



Understanding academic performance of TLE pre-service teachers in AI-influenced learning environments

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ABSTRACT

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This study investigated the determinants of academic performance among pre-service students in an AI-influenced learning environment by examining the roles of expectations about artificial intelligence and its impact on education, learning experience, and motivation. A quantitative research design was employed, utilizing an online survey distributed through Google Forms to undergraduate students enrolled in the Bachelor of Technical-Vocational Teacher Education (BTVTED) and Bachelor of Technology and Livelihood Education (BTLED) programs at a major state university in Cebu, Philippines. Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to assess both the measurement model and the structural model. The findings showed that expectations about AI exerted the strongest positive influence on academic performance, followed by learning experience and motivation. The proposed model accounted for 78.1% of the variance in academic performance ($R^2 = 0.781$), indicating substantial explanatory power. Overall, the results suggest that strengthening students' positive expectations toward AI, enriching their learning experiences, and fostering stronger motivation may significantly enhance academic outcomes in TLE teacher education. These findings highlight the importance of creating supportive AI-integrated learning environments that encourage engagement, confidence, and meaningful educational experiences among future teachers. The study also underscores the growing educational relevance of AI readiness in shaping student success within teacher preparation programs.

Contribution/Originality: This study uniquely focuses on TLE pre-service teachers in the Philippines, integrating AI expectations, learning experience, and motivation into one PLS-SEM model. It is among the first to empirically quantify how AI readiness factors jointly predict academic performance within an AI-influenced teacher education context.

1. INTRODUCTION

Educational institutions, which were initially developed for the Industrial Revolution era, are currently confronted with unprecedented challenges as a result of the digital transformation and the artificial intelligence (AI) revolution (Arar, Saiti, & Guajardo, 2023). These forces are transforming the organizational culture, professional capital, learning paradigms, and teaching methodologies within educational institutions (Arar & Chen, 2021; Arar et al., 2023). Recently, educational institutions are implementing novel technologies, for instance, Learning Management Systems (LMS), Intelligent Tutoring Systems (ITS), and online learning platforms, which enable them to accumulate large amounts of data about the students and the learning environment (Gašević, Kovanović, Joksimović, & Siemens, 2015). Amid these rapid changes, academic performance remains a commonly used outcome

indicator to study how “educational technologies, including AI-enabled tools, affect student learning (Valverde-Berrocso, Acevedo-Borrega, & Cerezo-Pizarro, 2022). Accordingly, researchers from diverse sectors focus on improving the quality of education by exploring factors that enhance students’ academic performance (Alwarthan, Aslam, & Khan, 2022). Thus, students are expected to spend much of their time on their education and need to graduate with good academic results, despite substantial investment in education, a substantial proportion of students fail to achieve good academic performance at all levels of education (Tadese, Yeshaneh, & Mulu, 2022). Thus, understanding TLE pre-service students’ academic performance in today’s digital learning environment is crucial for assessing how emerging educational technologies, particularly AI, are affecting students’ learning and preparedness for future teaching.

Martín-Del-Pozo and Martel-Santana (2026) emphasized that pre-service teachers are increasingly using AI tools for school-related tasks, such as learning, writing, and receiving feedback, as artificial intelligence (AI) becomes more prevalent in educational institutions. This is particularly true in light of the rapid proliferation of generative AI applications such as ChatGPT in the field of education (Hassan, 2023; Mittal, Sai, Chamola, & Sangwan, 2024). Recent research underscores that these tools can facilitate learning (e.g., practice, explanation, feedback, and personalization), nonetheless, their educational efficacy is significantly contingent upon their application and integration into instructional practices (Kasneci et al., 2023). Multidisciplinary assessments of generative conversational AI underscore that learners’ acceptance and appropriate utilization of AI tools determine whether the technology facilitates meaningful learning or merely accelerates task completion (Dwivedi et al., 2023). Moreover, UNESCO (2023) acknowledges that generative AI is transforming education and advocates for evidence-based, contextually relevant integration that enhances learning quality and student outcomes. For pre-service students, this context is especially significant, as their training is heavily reliant on practical application and is closely associated with classroom preparedness, as they are anticipated to interact with AI-enabled tools as both learners and practitioners in technologically enhanced educational environments (Hong, Moon, Eom, Awoyemi, & Hwang, 2025).

