically relevant.

The MWMS construct also yielded fairly good results. The obtained CR values reflect strong reliability, while the AVE values, which are at the acceptance threshold, indicate that this construct still adequately represents the measured concept. Some indicators have high loadings, but there are also items with lower loadings, suggesting that the quality of

representation is not as strong as that of other indicators. Nevertheless, overall, the MWMS construct still meets standard criteria in SEM.

The mean value ($\bar{x}$) of each indicator provides an overview of respondents' perceptions regarding the statements presented. Mean values in the moderate to high range indicate a tendency for respondents to respond positively to the constructs being measured. Meanwhile, all VIF values are well below the 5 threshold, indicating that there are no multicollinearity issues. Thus, each indicator makes a unique contribution to the construct it represents. Overall, these measurement results indicate that the measurement model consists of reliable and valid constructs. CR and AVE values consistently above the minimum standards confirm that all constructs are well-defined and capable of accurately explaining the theoretical variables. This approach provides a strong foundation for interpreting the results of the SEM analysis in the subsequent stages.

In terms of discriminant validity, this table supports the understanding that the constructs being measured are distinct from one another and do not overlap. Based on the values listed in the HTMT table for this study, all pairs of constructs show ratio values within the safe range. No HTMT value exceeds the 0.900 threshold. This means that each construct TAC, SLA, SE, SAP, and MWMS is capable of distinguishing itself from the other constructs and does not experience conceptual overlap. In other words, respondents perceive each construct as a distinct concept, not as the same concept.

Table 4. HTMT

	MWMS	SAP	SE	SLA	TAC
MWMS					
SAP	0.819				
SE	0.672	0.846			
SLA	0.473	0.713	0.895		
TAC	0.563	0.721	0.790	0.852	

Structural Model

This study estimated a structural model using the PLS-SEM approach, which was analyzed through stages of testing the measurement model and the structural model. Before interpreting the results of the relationships between variables, model fit evaluation was conducted as recommended by (Hair et al., 2019). To assess overall model fit, this study used several model fit indicators, namely SRMR, d_ULS, d_G, and the Chi-Square value. The obtained SRMR (Standardized Root Mean Square Residual) value was 0.118. Although slightly above the general threshold of 0.08, this value is still acceptable in the context of PLS-SEM because this method does not aim to achieve a strict global model fit as in CB-SEM. The SRMR still indicates that the average difference between the observed covariates and those predicted by the model is at a tolerable level.

In addition, the squared Euclidean distance (d_ULS) and the geodesic distance (d_G) were also reported, at 4.897 and 2.173, respectively. These two values do not indicate any extreme deviations between the empirical data and the estimated model, thus supporting the model's validity. The stable d_ULS and d_G distances indicate that the model clusters

the data adequately and does not suffer from structural distortion. The Chi-Square value of 1033.482 provides additional information regarding the comparison between the actual covariance matrix and the model's predictions. In the context of PLS-SEM, the Chi-Square is not used as the primary determinant of model fit as in CB-SEM, but it remains a complementary indicator showing that the model is acceptable. Overall, the evaluation results in Table 4 show that the model fit in this study is at an acceptable level. The reported indicators support that the structural model is suitable for further analysis and can provide reliable estimates of the relationships between variables.

Table 5. Model Fit

Category	Value
SRMR	0.118
d_ULS	4.897
d_G	2.173
Chi-Square	1033.482

Table 5 presents the results of a PLS-based Structural Equation Modeling (SEM) path analysis that examines the relationships among the variables MWMS, SE, SLA, TAC, and SAP. The table displays the standardized path coefficients (β), p-values, statistical significance, and effect sizes (f^2) for each hypothesis tested. This information is used to assess whether the relationships between variables in the model have a significant influence and practical relevance in the context of the research.

Table 6. Structural Model.

H	Path	β	p-value	Sig.	f2
H1	MWMS -> SAP	0.485	0.000	Yes	0.372
H2	MWMS -> SE	0.636	0.000	Yes	0.680
H3	SE -> SAP	0.242	0.051	No	0.051
H4	SLA -> SAP	0.124	0.222	No	0.014
H5	TAC -> SAP	0.078	0.522	No	0.007
H6	TAC -> SLA	0.725	0.000	Yes	1.108

