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Exploring the Influence of AI Learning Tool Use on Academic Performance: A Mediation Analysis of the Role of Learning Engagement

Menjelajahi Pengaruh Penggunaan Alat Pembelajaran AI Terhadap Prestasi Akademik: Analisis Mediasi Peranan Penglibatan Pembelajaran

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ABSTRACT

The main purpose of this study is to determine the effect of AI Learning Tool Use (AILTU) on Academic Performance (AP) with Learning Engagement (LE) as a mediating variable among students in State Universities and Colleges (SUCs) in Region 10. The data were collected from 156 student respondents using a standardized survey questionnaire distributed via Google Forms. The study used Partial Least Squares – Structural Equation Modeling (PLS-SEM) through WarpPLS 8.0 (Kock, 2020) to assess both direct and mediated effects among the variables (Hair et al., 2021). The research shows that AI Learning Tool Use has a positive and significant effect on both Learning Engagement and Academic Performance. Furthermore, Learning Engagement has a significant mediating effect on the relationship between AILTU and AP. The study revealed some gaps such as unequal access to AI tools, lack of structured digital literacy training, and inconsistent integration of AI platforms in education. Furthermore, the findings highlight the need to encourage active learning strategies and digital tool adoption to enhance student performance and engagement, especially in the context of disruptions caused by rapid technological changes or challenges to traditional educational delivery. The study contributes to the expanding research on digital learning transformation by emphasizing the strategic importance of AI Learning Tool Use (AILTU) in improving academic engagement and performance. The study offers important findings that educational institutions can use to enhance their AI tool integration and build resilience in digital learning environments.

Keywords**:** AI Learning Tool Use, Learning Engagement, Academic Performance, Digital Learning Transformation, Higher Education Resilience

ABSTRAK

Tujuan utama kajian ini adalah untuk menentukan kesan Penggunaan Alat Pembelajaran AI (AI Learning Tool Use - AILTU) terhadap Prestasi Akademik (Academic Performance - AP) dengan Penglibatan Pembelajaran (Learning Engagement - LE) sebagai pemboleh ubah perantara dalam kalangan pelajar di Universiti Awam dan Kolej Negeri (SUCs) di Wilayah 10.

Data dikumpulkan daripada 156 orang pelajar menggunakan soal selidik piawai yang diedarkan melalui Google Forms. Kajian ini menggunakan kaedah Partial Least Squares – Structural Equation Modeling (PLS-SEM) melalui WarpPLS 8.0 (Kock, 2020) untuk menilai kesan langsung dan tidak langsung antara pemboleh ubah (Hair et al., 2021).Hasil kajian menunjukkan bahawa Penggunaan Alat Pembelajaran AI mempunyai kesan positif dan signifikan terhadap Penglibatan Pembelajaran dan Prestasi Akademik. Selain itu, Penglibatan Pembelajaran didapati mempunyai kesan mediasi yang signifikan dalam hubungan antara AILTU dan AP. Kajian ini turut mendedahkan beberapa jurang seperti akses yang tidak seimbang terhadap alat AI, kekurangan latihan literasi digital berstruktur, serta ketidakkonsistenan dalam pengintegrasian platform AI dalam pendidikan.Dapatan kajian menekankan keperluan untuk menggalakkan strategi pembelajaran aktif dan penggunaan alat digital bagi meningkatkan prestasi serta penglibatan pelajar, khususnya dalam konteks gangguan akibat perubahan teknologi yang pesat atau cabaran terhadap penyampaian pendidikan tradisional. Kajian ini menyumbang kepada pengembangan penyelidikan dalam transformasi pembelajaran digital dengan menekankan kepentingan strategik Penggunaan Alat Pembelajaran AI (AILTU) dalam memperkukuh penglibatan dan prestasi akademik. Kajian ini menawarkan penemuan penting yang boleh digunakan oleh institusi pendidikan untuk menambah baik integrasi alat AI dan membina ketahanan dalam persekitaran pembelajaran digital.