Several studies suggest that students’ expectations toward AI, together with the quality of their learning experiences and their academic motivation, play pivotal roles in shaping learning outcomes in AI-supported environments. For instance, Kasneci et al. (2023) emphasized that expectations about AI and its impact on education capture students’ beliefs that AI-enabled tools will either improve learning or threaten learning (Yan, Alwabel, & Mohamad, 2025). These expectations matter because they shape whether students adopt AI at all and, more importantly, how they use it, as a learning scaffold versus as a shortcut that replaces effort and reduces deep cognitive processing (George, 2023). Moreover, AI-supported learning outcomes are dependent upon students’ engagement and self-regulation (Hu & Zhang, 2025). Recent educational analyses of large language models highlight that benefits are not inherent; instead, they require intentional use and instructional design that directs learners towards comprehension rather than mere output (Achuthan, 2025; Zhang, Zhou, & Bai, 2026). This connects directly to learning experience, which reflects students’ perceived quality of instruction and learning processes, clarity, feedback usefulness, engagement, interaction, perceived learning gains, and the overall effectiveness and fairness of the learning environment. Expectations about AI can color this experience by shaping confidence and willingness to participate (Glassberg, Ilan, & Zwilling, 2025) students who anticipate value and manageable risk are more likely to engage actively, seek feedback, and persist through complex tasks (George & Wooden, 2023) whereas students who anticipate harm or unpredictability may disengage, mistrust AI-mediated activities, or rely unproductively on AI (Favero, Pérez-Ortiz, Käser, & Oliver, 2026) diminishing the quality of their learning experience. Research on technology-enhanced learning continuously demonstrates that student engagement is a pivotal factor influencing the quality of learning in digital settings, underscoring the connection between students’ educational and interactive experiences in technology-rich environments and their academic performance (Owusu-Cole, Entsie, Bosu, Akore Sarpong, & Kwadwo Mensah, 2025; Sabri et al., 2024).

Aside from expectations toward AI and learning experience, motivation further strengthens this chain because it drives effort, persistence, and goal-directed behavior, determining whether students explore tools thoughtfully, sustain practice, and self-regulate when tasks become difficult (Bembenutty et al., 2024; Hanayanti et al., 2025). In the context of generative AI, two ways to boost motivation. First, it can enable productive, mastery-oriented use (iterative improvement, feedback-seeking), or it can impede learning when students use AI instead of practice, despite faster completion (Hajian, Chang, Wang, & Lin, 2025). Multidisciplinary work on generative conversational AI highlights that perceived value, trust, and responsible-use intentions are pivotal in steering adoption toward meaningful learning rather than superficial task completion (Weis, Bele, & Erčulj, 2026). TLE pre-service students are notably affected by these dynamics because academic performance is a measure of current success and readiness for practice-oriented coursework and technology-integrated teaching. This follows global guidelines for evidence-based generative AI integration to improve learning quality and student outcomes (UNESCO, 2023). Despite these crucial insights from the literature, a holistic framework describing pre-service teachers' academic performance, particularly in the advent of artificial intelligence, is missing. It serves as the main departure of this work.

Despite these insights, research remains fragmented, with many studies examining AI tools, learning experience, or motivation in isolation and often focusing on general student populations. Consequently, a holistic model explaining TLE pre-service students' academic performance in the context of AI-enabled learning is still limited. This study addresses this gap by proposing and testing an overarching model in which expectations about AI and its impact on education (EAI-IE), learning experience (LE), and student motivation (SM) are examined as predictors of academic performance (AP) among TLE pre-service students. To evaluate these relationships simultaneously while accounting for measurement quality, the study employs partial least squares structural equation modeling (PLS-SEM). Moreover, PLS-based SEM offers a more comprehensive and resilient statistical approach for identifying structural models. It works best with complicated models, small sample sizes, data that isn't normally distributed, formative measures, and research that is both predictive and exploratory. Additionally, PLS is suitable for analyzing a small sample size. The findings aim to provide evidence that can guide TLE and teacher education programs in strengthening learning conditions, promoting responsible AI use, and improving academic performance. The remainder of the paper is structured as follows. Section 2 discusses the literature review on and the development of the hypothesized model. Section 3 describes the methodological approach for PLS-SEM. Section 4 discusses the insights derived from the results. Section 5 presents the concluding remarks and future research priorities.

