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Academic performance in AI Era: salient factors in higher education

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Abstract

This research integrates teacher AI competence (TAC), student learning agility (SLA), and student engagement (SE), as factors affecting student academic performance (SAP). We employed a survey methodology in which the instrument's validation was conducted through content and face validity, as well as a content validity index and measurement model in SmartPLS. A total of 380 lecturers from three universities participated as respondents in this survey study. Partial least squares structural equation modeling (PLS-SEM) procedures were employed for the primary data analysis of the study. The findings informed the validity and reliability of the model, highlighting the important roles of SLA and SA in relation to SAP. In addition, TAC was also correlated with SAP and SLA, while it has no relationship with SA.

KEYWORDS: AI Competence; Higher Education; Learning Agility; Engagement; Academic Performance.

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1. Introduction

In recent years, the integration of artificial intelligence (AI) in educational settings has garnered considerable attention for its potential to enhance teaching and learning processes, as well as teacher competence (Guillén-Gámez, Tomczyk, et al., 2024). The emergence of AI has not only transformed the way information is delivered but also redefined the roles of educators and students (Alenezi et al., 2023). As technology continues to evolve, the competence of teachers in utilizing AI tools has become crucial in influencing student outcomes (Dimitriadou & Lanitis, 2023). Teacher AI competence refers to the ability of educators to effectively implement AI-driven methodologies in their instructional practices (Kim, 2024). This competence is not just about familiarity with AI technologies, but also about the ability to leverage these tools to foster a conducive learning environment that meets the diverse needs of learners.

The integration of AI in education has the potential to personalize learning experiences, thereby improving student engagement and enhancing academic achievement (Almusaed et al., 2023; Kim, 2024). However, the effectiveness of AI in education is also dependent on student factors, such as students' learning

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agility, which refers to their ability to adapt and thrive in dynamic learning environments. Learning agility is a critical attribute in the digital age, where the pace of change demands that students be quick learners, able to apply knowledge in novel situations, and continually evolve their skill sets.

This study aims to investigate the intricate relationships between teacher AI competence (TAC), student learning agility (SLA), and student engagement (SE) to student academic performance (SAP) from the perspectives of three Indonesian university lecturers. The existing literature highlights the significant role that teacher competence plays in influencing student outcomes; however, there is a need to explore how specific competencies, such as those related to AI, impact student achievement in technologically advanced learning environments. Furthermore, while student engagement has long been recognized as a critical factor in academic success, understanding how AI-enhanced engagement interacts with students' learning agility to affect academic performance remains an area ripe for exploration.

By examining these interrelationships, this study aims to contribute to the growing body of knowledge on AI in education and offer insights into how educational stakeholders can optimize the use of AI to improve student learning outcomes. Ultimately, the findings of this research can inform policy and practice, guiding the development of teacher training programs and student support initiatives that align with the demands of the AI-driven educational landscape.

2. Literature review

In the development of AI, teacher proficiency or competence using the technology has emerged as an essential factor that significantly influences learning agility, engagement, and performance. Nazaretsky et al., (2022) emphasize the influence of AI competence on the development of students' learning agility, revealing a significant correlation between the two variables. Kitcharoen et al., (2024) present a compelling case for ensuring a smooth and effective transition towards integrating advanced technologies into the learning process, thereby promoting the efficient use of technology in education. On the other hand, educational models that prioritize student interaction have also attracted significant attention. (J. Kim, 2024) examined the potential of AI support in enhancing student engagement in a blended learning context, drawing on the theoretical framework of self-determination theory. This implies that, in addition to having AI proficiency, practical strategies and techniques in utilizing AI are also crucial in optimizing student engagement and achievement (J. Kim, 2024; Sun et al., 2024; Wang et al., 2023).

2.1 TAC towards SLA, SE and SP

AI expertise has become essential in modern education, influencing learning agility, student engagement, and performance. Teachers need AI skills to effectively apply these technologies in educational settings. Teacher AI competence includes ethical and responsible development, use, and assessment of AI in education (Delcker et al., 2025). Research indicates that teachers' technical, pedagogical, content, and ethical understanding of AI develops to varying extents. Consequently, to fully cultivate these skills, teachers require professional learning opportunities (Delcker et al., 2025). Previous research has explored teacher competence (Guillén-Gámez et al., 2024; Kim, 2024). Teachers who utilize AI to personalize learning and offer real-time feedback can enhance student engagement (Hanaysha et al., 2023; Long et al., 2025; Ali et al., 2025). AI can also automate administrative tasks, allowing teachers to focus on dynamic and engaging lessons (Gowthambalagi et al., 2025). Teacher support, including emotional and competency assistance, significantly boosts student engagement and academic success (Guo et al., 2025). Learner agility mediates the link between teacher technological skills and learning outcomes, according to Ng et al. (2023). In a technology-driven era, Jamal (2023) described instructor digital learning agility. Montilla et al. (2023) linked teacher technology competence to motivation and academic achievement, particularly in the context of education.