Kata kunci: Penggunaan Alat Pembelajaran AI, Penglibatan Pembelajaran, Prestasi Akademik, Transformasi Pembelajaran Digital, Ketahanan Pendidikan Tinggi

INTRODUCTION

The pace of technology change in universities and colleges throughout the globe is creating some of the most important changes that are being seen in today’s learning environment. Indeed, one of the most significant innovations that is starting to impact the educational experience is the use of Artificial Intelligence (AI) learning tools and its applications. These artificial intelligence-based platforms and apps are fundamentally changing how we learn and provide student experience in helping to shape traditional pedagogical models as well as enhancing the overall educational experience (Zhai, 2023; Holstein et al., 2019). As AI learning tools such as ChatGPT, Grammarly, and other artificial intelligence-based tutors come more into students’ daily lives, there is growing interest in looking at the broader implications these tools have on student learning outcomes.

Current studies on AI educational tools emphasize their increasing influence on significant learning results such as student behavior and academic performance (Dwivedi et al. 2021; Smutny & Schreiberova 2020). A recent meta-analysis revealed that ChatGPT significantly enhances learning performance and has a moderate positive effect on learning perception and higher-order thinking (Wang & Fan, 2025). The use of AI in academic settings supports knowledge acquisition, enhances cognitive processes, and facilitates the completion of academic tasks by providing targeted feedback and guidance. Furthermore, AI learning tools offer new possibilities to enhance student academic performance and continue to be a relatively innovative approach in educational settings. This research investigates how the use of AI learning tools affects students’ academic performance, considering learning engagement as a mediating variable that helps explain this relationship.

Learning engagement (LE) plays a crucial role in influencing the effectiveness of educational outcomes. It pertains to the concentration, engagement, and active participation of students in learning activities, and is closely associated with ongoing academic success (Fredricks et al, 2016). A previous study about the systematic review showed that ChatGPT enhances behavioral, cognitive, and emotional engagement across diverse student populations (Wang & Fan, 2025). Utilizing AI learning tools can increase engagement by providing personalized and interactive learning experiences that maintain interest and motivation. In this context, LE acts as a potential mediating variable that explains how the use of AI learning tools (AILTU) affects academic performance (AP) by reflecting the cognitive and emotional engagement of learners in their education.

It is important to highlight the role of learning engagement when assessing the influence of AI tools in academic settings as it integrates the AI's productivity and flows of learning processes together. Several researchers have concluded that students using AI-integrated learning environments tend to be more engaged and derive better results than students using non-AI-integrated environments (Chen et al, 2020; Zhao et al, 2021). For instance, research on generative AI chatbots showed improved student engagement and academic support experiences (Bimpong, B.W., 2025). These results suggest that the advantages offered by AI learning tools might stem not only from the assistance they provide, but also from the engagement they facilitate. Thus, by incorporating learning engagement into the analysis, this study seeks to elucidate the way in which AI Learning Tool Use (AILTU) affects Academic Performance (AP) as a mediating variable.

This research lies within the scope of postsecondary education where the systems are undergoing a change to embrace modern digital technologies and smart learning systems. This research takes up mediation analysis concerning the effect of using AI learning tools on academic performance through the lens of learning engagement as a mediator. In this study, AI learning tools use (AILTU), Learning Engagement (LE), and Academic Performance (AP) are employed in the direct and indirect relations among the variables using Structural Equation Modeling (SEM). The findings will be beneficial to students, instructors and decision makers in educational institutions on the appropriate use of AI tools designed for education with respect to fostering greater engagement and academic performance of students.
In summary, this study seeks to determine if AI learning tools directly enhance academic performance or if learning engagement serves as a better mediator of their influence. The study adds to the expanding body of knowledge on technology-enhanced learning and provides useful advice for maximizing the use of AI in classrooms.

OBJECTIVES OF THE STUDY

The purpose of this research is to determine the effect of AI Learning Tool Use (AILTU) on the Academic Performance (AP) of students in State Universities and Colleges (SUCs) in region 10, Philippines, with a primary focus on its mediation which is Learning Engagement (LE). It aims to understand the impact of AI tools like ChatGPT, Grammarly, and AI tutoring systems on students' scholastic performances. Specifically, this study's objectives were:

1. Determine the direct relationship between AI Learning Tool Use (AILTU) and Academic Performance (AP);
2. Assess the relationship between AI Learning Tool Use (AILTU) and Learning Engagement (LE);
3. Examine the relationship between Learning Engagement (LE) and Academic Performance (AP);

4. Analyze whether Learning Engagement (LE) mediates the relationship between AI Learning Tool Use (AILTU) and Academic Performance (AP).