Moreover, this research contributes by offering an integrated, PLS-SEM-based model of academic performance among TLE pre-service students in AI-enabled learning, clarifying how expectations about AI, learning experience, and motivation jointly shape outcomes. It also provides context-specific evidence to inform teacher education policies, curriculum design, and responsible AI integration practices in schools.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Artificial Intelligence

Artificial intelligence (AI) is increasingly reshaping education through tools that support explanation, feedback, practice, and content generation, with recent attention focusing on large language models used in learning and teaching (Alqahtani et al., 2023; Kumar et al., 2023). Current research notes that AI can enhance learning processes when used as a scaffold for understanding and iteration (Memmert, Tavanapour, & Bittner, 2023), but it can also introduce risks such as inaccurate outputs, overreliance, and academic integrity challenges, meaning educational impact depends on how AI is integrated into pedagogy and how learners engage with it (Kasneci et al., 2023; Ncube, Dzvapatsva, Matobobo, & Ranga, 2026). Broader multidisciplinary evidence on generative conversational AI similarly emphasizes that perceived value, trust, and responsible-use intentions influence whether AI adoption supports meaningful learning or merely speeds up task completion (Weis et al., 2026). These developments make AIED research relevant for pre-service teacher preparation today.

2.2. Academic Performance

Academic performance, commonly operationalized through course grades, GPA, or standardized achievement tests, remains a central outcome in educational research and policy because it reflects mastery of curricular objectives and predicts progression and completion (Greene, Cartiff, & Duke, 2018; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006). Moreover, large-scale monitoring programs such as OECD's PISA track achievement trends to inform quality and equity reforms (OECD, 2023). Evidence from the COVID-19 period further shows that academic performance is sensitive to learning conditions: disruptions such as school closures were associated with measurable achievement losses (Engzell, Frey, & Verhagen, 2021; Kuhfeld et al., 2020). Together, this literature supports treating academic performance as a policy-relevant indicator for evaluating how changes in learning environments, including technology-rich and AI-supported settings, translate into student outcomes.

2.3. Motivation

Motivation refers to the internal drive that initiates, directs, and sustains students' learning behaviors, such as paying attention, investing effort, persisting through difficulties, and completing academic tasks (Greer, 2016). From a self-determination perspective, when students learn for autonomous reasons (e.g., interest, personal value), they tend to use deeper learning strategies, persist longer, and show stronger achievement than when they are driven mainly by pressure or external rewards (Ryan & Deci, 2020). Evidence synthesis in higher education also shows that motivational factors (together with related beliefs such as self-efficacy) are among the consistent psychological predictors of academic performance outcomes (Richardson, Abraham, & Bond, 2012). Overall, this indicates that more motivated students are more engaged and persistent in learning, which supports higher academic achievement. Thus, the hypothesis was constructed:

H₁: Motivation has a positive influence on academic performance.

2.4. Learning Experience

Learning experience refers to students' overall perception of the teaching–learning process, including the clarity of instruction, usefulness of feedback, opportunities for interaction, engagement in learning activities, and how supportive and effective the learning environment feels (Amerstorfer & Freiin von Münster-Kistner, 2021; Zerihun, Beishuizen, & Van Os, 2012). A more positive learning experience is expected to strengthen students' engagement and learning behaviors, which are consistently linked to stronger academic outcomes in technology-rich settings (Godzicki, Godzicki, & Han, 2013; Sabri et al., 2024). Evidence also shows that when learning conditions are disrupted, and instructional experiences are weakened (e.g., reduced structure and interaction during school closures), students tend to show measurable declines in academic achievement (Engzell et al., 2021). Thus, better learning experiences support stronger achievement, making learning experience a meaningful predictor of academic performance. Thus, the hypothesis was constructed:

H₂: Learning experience has a positive influence on academic performance.