Along with instructor competence, student AI competence is becoming increasingly important in education. Recently validated measures of students' AI competence self-efficacy emphasize the importance of students' confidence in their AI technology skills (Chiu et al., 2025). AI in higher education has also been shown to enhance students' self-efficacy, creativity, and learning performance, demonstrating that both institutional support and individual competence are necessary to maximize the benefits of AI in education (Wang et al., 2023). Lee et al. (2024) found that technology competence parameters influence SLA, SE, and SP in student informal digital learning. Their findings support Falloon's (2020) shift from digital literacy to technical competence, which established a comprehensive framework to capture the diversity of digital education. Koh et al. (2023) found that technology competence has a strong impact on student performance. Qureshi et al. (2023) found that collaborative learning enhances student performance, demonstrating that successful engagement and learning experiences are interrelated. Wu et al. (2020) identified a complex relationship among motivation, academic performance, self-efficacy, and engagement, underscoring their significance in learning. High learning agility enables students to adapt to new learning environments and challenges, thereby enhancing their long-term engagement and academic success (Jian, 2022). AI-enabled adaptive learning paths and problem-solving opportunities foster student engagement and academic achievement (Long et al., 2025; Posekany, 2025). Student engagement, particularly cognitive engagement, predicts academic success, while emotional and behavioral engagement contribute less (Huang, 2025). AI-assisted language learning environments enhance student engagement and speaking skills by providing personalized and engaging learning experiences (Ali et al 2025).

Collectively, these studies highlight the complex interactions between teacher and student technology competence, emphasizing their importance in shaping learning agility, student engagement, and overall academic performance in education. In this study, we identified AI as a technology-based component that reflects the novelty of modern technology used by educational users. Three hypotheses were proposed based on the background information provided by the current work perceived by teachers who used AI in teaching.

H1: TAC influences SLA

H2: TAC influences SE

H3: TAC influences SAP

2.2 SLA, SE towards SP

Student learning agility – a fast-growing educational concept – is linked to student engagement and performance. The digital age encourages instructors and students to adapt quickly to new digital platforms and technologies (Greener & MacLean, 2013). In the era of exponential technology, Khambari et al. (2022) argue that adaptability is essential to digital pedagogy. SLA irectly affects SE and SP (Patwardhan et al., 2022). Oppici et al. (2022) found that exergaming technology affects children's foundational movement skill development, demonstrating the many uses of agility. Student involvement is crucial in online learning environments, according to Martínez-Zarzuelo et al. (2022), who note that students perceive different engagement tactics as affecting their learning experience (Korlat et al., 2021). Thornberg et al. (2022) found a substantial correlation between teacher-student relationship quality and student involvement, suggesting interpersonal aspects are essential. Several studies have demonstrated that participation has a direct and indirect impact on student performance. Maricuțoiu & Sulea (2019) use multilevel structural equation modeling to study student engagement, burnout, and performance. Paloș et al. (2019) found complex relationships between academic performance, student involvement, and burnout. T. K. F. Chiu (2021) tested and confirmed the association between student engagement and learning results. Tharapos et al. (2023) highlighted the importance of effective teaching and student participation during the COVID-19 pandemic, emphasizing the link between engagement and performance, particularly in critical times. As shown in various academic situations, SLA, SE, and SP are interconnected (Figure 1). Two hypotheses were proposed regarding SLA, SE, and SP in the context of AI technology use in teaching.

H4: LA influences SAP

H5: SE influences SAP

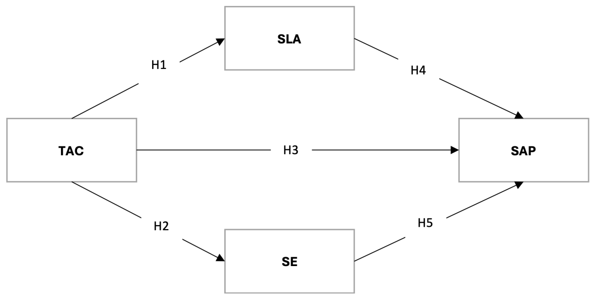

Figure 1 - Proposed model.

3. Methods

3.1 Instrumentation process

Adjusting and creating survey items was the initial step in developing the instrument for a survey investigation. Thus, we included some demographic questions and 28 statements for the primary data analysis. The instrument was designed to suit the study objectives. TAC was developed and adapted from a prior study (Cabero-Almenara et al., 2021). SLA and SE items were adapted with five statements, respectively (H. J. Kim et al., 2018). SAP or student academic performance factor was included to assess the achievement of the students who are taught in their class using AI technology (Mehrvarz et al., 2021). The survey instrument employed a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree) (Dawes, 2008; Drumm et al., 2022). We used back-translation to translate the instrument from English to Indonesian for linguistic correctness (Habibi et al., 2023). This project employed two translators to assess the accuracy of the questionnaire's translation.