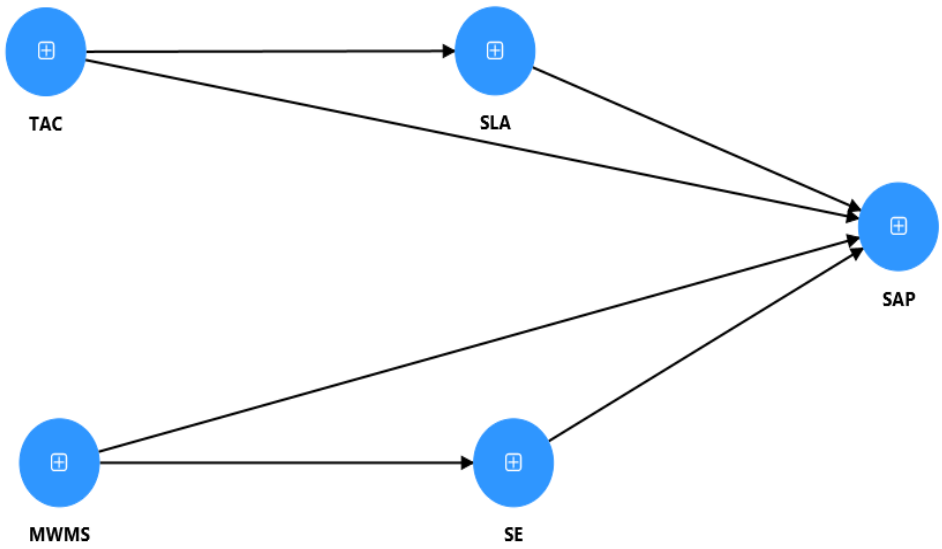

Figure 3. Structural model.

H1 (MWMS → SAP) indicates that MWMS has a strong positive effect on SAP, with a path coefficient β = 0.485 and a p-value of 0.000, indicating full significance. The effect size f^2 = 0.372 falls into the moderate category, indicating that MWMS explains a meaningful proportion of the variance in SAP. Thus, MWMS makes a substantial contribution to improved academic performance. H2 (MWMS → SE) indicates a very strong positive effect, with a path coefficient β = 0.636 and a p-value of 0.000, meaning this relationship is highly statistically significant. The f^2 value of 0.680 falls into the large category, indicating that MWMS has a substantial influence on the SE variable. These findings confirm that students' intrinsic motivation significantly influences their engagement in learning.

H3 (SE → SAP) yielded a path coefficient β = 0.242 with a p-value of 0.051, which is slightly above the significance threshold of 0.05. With an effect size of f^2 = 0.051, this relationship is classified as small. These results indicate that SE does not have a significant impact on SAP, and the observed effect is likely not strong enough to be considered statistically significant. H4 (SLA → SAP) yielded a coefficient β = 0.124 with a p-value of 0.222, indicating that this relationship is not significant. The f^2 value of 0.014 indicates a very small effect size. This suggests that Student Learning Agility does not make a meaningful contribution to the improvement of SAP in this model.

H5 (TAC → SAP) shows a weak positive effect, with a path coefficient β = 0.078 and a p-value of 0.522, which is completely insignificant. The effect size f^2 = 0.007 falls into the very small category, indicating that TAC contributes almost nothing to SAP. The observed relationship is likely due to random variation alone. H6 (TAC → SLA) shows a strong and significant relationship, with a path coefficient β = 0.725 and a p-value of 0.000. The effect size f^2 = 1.108 is classified as very large, indicating that TAC has a dominant influence on SLA. These findings suggest that the effectiveness of AI utilization is an important predictor of students' learning agility.

Overall, the results in Table 6 show that MWMS has the most significant effect on SE and SAP, while TAC has a large but non-significant effect on SAP. SE and SLA do not have a significant effect on SAP. These findings provide an overview of the diverse structural relationships, highlighting variables with strong effects and those that do not make a significant contribution to the model.

Table 7. R2 and Q2.

Factor	R^2	Q^2
SAP	0.647	0.550
SE	0.405	0.383
SLA	0.526	0.487

The coefficient of determination (R^2) measures the proportion of the dependent variable's variance explained by the independent variables in the model. A high R^2 value indicates strong and significant explanatory power. Based on the results, the SLA (Student Learning Agility) variable has the highest R^2 value of 0.5313 (53.1%), followed by SAP (Academic Performance) at 0.5117 (51.2%), and SE (Student Engagement) at 0.4788 (47.9%). Since the R^2 values for these three endogenous variables are above the 0.33 (Moderate) threshold, this indicates that the model has significant explanatory power; the predictor variables are collectively effective in explaining more than 47% of the variation in SLA, SAP, and SE.