2.5. Expectations about AI and Its Impact on Education

Expectations about AI and its impact on education refer to students' beliefs that AI-enabled tools can enhance learning or, conversely, harm learning through risks such as inaccurate outputs, overreliance, and integrity issues (Bhambri, Kumar, & Wadhwa, 2026; Williamson & Prybutok, 2024). Recent work on AI in education shows that AI tools can support learning outcomes, but the benefits depend on *how* they are used and integrated into learning activities (Chen, Xie, Zou, & Hwang, 2020; Kasneci et al., 2023). Research on generative conversational AI further emphasizes that perceived value, trust, and responsible-use intentions shape adoption and usage patterns, which can determine whether AI use leads to meaningful learning rather than superficial task completion (Dwivedi et al., 2023). Because productive engagement and sustained learning activities are closely tied to achievement, students with more

positive and realistic expectations about AI are more likely to use AI in ways that support stronger academic outcomes. Thus, the hypothesis was constructed:

H₃: Expectations about AI and its impact on education have a positive influence on academic performance.

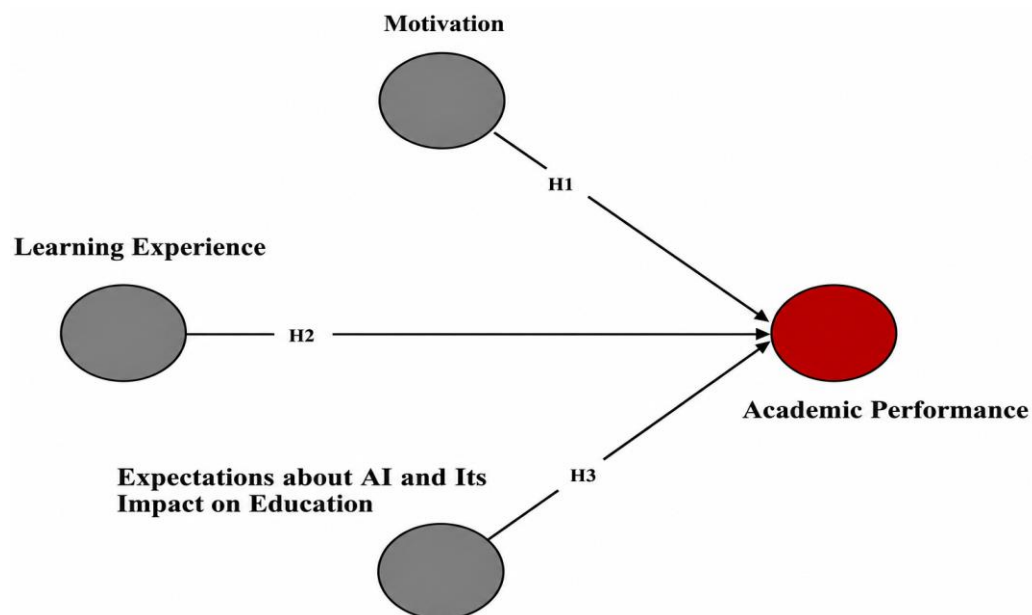


Figure 1. The Proposed Model for Students' Academic Performance among TLE pre-service students in the Context of AI-Enabled Learning.

Figure 1 illustrates the proposed model of academic performance among TLE pre-service students in an AI-enabled learning environment. The model shows that three key independent variables, such as motivation, learning experience, and expectations about AI and its impact on education, have direct paths toward academic performance. Each relationship is represented by directional arrows (H1, H2, and H3), indicating hypothesized positive influences. Motivation reflects students' drive to learn, while learning experience captures the quality of their engagement in AI-integrated settings. Expectations about AI represent students' perceptions of its usefulness and role in education. Among these factors, expectations about AI are positioned as the strongest predictor, highlighting the importance of students' readiness and outlook toward AI in shaping their academic success.

3. METHODS

3.1. Instruments

The constructs of the proposed model were adapted from two validated instruments to ensure strong content coverage and measurement quality. Items measuring Expectations about AI and Its Impact on Education (EAI-IE) were adapted from the teacher-focused AI training questionnaire developed and validated by Reina-Parrado, Román-Graván, and Hervás-Gómez (2025), while items for Motivation, Learning Experience, and Academic Performance were adapted from Capinding (2024), which was designed to assess AI's impact on higher education students. All items were rated using a 7-point Likert scale anchored from Strongly Disagree (1) to Strongly Agree (7). Following data collection, the measurement model was evaluated using PLS-SEM, and several indicators were removed during the measurement-model refinement stage (e.g., indicators with weak outer loadings or those that weakened reliability/convergent and discriminant validity).