The instrument was carefully tested with five experts who scored statements for relevance, clarity, and simplicity. In two group conversations, five teachers who resembled the main respondents rated the statement clarity to ensure face validity. Two teachers, one researcher, and two students verified the study. We used the content validity index to validate instruments (Hertzog, 2008; Polit & Beck, 2006). The results of the assessment of the content validity index exceeded the 0.8 (threshold), confirming the statement items' authenticity and emphasizing the value of expert opinions in judging relevance, clarity, and simplicity

3.2. Population and sample

The population of this study consisted of lecturers at three universities in one Indonesian province, approximately 2,210 lecturers. The inclusion criteria were active lecturers at the three universities during data collection, while those on leave, retired, or inactive were excluded. The sample was chosen for representativeness and accessibility. We utilized GPower, a tool commonly used in social and behavioral science research, to assist researchers in selecting the sample size (Erdfelder et al., 2009; Kang, 2021).(Erdfelder et al., 2009; Kang, 2021) The software calculated the sample size for the analysis of 380 samples. We increased sample diversity by stratified random sampling. This involved taking samples from each gender group of the target population. Systematic responses were coded in Excel. Table 1 provides the demographics of the participants. The data provided offers a demographic breakdown of the respondents, categorized by four key factors: gender, institution, education, and teaching experience. Among the respondents, a majority are women, comprising 68.42% (260 respondents), compared to 31.58% (120 respondents) men. The respondents are predominantly affiliated with University B, which constitutes 47% (178 respondents) of the total sample, followed by University A at 30% (114 respondents), and University C at 23% (88 respondents). In terms of educational background, most respondents (80.53%, 306) have pursued or completed a Master's degree, while the remaining 19.47% (76) are pursuing or have completed a Doctoral degree.

Table 1 - Demography.

Respondents	*Category*	*n.*	*(%)*
Gender	Male	120	35.87%
	Female	260	68.42%
Institution	University A	114	30%
	University B	178	47%
	University C	88	23%
Education	Master	304	80.53%
	Doctorate	76	19.47%
Teaching experience	< 5 years	202	53%
	5 or more years	178	47%

Regarding teaching experience, a slight majority of the respondents (53%, 202 respondents) have less than 5 years of teaching experience, while 47% (178 respondents) have five or more years of experience. Respondents were selected randomly within each stratum, ensuring that each group was proportionally represented in the sample, based on gender, institution, educational level, and teaching experience. This process was carried out to minimize bias and to ensure that the findings could be generalized to the entire population However, it is essential to note that this study did not specifically test or analyze the effects of these demographic factors – such as gender, educational background, and teaching experience – on the research outcomes This diverse sample provides a comprehensive view of the demographic distribution across gender, institutional affiliation, academic level, and teaching experience, which can be instrumental in analyzing trends, attitudes, and behaviors in the study population.

3.2 Data analysis

The data was quantitatively analyzed using SEM. PLS-SEM estimates structural models more accurately than CB-SEM (Sayginer, 2023). The strong multivariate statistical method uses factor analysis and multiple regression to study structural relationships between measurable and latent variables. SEM aims to determine variable correlations/covariances and correct for variance. Like traditional statistical procedures, missing data, outliers, and sample size might affect the results. SEM is widely used in economics, education, finance, and healthcare. Endogenous and exogenous latent components make up SEM. Independent factors are exogenous, while dependent variables are endogenous. The PLS-SEM protocol recommends measurement and structural assessment. Before presenting the steps, data preparation and descriptive statistics are shown. Variable associations were examined using path coefficients (β), t-value, p-value, coefficient of determination (R2), predictive relevance (Q2), and effect size (f2). SPSS also performed a t-test on geographical areas for instructional use, material access, motivational access, and skills access.

4. Findings

4.1 Measurement Model

We evaluated the reliability of the data through the measurement model (Habibi, Mailizar, et al., 2024; Habibi, Mukminin, et al., 2024; Sayginer, 2023). Table 2 and Figure 2 display important statistical indicators for the measurement model, such as Composite Reliability (CR), Average Variance Extracted (AVE), Means ($\bar{x}$), Variance Inflation Factor (VIF), and Loadings. These metrics are essential for assessing the reliability and validity of the measurement model, ensuring that items accurately represent the constructs and are consistent and distinct. CR measures the internal consistency of items that represent a latent construct. It is similar to Cronbach's Alpha but is more accurate when using SEM because it accounts for item loadings. Each factor has CR values in the Table 2. TAC, SLA, SE, and SAP have CR values of 0.922, 0.876, 0.864, and 0.850, respectively. These values all exceed the 0.7 threshold, suggesting good internal consistency. High CR values indicate that items within each construct measure the same concept, which is essential for valid representations of theoretical variables.