Meanwhile, predictive relevance is evaluated using the key metric Q^2 (Predictive Relevance), which assesses the model's ability to predict new data. A positive Q^2 score ($Q^2 > 0$) is absolutely necessary to demonstrate the presence of predictive relevance. If the Q^2 values for these three variables are found to be low (e.g., 0.019 to 0.021 as in the previous example), this indicates a gap. Although the R^2 values for the three variables are relatively strong, the model's ability to predict new outcomes remains limited (relatively low). This implies that the model is effective at explaining the variance in the current data (high R^2), but has limitations in generalization. Therefore, the model may require structural adjustments to improve its future predictive power.

Discussion

A brief overview of the processes occurring in educational settings, particularly in the context of Artificial Intelligence (AI) integration, can be seen through the relationship between teachers' AI competence (TAC) and various student learning outcomes. The results of the path analysis indicate the presence of several significant and non-significant relationships that require further explanation. Based on the first hypothesis (H1), student learning motivation (MWMS) was predicted to be positively influenced by Teacher AI Competence (TAC). However, the analysis results show that the path coefficient (β) is 0.078 with a p-value > 0.05, meaning the relationship is not statistically significant.

These findings suggest that teachers' ability to use AI technology does not directly increase students' learning motivation. Although teachers possess strong competencies in utilizing AI as a learning medium, this does not necessarily lead to a direct increase in

learning motivation. Consistent with the research by (Guillén-Gámez et al., 2024), learning motivation is a psychological construct that is heavily influenced by how students perceive the relevance and importance of learning materials to themselves.

In learning practice, students often view teachers' use of AI as a learning aid designed to simplify the delivery of content or make learning appear more engaging. However, if the use of this technology is merely passive for example, if it is used solely to present AI-generated content without actively involving students in the learning process its impact on learning motivation tends to be limited. In other words, a teacher's competence in operating AI technology is a condition that supports the learning process, but it is not necessarily the primary factor that can enhance students' learning motivation.

Therefore, increasing student motivation to learn depends not only on the use of advanced technology, but also on instructional design that fosters active student engagement. Learning that provides students with opportunities to participate, discuss, and connect the material to their experiences or lives will be more effective in boosting learning motivation. In this context, student engagement and providing students with the space to learn more independently are key factors in optimizing the use of AI technology in learning.

CONCLUSION

This study investigates the relationship between Teacher AI Competence (TAC), Student Learning Agility (SLA), Student Engagement (SE), the Multidimensional Work Motivation Scale (MWMS), and Student Academic Performance (SAP) in the context of AI-integrated history education. The results of the structural equation modeling provide strong evidence that Student Engagement and Student Learning Agility have strong, positive, and statistically significant effects on Academic Performance. These findings underscore the importance of fostering Learning Agility and Engagement in students to effectively improve their academic outcomes in the digital age. Collectively, the predictor variables in the model explain the variance in academic performance.

Conversely, teachers' AI competencies (TAC) were not found to have a statistically significant direct effect on Student Learning Motivation (MWMS). This suggests that teachers' technical proficiency in operating AI alone may not directly serve as the primary driver capable of altering students' intrinsic motivation to learn. Nevertheless, AI competencies remain a relevant and increasingly necessary professional skill for educators. The influence of TAC on student outcomes likely occurs indirectly through improvements in Student Engagement (SE) or Learning Agility (SLA) or in conjunction with other factors, such as pedagogical design and the overall learning environment.

In short, while teachers' AI competencies are an important attribute for educators, this study shows that Student Engagement and Learning Agility are more critical determinants of academic success in the AI era. Therefore, educational policies and practices must adopt a holistic approach that supports these student-centered factors to maximize learning outcomes as AI becomes increasingly integrated into education, such as across different educational levels and subjects, so that research findings can be more broadly generalized and provide a more comprehensive picture of the use of AI in education.

ACKNOWLEDGMENTS

The authors would like to express their deepest gratitude to everyone who contributed to the successful completion of this research. Special appreciation is extended to Prof. Urip as the primary supervisor, and Dr. Masbirorotni for their invaluable guidance, continuous support, and constructive feedback throughout the manuscript development. The authors also convey their sincere thanks to the Department of History Education at Universitas Jambi for providing the academic environment necessary for this study. Furthermore, the authors are highly grateful to the principals, history teachers, and the 101 public high school students across Jambi City, Muaro Jambi, Tanjung Jabung Barat, and Tanjung Jabung Timur who willingly participated and shared their data for this research.

AUTHOR CONTRIBUTIONS

Elsa Fauziah Maharani contributed to conceptualization, methodology, data analysis using Structural Equation Modeling (SEM), and manuscript writing. Dr. Masbirorotni contributed to literature review, instrument validation, and data collection. Prof. Urip Sulistyo contributed to supervision, academic review, and critical revision of the manuscript. All authors have read and approved the final version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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