3.2. Data Collection

The participants were 81 TLE pre-service undergraduate students enrolled in the Bachelor of Technical-Vocational Teacher Education and Bachelor of Technology and Livelihood Education programs at a major state

university in the Philippines. Data were collected through an online survey administered via Google Forms. Of the respondents, 76.5% were female and 23.5% were male, while the largest age group was 20–21 years old at 33.3%. Participation was voluntary, and informed consent was obtained electronically before participants accessed the survey. The consent statement explained the study purpose, procedures, voluntary nature of participation, right to withdraw without penalty, confidentiality safeguards, and intended use of the data. No personally identifying information was collected, and all responses were kept anonymous and used solely for research purposes. For Partial Least Squares Structural Equation Modeling, the ten-times rule recommends a minimum sample size equal to ten times the maximum number of structural paths directed at an endogenous construct (Hair, Hult, Ringle, & Sarstedt, 2017). Since three paths were directed toward academic performance, the minimum required sample size was 30; thus, the sample of 81 participants was considered adequate for the analysis.

3.3. Data Analysis Results

Hair et al. (2017) emphasized that the first step in PLS-SEM is the assessment of the measurement model to establish the reliability and validity of the constructs. Before the main analysis, the instrument underwent content validation through expert review to ensure the relevance, clarity, and appropriateness of the items for measuring the study variables. Necessary revisions in wording and item phrasing were made based on the validators' comments to improve clarity and contextual fit. After data collection, indicator reliability and convergent validity were assessed. As shown in Table 1, all item loadings exceeded the recommended threshold of 0.70 (Henseler, Ringle, & Sinkovics, 2009), indicating that the indicators adequately represented their respective constructs. Likewise, the Average Variance Extracted (AVE) values ranged from 0.703 to 0.750, surpassing the minimum criterion of 0.50 (Fornell & Larcker, 1981), thereby confirming convergent validity. Internal consistency reliability was also established, as Cronbach's alpha and Composite Reliability (CR) values for all constructs were above the acceptable threshold of 0.70 Hair et al. (2017). Discriminant validity was further examined using the Fornell–Larcker criterion. As presented in Table 2, the square roots of the AVE values, shown in bold along the diagonal, were higher than the inter-construct correlations, indicating adequate discriminant validity. These results confirm that the measurement instrument demonstrated acceptable psychometric properties and was suitable for subsequent structural model assessment.

Table 1. Measurement model of assessment results.

Convergent Validity		Discriminant Validity			Convergent Validity		Discriminant Validity		
Loadings		Ave	α	CR	Loadings		Ave	α	CR
AP2	0.874				LE1	0.813			
AP3	0.816				LE2	0.856			
AP4	0.884				LE3	0.838			
AP6	0.850	0.75	0.993	0.35	LE4	0.770			
AP7	0.867				LE5	0.877	0.705	0.948	0.952
AP8	0.902				LE7	0.856			
					LE8	0.870			
					LE9	0.848			
					LE10	0.822			
EAI-IE 1	0.898								
EAI-IE 2	0.891								
EAI-IE 3	0.898				M1	0.771			
EAI-IE 4	0.879				M2	0.789			
EAI-IE 5	0.853				M3	0.876			
EAI-IE 7	0.865	0.763	0.956	0.957	M4	0.725			
EAI-IE 8	0.843				M5	0.895			
EAI-IE9	0.859				M6	0.792	0.703	0.952	0.954
					M7	0.865			
					M8	0.887			
					M9	0.883			
					M10	0.882			

Note: α = Cronbach's alpha; CR = composite reliability; AVE = average variance; AP = academic performance; EAI-IE = Expectations about AI and its Impact on Education; LE = Learning Experience; M = Motivation.

Table 2. Correlation and Testing Discriminant Validity.

	Academic Performance	Expectations about AI and Its Impact on Education	Learning Experience	Motivation
Academic Performance	0.866			
Expectations about AI and Its Impact on Education	0.854	0.874		
Learning Experience	0.827	0.84	0.839	
Motivation	0.715	0.684	0.735	0.839

Note: The square root of the AVE values appears in bold along the diagonal of the matrix, while the correlations between constructs are shown in the off-diagonal cells.