AVE compares a construct's variance to measurement error. AVE measures convergent validity, which determines if construct items are representative. AVE values for each construct are listed in the table. TAC, SLA, SE, and SAP had AVEs of 0.663, 0.669, 0.649, and 0.691, respectively. AVE values above 0.5 indicate high convergent validity because the construct explains more than half of the item variation. Each construct has an AVE value above the threshold, indicating that the items are good predictors of their respective constructs.

Table 2 - $\bar{x}$, VIF, and loads, CR and AVE.

Factor	Code	$\bar{x}$	VIF	Loads	CR	AVE
TAC	TAC1	4.155	1.602	0.886	0.922	0.663
	TAC2	3.697	2.070	0.597		
	TAC3	4.263	2.040	0.843		
	TAC4	4.118	2.190	0.780		
	TAC5	3.884	1.969	0.809		
	TAC6	4.026	2.118	0.754		
	TAC7	3.621	2.051	0.638		
	TAC8	3.532	2.472	0.550		
	TAC9	3.753	1.717	0.616		
	TAC10	3.861	1.487	0.678		
	TAC11	3.650	1.990	0.585		
	TAC12	3.771	3.214	0.704		
	TAC13	3.595	2.376	0.618		
	TAC14	3.774	3.513	0.696		
SLA	SLA1	3.771	2.350	0.799	0.876	0.669
	SLA2	3.595	2.186	0.830		
	SLA3	3.774	1.951	0.822		
	SLA4	4.146	2.053	0.864		
	SLA5	4.187	3.457	0.772		
SE	SE1	4.111	3.120	0.723	0.864	0.649
	SE2	4.145	2.315	0.808		
	SE3	3.974	3.379	0.848		
	SE4	4.097	3.748	0.843		
	SE5	3.658	3.480	0.801		
SAP	SAP1	3.850	3.266	0.785	0.850	0.691
	SAP2	3.908	3.404	0.847		
	SAP3	3.684	3.430	0.836		
	SAP4	3.979	3.831	0.855		

The table includes the mean values ($\bar{x}$) for each item. These are the sample-wide average replies for each item. TAC1 has a mean score of 4.155, TAC2 has a mean score of 3.697. These methods show how respondents rate items. Depending on the scale, higher mean scores imply agreement or positive perceptions, whereas lower values indicate the reverse. The mean values can also reveal the subjective nature of the concept being measured. If all TAC items have high mean scores, it may indicate a positive view of the construct.

Multicollinearity is detected via VIF. Multicollinearity arises when two or more variables are highly correlated, which increases the standard errors of regression model coefficients and reduces construct reliability. Each item has VIF values in the table. The VIFs of TAC2 and SLA1 are 2.070 and 2.350, respectively. Multicollinearity is typically not a problem when the VIF is below 5. All VIF values in this table are below this threshold, indicating that the elements do not exhibit multicollinearity and each contributes uniquely to the construct. The coefficients that represent the link between each item and its latent concept are called factor loadings. Items with higher loadings are strong indicators of a strong build. SEM loadings above 0.7 are considered good, but those above 0.5 may be acceptable depending on the situation. The table shows each item's loading, indicating its relevance to the construct. TAC1, SLA1, and SE1 have loadings of 0.886, 0.799, and 0.723, respectively. These results suggest that most items have strong loadings, indicating solid construct indicators. TAC2 (0.597) and TAC8 (0.550) exhibit lower loadings, suggesting they are weaker markers of

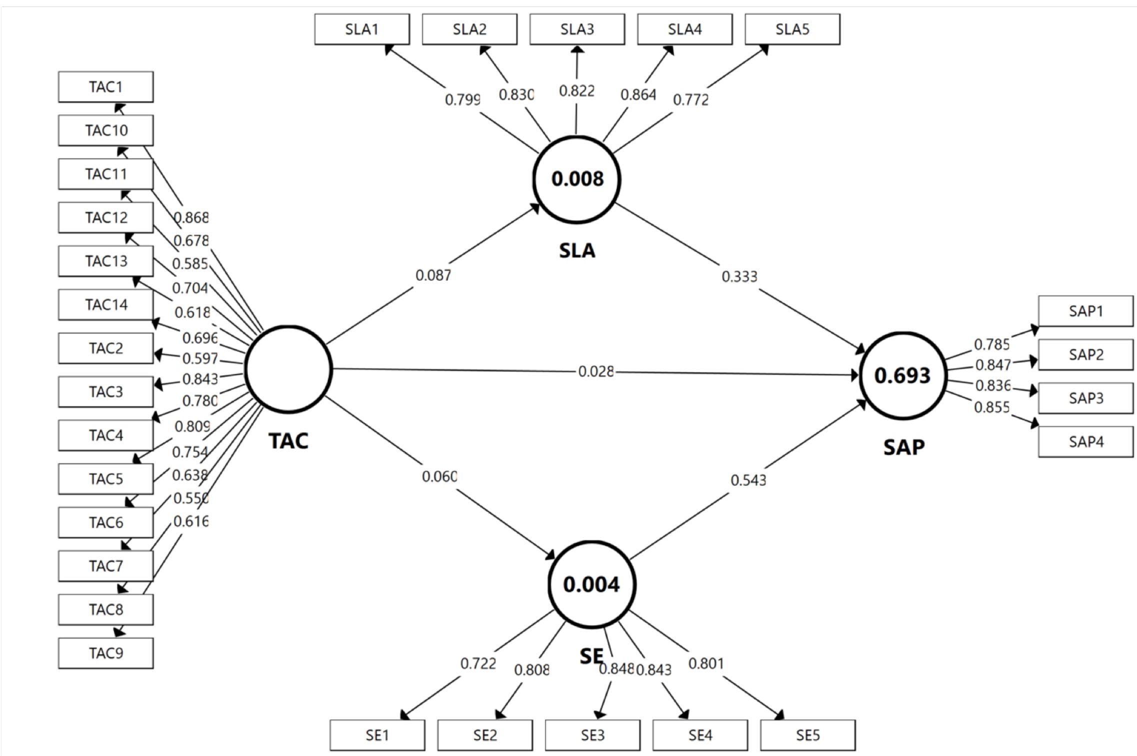

Figure 2 - Measurement model reflective indicator loadings.

the TAC construct. Depending on their theoretical value, these items may be kept or changed.

TAC, SLA, SE, and SAP are measured using statistically examined items for reliability and validity. TAC (TAC1–TAC14) has a CR of 0.922 and an AVE of 0.663, indicating good reliability and validity. Some elements have lesser loadings, suggesting they may not be as powerful a building indicator. SLA, SE, and SAP likewise have high reliability and validity, with CR values above 0.7 and AVE values above 0.5. Most items substantially reflect the constructs they assess, indicating well-defined constructs. The measurement properties of the constructions are shown. AVE values suggest that the constructs are valid representations of the theoretical variables, while high CR values imply that items within each construct consistently measure the same notion. Means give an overview of respondents' perceptions, whereas VIF values indicate low multicollinearity. Most items' factor loadings indicate their structures well, but others may need extra analysis. The results demonstrate that the measurement model comprises trustworthy and valid constructs, as supported by the data. This approach is essential for precisely measuring constructs and confidently interpreting SEM results.

Discriminant validity tests distinguish unrelated constructs (Sarstedt et al., 2019, 2020). We employed the heterotrait-monotrait ratio (HTMT) as the most robust assessment for discriminant validity. Discriminant validity is considered good when the value is below 0.900 (Afthanorhan et al., 2020, 2021; Roemer et al., 2021). This study found all HTMT values between 0.569 and 0.889 (Table 3). The measurement model exhibited no validity issues, indicating our study's survey method is reliable. Based on the results obtained, it can be concluded that the research instrument used has adequate discriminant validity. In this study, all HTMT values are less than 0.9, indicating good discriminant validity. Items of the survey are attached in Appendix 1.

Table 3 - HTMT.

	SAP	SE	SLA
SE	0.879		
SLA	0.838	0.898	
TAC	0.051	0.044	0.054

4.2 Structural model

This study estimated the structural model using bootstrapping PLS selection and 5000 samples. PLS-SEM recommends bootstrapping, which involves randomly selecting and replacing subsamples from the original dataset (Sarstedt et al., 2019). Hair et al. (2019) recommend reporting model fit indices before providing the structural model. PLS-SEM studies should evaluate model fit using SRMR (Standardized Root Mean Square Residual), with a maximum of 0.08. Geodesic and squared Euclidean distances (d_ULS and d_G) were also reported, supporting the HTMT. Table 4 shows that SRMR is below 0.08 and d_ULS and d_G are excellent at 0,785 and 0.416, respectively.

Table 4 - Model Fit.

Category	Value
SRMR	0.061
d_ULS	0.785
d_G	0.416
Chi-Square	844.839

Table 5 details a Structural Equation Modeling (SEM) path analysis. This study examines the links between TAC, SLA, SE, and SAP. The table displays standardized path coefficients (β), p-values, significance levels, and impact sizes (f^2) for five predicted associations, assessing their statistical significance and practical relevance. H1 compares TAC and SLA. A weak positive association is indicated by the path coefficient (β) of 0.087. The observed link may have been random due to the non-significant p-value of 0.449. TAC has a minimal impact on SLA, as indicated by the effect size (f^2) of 0.006. This shows that TAC does not affect SLA in this model.

Table 5 - Structural model.