The discriminant validity was introduced by Fornell and Larcker (1981). They showed that the average variance extracted (AVE) for each construct should be higher than the squared correlations between latent variables. In Table 2, the numbers in bold are the square roots of the AVE, and the numbers that aren't in bold are the relationships between the constructs. The Fornell and Larcker criterion says that the discriminant is valid when the off-diagonal values are less than the appropriate square root of the AVE.

Table 3. Path coefficients and hypothesis results.

Hypothesis	β	p-Values	Decision
H1: Motivation $\rightarrow$ Academic Performance	0.159	0.042	Supported
H2: Learning Experience $\rightarrow$ Academic Performance	0.286	0.006	Supported
H3: Expectations about AI and its impact on education $\rightarrow$ Academic performance	0.504	0.000***	Supported

Note: *** $p < 0.001$, indicating a highly statistically significant relationship.

Table 3 indicates that all three hypothesized relationships with Academic Performance are positive and statistically significant. Motivation has a small but significant effect on Academic Performance ($\beta = 0.159$, $p = 0.042$), supporting H1. Learning Experience shows a moderate, significant effect on Academic Performance ($\beta = 0.286$, $p = 0.006$), supporting H2. Expectations about AI and Its Impact on education have the strongest and highly significant effect on Academic Performance ($\beta = 0.504$, $p = 0.000$), supporting H3. Overall, Expectations about AI emerge as the most influential predictor, followed by Learning Experience and Motivation.

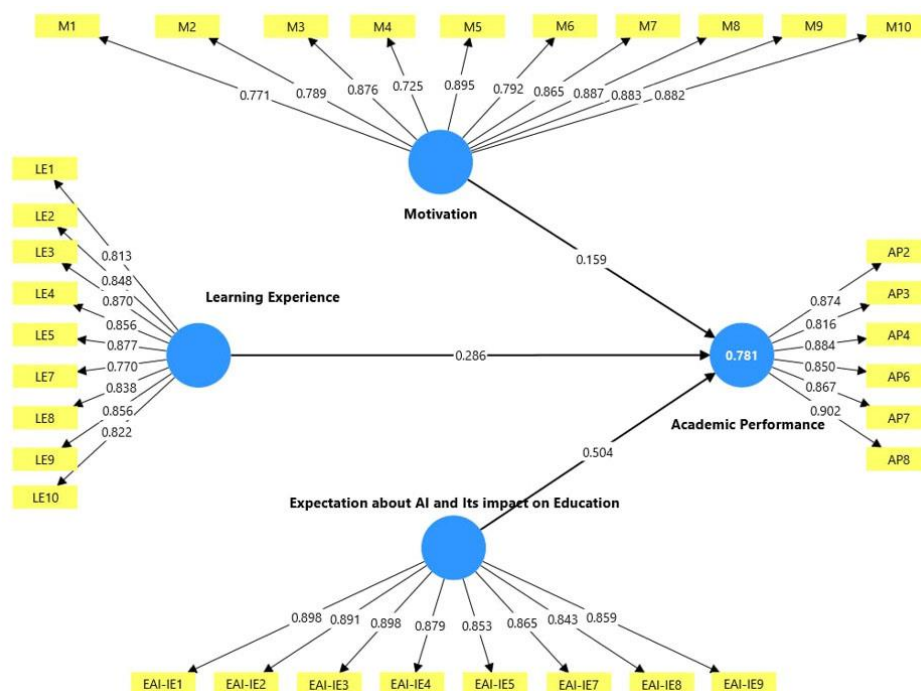
**Figure 2.** Structural model path coefficients.

Figure 2 illustrates the structural equation model results, showing the relationships between motivation, learning experience, and expectations about AI and their effects on academic performance. The figure presents the standardized path coefficients, where expectations about AI have the strongest direct effect ($\beta = 0.504$), followed by learning experience ($\beta = 0.286$) and motivation ($\beta = 0.159$). It also displays the measurement model through indicator loadings for each construct, with most values exceeding acceptable thresholds, indicating good reliability. The model explains a substantial proportion of variance in academic performance ($R^2 = 0.781$), demonstrating strong explanatory power.