H	Path	β	p-value	Sig.	f^2
H1	TAC → SLA	0.087	0.449	No	0.006
H2	TAC → SE	0.060	0.722	No	0.002
H3	TAC → SAP	0.028	0.341	No	0.002
H4	SLA → SAP	0.333	0.000	Yes	0.140
H5	SE → SAP	0.543	0.000	Yes	0.375

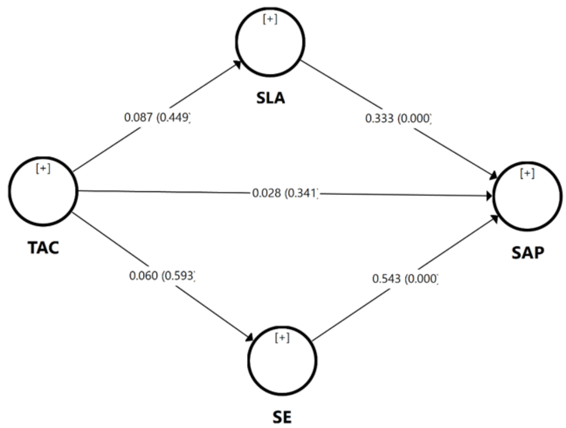

Figure 3 - Structural model.

TAC had little effect on SLA, suggesting that other factors may be more critical. Hypothesis 2 examines TAC and SE. This association's path coefficient is 0.060, indicating a weak positive relationship, consistent with H1. The effect size is 0.002, indicating that TAC has little practical influence on SE. This suggests that technology acceptance does not significantly affect SE in this study, and any observed association is likely due to random fluctuation. The third hypothesis (H3) examines the relationship between TAC and SAP. The path coefficient of 0.028 is the smallest positive association among all examined paths. This association is not statistically significant ($p = 0.341$). The low effect size (f^2) of 0.002 suggests that TAC has a minimal impact on SAP. These results indicate that TAC does not significantly alter SAP in this investigation. This matches H1 and H2, when TAC had little to no effect on SLA and SE.

H4 compares SLA with SAP. This link has a significantly higher positive path coefficient ($\beta = 0.333$) than earlier hypotheses. A substantial association is indicated by the $p <.001$. The effect size is 0.140, indicating a medium effect, which demonstrates that SLA has a significant impact on SAP. The last hypothesis (H5) examines the relationship between SE and SAP. This association has the highest positive path coefficient ($\beta = 0.543$) among the investigated hypotheses. A p-value of <.001 indicates that this association is significant. SE has a considerable impact on SAP, as evidenced by the substantial effect size (f^2) of 0.375. This suggests that academically confident individuals perform better in social academic settings. The considerable significance and large effect size underscore the relevance of student self-efficacy in improving academic performance. The path analysis shows that TAC did not significantly affect SLA, SE, and SAP. The moderate effect size for SLA and the significant effect size for SE show their value in SAP. These findings suggest that educational interventions to improve outcomes should focus on SLA and SE to improve SAP.

Table 6 displays R^2 and Q^2 values for SAP, SLA, and SE factors. The model's explanatory capacity and predictive significance depend on these values.

Table 6 - R^2 and Q^2.

Factor	R^2	Q^2
SAP	0.693	0.019
SLA	0.006	0.021
SE	0.002	0.019

The coefficient of determination (R^2) measures the proportion of variance in the dependent variable that is accounted for by the independent variables in the model. A high R^2 value indicates a strong relationship between the independent variables and the dependent variable, explaining a significant portion of the variability in the results. The R^2 value for SAP is 0.693, indicating that the SAP factor accounts for 69.3% of the variance in the dependent variable. The high R^2 value indicates that SAP is a significant predictor in the model, accounting for a substantial portion of the variation in the dependent variable. SAP is vital to the model; thus, 0.693 is a significant value. SLA has an R^2 value of 0.006, indicating that it explains just 0.6% of the variance in the dependent variable. A low R^2 value suggests SLA is not a reliable predictor in this model. It explains little of the variance, suggesting that other factors, either outside or inside the model, explain more. The R^2 value for SE is much lower, at 0.002. SE explains only 0.2% of the variation in the dependent variable, indicating its low explanatory power. SE does not forecast the outcome like SLA.

Key measure Q^2 evaluates model predictive relevance using the Stone-Geisser criterion. R^2 measures the model's ability to explain variance in estimation data, whereas Q^2 assesses its ability to forecast new data. A positive Q^2 score implies predictive relevance in the model. The Q^2 value for SAP is 0.019, indicating a low but acceptable level of predictive relevance. This result suggests that the model can predict SAP-based data with some accuracy. Compared to SAP, SLA has a slightly higher Q^2 value (0.021), indicating improved predictive relevance, although it remains poor. Although SLA does not explain much variance in the model (as seen by its R^2), it is marginally more effective at predicting fresh data. SE and SAP have the same Q^2 value of 0.019, showing equivalent predictive relevance. While SE has a low R^2, the Q^2 value suggests that it can still predict new outcomes, albeit to some extent. The model demonstrates that SAP is a significant explanatory factor but that SAP, SLA, and SE have limited predictive relevance. This indicates that SAP accounts for a substantial portion of the variance in current data; however, none of the components can accurately predict new data. Thus, the model may require adjustment or additional features to enhance its explanatory power and predictive relevance.

5. Discussion

A fascinating glimpse into the processes at play within the educational environment, particularly in the context of AI integration, is provided by the investigation of the relationship between teacher AI competency (TAC) and various student outcomes. The route analysis's findings highlight several significant conclusions that warrant an in-depth explanation. According to the first hypothesis (H1), student learning agility (SLA) is expected to be positively impacted by teachers' AI competency. At the usual levels, the relationship's path coefficient (β) is 0.087, with a p-value of 0.449, indicating that it is not statistically significant. This implies that the idea that teachers' proficiency with AI directly improves students' learning agility is not well-supported by data (Guillén-Gámez, et al., 2024; Kim, 2024). This outcome may indicate several underlying issues. Firstly, while instructor AI proficiency is essential, its direct impact on student learning agility may not always be clear. Learning agility is the ability of students to absorb, process, and apply new information quickly. It is possible that intrinsic elements, such as students' motivation, cognitive capacities, and prior knowledge, have a greater impact on learning agility than do teachers' technological expertise (Greener & MacLean, 2013). On the other hand, it's possible that AI integration in the classroom is not yet advanced enough to significantly enhance students' learning capacity. Another argument is that the ineffective use of AI tools could prevent pupils from being adequately challenged to improve their agility, thereby limiting the potential influence of teacher AI competency in this area.

The second hypothesis (H2) looked at the relationship between student engagement (SE) and teacher AI competency. Here, the p-value of 0.722 and the path coefficient of 0.060 both show that there is no significant link. A key element of academic achievement is student engagement, defined as the degree of interest, enthusiasm, and involvement that students exhibit in their learning activities. This lack of a substantial association shows that higher levels of student involvement are not always correlated with a teacher's AI skill (Koh et al., 2023). This study may suggest that involvement is more intricate and multidimensional, necessitating from educators more than just technological know-how. Interpersonal relationships between teachers and students, curricular relevance, classroom atmosphere, and teaching style are perhaps more critical factors in promoting engagement. Furthermore, because AI in education is still relatively new, both educators and learners may still be adjusting to the technology, meaning that its full potential for engaging pupils has not yet been reached. Furthermore, AI technologies may struggle to hold students' attention if they are not user-friendly or integrated adequately into pedagogy, which may account for their limited influence.

The direct relationship between TAC and SAP was investigated in Hypothesis 3 (H3). The study reveals a path coefficient of 0.028 with a p-value of 0.341, which is also not statistically significant. This result implies that raising students' academic success is not directly correlated with instructor AI competency. A wide range of factors outside the purview of teacher AI competency likely influence academic performance, which serves as a gauge of students' success in their educational pursuits (Alam & Mohanty, 2023; Garrison, 2019). This finding suggests that, even if AI technologies can enhance instruction, their ability to immediately improve student achievement may be limited in the absence of additional beneficial variables. A well-organized curriculum, ongoing evaluation, feedback systems, and a positive learning environment are a few examples of these. Furthermore, the subject matter, the way AI is integrated, and the general level of digital literacy among teachers and students may all impact how well AI improves academic performance (Casal-Otero et al., 2023). The results suggest that academic success can be achieved through AI proficiency alone, potentially due to the need for a more comprehensive strategy that incorporates AI with other educational techniques.

The association between student learning agility and academic achievement is examined in the fourth hypothesis (H4), which demonstrates a substantial positive path coefficient ($\beta = 0.333$, p-value < 0.001). This suggests a positive correlation between learning agility and academic success among students. This association is further supported by the f2 value of 0.140, indicating a medium effect size and suggesting that learning agility is a significant predictor of academic performance. The ability of pupils to absorb new material, adapt to various learning situations, and apply their knowledge effectively is reflected in their learning agility. This result is consistent with educational theories that highlight the role adaptive learning habits have in helping students succeed academically (Alam, 2022; Linnenbrink-Garcia et al., 2016; Schwartz et al., 2013; Van Der Vorst & Jelicic, 2019). Agile learners are better equipped to navigate the complexities of academic challenges, effectively manage their learning processes, and apply their knowledge in diverse situations. This finding highlights the importance of helping students develop their learning agility as a means of enhancing their academic achievement. Teachers may need to focus on developing curricula and instructional methods that foster adaptability, such as problem-based learning, adaptive learning technologies, and other active learning techniques.

The relationship between academic achievement and student participation was the subject of the last hypothesis (H5). A considerable positive path coefficient ($\beta = 0.543$, p-value < 0.001) is revealed by the research, suggesting that improved academic achievement is strongly correlated with higher levels of student engagement. The significant contribution of involvement to academic performance is highlighted by the f2 value of 0.375, which indicates a strong impact size. This finding aligns with the extensive body of research that demonstrates student engagement as a crucial factor in predicting academic success. Increased motivation, active participation in class, meticulous completion of homework, and seeking assistance when needed are all characteristics of engaged students that lead to better academic results (August & Tsaima, 2021; Demartini et al., 2024; Wei, 2023). Since there is a direct correlation between engagement and performance, tactics such as individualized learning plans, interactive teaching techniques, and the use of engaging digital tools can all be highly effective in enhancing student achievement.