Table 4. Effect Size.

Relationship	f^2	Effect size
M $\rightarrow$ AP	0.052	Small effect
LE $\rightarrow$ AP	0.092	Small effect
EAI-IE $\rightarrow$ AP	0.332	Medium effect

Table 4 shows the effect size (f^2) of each predictor on Academic Performance (AP), indicating how much each construct contributes to AP's explained variance. Motivation (M) has a small effect on academic performance ($f^2 = 0.052$), meaning it adds only a modest contribution to predicting AP when the other predictors are included. Learning Experience (LE) also shows a small effect ($f^2 = 0.092$), suggesting that improvements in learning experience contribute to AP, but the unique contribution is still limited relative to the stronger predictor. In contrast, Expectations about AI and Its Impact on Education (EAI-IE) demonstrates a medium effect ($f^2 = 0.332$), indicating that it provides the most substantial unique contribution to explaining academic performance. Overall, the results imply that while motivation and learning experience matter, students' expectations about AI are the most influential driver of academic performance in the model.

4. DISCUSSION

The proposed model explains a substantial proportion of variance in Academic Performance among TLE pre-service students ($R^2 = 0.781$) and shows that all three hypothesized paths are positive and significant. Expectations about AI and Its Impact on Education (EAI-IE) emerged as the strongest predictor of academic performance ($\beta = 0.504$, $p < 0.001$), followed by Learning Experience (LE) ($\beta = 0.286$, $p = 0.006$) and Motivation (M) ($\beta = 0.159$, $p = 0.042$). This pattern supports what you argued in the introduction and literature review that in AI-influenced learning settings, students' AI-related beliefs shape how constructively they engage with AI tools and learning tasks, which can translate into better academic outcomes (e.g., the benefits of LLMs depend on purposeful use and how learners engage with the tool (Kasneci et al., 2023), and adoption/responsible-use intentions matter for meaningful learning: Dwivedi et al. (2023). At the same time, the significant LE and motivation paths align with your discussion that high-quality learning experiences and stronger motivational drive are associated with better achievement, even when AI-related factors are present (Ryan & Deci, 2020). The effect size (f^2) results reinforce the same conclusion about relative importance. EAI-IE has a medium effect on academic performance ($f^2 = 0.332$), indicating the largest unique contribution to AP, whereas LE ($f^2 = 0.092$) and motivation ($f^2 = 0.052$) show small effects. In other words, while learning experience and motivation remain statistically meaningful contributors, AI expectations are the main driver of academic performance in your model, consistent with your literature review argument that students' beliefs about AI influence whether AI use becomes a productive learning scaffold or a shortcut that weakens learning quality. This also supports your study's practical framing: for TLE teacher education, strengthening academic performance in an AI-enabled environment likely requires not only maintaining quality learning experiences and student motivation, but also shaping realistic, pedagogically aligned AI expectations through AI literacy, guided-use policies, and learning designs that encourage checking, iteration, and understanding rather than mere output generation.

5. CONCLUSIONS

The study strengthens AI-in-education theory by showing that AI-related expectations function as a central belief-based mechanism linked to student outcomes. Rather than treating AI as merely a tool or external condition, the findings position expectations about AI's impact as a psychologically meaningful construct that can explain differences in academic performance, supporting the view that the effects of AI in learning environments depend on learners' beliefs and orientations toward the technology. Second, the results contribute to teacher education and pre-service research by providing evidence that the same factors emphasized in broader educational technology literature also apply to TLE pre-service students, a population that remains underrepresented in AI-focused empirical models. Integrating expectations, learning experience, and motivation in a single structural framework and demonstrating their relative strengths (with EAI-IE as the dominant predictor), the study offers a more coherent explanatory account of academic performance in AI-enabled contexts and supports future theory-building that connects AI beliefs with learning processes and achievement among future educators.

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Institutional Review Board Statement: The study involved minimal risk and followed ethical guidelines for social science fieldwork. Formal approval from an Institutional Review Board was not required under the policies of Cebu Technological University, Cebu, Philippines.

Transparency: The author states that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.

Competing Interests: The author declares that there are no conflicts of interest regarding the publication of this paper.

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