6. Conclusion

This study investigated the relationships among teacher AI competence (TAC), student learning agility (SLA), student engagement (SE), and student academic performance (SAP) in higher education. The results provide robust evidence that student learning agility and engagement are significant predictors of academic performance. Specifically, the path analysis revealed that both SLA ($\beta = 0.333$, $p < 0.001$) and SE ($\beta = 0.543$, $p < 0.001$) have strong, positive, and statistically significant effects on SAP, jointly explaining 69.3% of the variance in academic performance ($R^2 = 0.693$). These findings underscore the importance of cultivating learning agility and engagement in students to enhance their academic outcomes.

In contrast, teacher AI competence was not found to have a statistically significant direct effect on student learning agility, engagement, or academic performance (all $p > 0.3$). This suggests that, in the context of this study, teacher AI competence alone may not directly determine student outcomes. Nevertheless, AI competence remains a relevant and increasingly necessary professional skill for educators in the digital era. Therefore, efforts to enhance teachers' AI competence remain essential to ensure that educators are well-prepared to integrate technology effectively and adapt to future developments in education. Its influence on student achievement may operate indirectly or in conjunction with other factors, such as the overall learning environment and instructional approaches.

It is essential to note that demographic characteristics, such as gender, institution, educational background, and teaching experience, were not analyzed as moderating variables due to limitations in sample distribution. The uneven distribution of respondents in several categories, such as the predominance of female participants and the majority coming from a single institution or educational level, could introduce bias if demographic effects were analyzed. For this reason, the influence of demographic characteristics was excluded from the analysis to maintain the study's validity and focus. Future research with larger and more balanced samples is needed to examine the potential moderating effects of these demographic factors.

In summary, while teacher AI competence is an essential attribute for educators, this study demonstrates that student engagement and learning agility are more critical determinants of academic success in the era of AI. Educational policies and practices should therefore adopt a holistic approach that supports these student-centered factors to maximize learning outcomes as AI becomes increasingly integrated into higher education.

The availability of data

The dataset used in the present work can be accessed in the Figshare repository.

Authors' Contributions

Conceptualization by R.H. and A.H.; methodology by R.H., A.H.; software by T.M.A.; validation by R.H., A.H.; formal analysis by T.M.A.; investigation by L.N.Y.; data curation by L.N.Y.; original draft preparation by A.S.A.; writing-review and editing by A.S.A.; visualization by A.M.; supervision by A.M. All authors have read and approved the publication.

Informed Consent Statement

All subjects included in the study provided informed consent.

Conflict of Interest

The authors declare no conflicts of interest.

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Appendix: survey

Gender (Sex)	Male Female
Institution	University A University B University C
Highest Education Level	Master Doctorate
Teaching Experience	Less than 5 years 5 years or more than 5 years
TAC	1. AI technology is used to improve classroom learning. 2. AI-based applications or platforms (such as AI quiz generators and AI tutors) are used to explain material or offer exercises. 3. AI-based learning resources are selected by curriculum requirements. 4. AI-based materials are modified or adapted with attention to ethics, accuracy, and copyright. 5. AI-based learning materials are managed with a focus on student data privacy and security. 6. AI is used to facilitate communication and collaboration between educators. 7. AI is used to support interactions between teachers and students, as well as between students. 8. AI is used to enhance collaborative learning among students. 9. AI-based tools are used for formative and summative assessments. 10. AI is utilized to analyze learning outcomes and provide rapid and accurate feedback. 11. AI-based learning activities are selected or generated according to students abilities. 12. AI-based tools used in learning foster student learning interests. 13. AI is used to facilitate learning for students with special needs, making it more inclusive. 14. AI is used to adapt materials to students' competency levels, interests, and learning needs.
SLA	1. New experiences with AI technology become learning opportunities. 2. Information obtained through AI (e.g., chatbots, learning apps) is easy to remember and understand. 3. Students are optimistic about the potential benefits of AI for learning new topics. 4. Students enjoy researching or seeking out new information related to AI technology. 5. Students strive to find ways to apply the new knowledge gained through AI to academic pursuits.
SE	1. Students can find ways to make learning materials relevant to their daily lives with the help of AI. 2. Students can apply learning materials to real-life situations with the support of AI technology. 3. Students can enhance their learning experience by utilizing AI applications or tools. 4. Students often search for or explore materials through AI before the lesson begins. 5. Students have a strong desire to learn the material using AI technology.
SAP	1. Students trust their academic skills, including using AI to support learning. 2. Students can complete academic assignments, both independently and with the assistance of AI technology. 3. Students learn how to utilize AI to complete academic assignments more efficiently and effectively. 4. Students demonstrate academic achievement as expected by utilizing AI technology appropriately in the learning process.