SIGNIFICANCE OF THE STUDY

The purpose of this research is to assist higher education institutions understand how AI learning tools may improve student engagement and performance within the framework of the ongoing digital transformation in education. The findings will provide relevant information on the role of technology in learning processes and academic resilience during disruptions, especially for the following groups:

Students. This research may support learners in appreciating how responsible use of AI tools impacts their engagement and performance.

Teachers. The results may be useful to educators in design of teaching and learning processes that employ AI tools to enhance engagement and learning outcomes of students.

University Executives and Policy Makers. The research will help provide evidence-based evaluation on the strengths and weaknesses of AI use to inform policy, digital learning frameworks and support systems for ensuring academic continuity.

Instructional Materials and Curriculum Developers. This research will inform the design of learning modules that incorporate AI technologies based on students' and institutions' learning objectives.

Educators and Educational Institutions. The research will shape the discourse on AI in education, learners' engagement and performance, and will set the stage for strategic dialogue and collaboration between institutions

This study seeks to transform higher education by making it more adaptive, inclusive, and resilient through meaningful technology integration.

CONCEPTUAL FRAMEWORK

The particular framework applies to this study by aiding in the defining the relationships within influential variables which are the most important in the graph. It shows how AI Learning Tool Use (AILTU) is expected to influence Academic Performance (AP) through the mediating variable Learning Engagement (LE).

The University's approaches, guidelines and protocols emphasize the significance of AI Learning Tool Use (AILTU) in fostering academic development in the current educational environment. In this research, Learning Engagement (LE) is analyzed as a mediating variable that influence AILTU with Academic Performance (AP), which pertains to the academic success of college students, particularly in times of academic difficulty or disruption.

THEORETICAL FRAMEWORK

Technology Acceptance Model (TAM). To understand the interconnections of the AI Learning Tool Use (AILTU), Learning Engagement (LE), and Academic Performance (AP), study rely on four interrelated theories. Technology Acceptance Model (TAM) (Davis, 1989) contends that the acceptance and utilization of any technology is influenced by its perceived usefulness and ease of use. In educational settings, students are more likely to adopt AI tools when they believe these tools enhance their learning experience and are user-friendly factor which in turn affects engagement and academic performance (Dwivedi et al., 2021; Zhai, 2023)

Self-Determination Theory (SDT) (Deci & Ryan, 1985) highlights that motivation is influenced by satisfying three fundamental psychological needs: autonomy, competence and connection. In the realm of AI Learning Tool Use (AILTU), the independence provided by self-directed learning, instant feedback, and chances for collaborative engagement can increase Learning Engagement (LE), potentially leading to better Academic Performance (AP) (Chen et al., 2020).

The Constructivist Learning Theory suggest that learners actively build knowledge via experiential learning and social engagement in their surroundings (Piaget, 1950; Vygotsky, 1978). In this research, AI Learning Tools Use (AILTU) enhances this process by offering adaptive, engaging environments that foster critical thinking and active involvement. These attributes enhance Learning Engagement (LE), which could subsequently impact Academic Performance (AP) (Holstein et al., 2019; Zhao et al., 2021).

Lastly, the Cognitive Load Theory (CLT) (Sweller, 1988) emphasizes the significance of reducing unnecessary cognitive load to enhance learning. AI Learning Tools Use (AILTU) facilitate this by streamlining intricate information, providing prompt support and personalizing content to meet learners' requirements, thus enhancing cognitive efficiency and understanding (Labadze et al., 2023). Collectively, these four theories establish a unified framework for comprehending how AILTU affects Learning Engagement (LE) and, in the end, Academic Performance (AP) in higher education.

STATEMENT OF THE PROBLEM

The study aims to know the effectiveness of AI Learning Tool Use (AILTU) at the State Universities and Colleges (SUCs) in region 10, Philippines. Specifically, this study seeks to answer the following questions:

1. Assess the level AI Learning Tool Use (AILTU), Learning Engagement (LE) and Academic Performance (AP) among students in State Universities and Colleges in Region 10.
2. Examine how AI Learning Tool Use (AILTU) significantly influence Academic Performance (AP).
3. Determine whether AI Learning Tool Use (AILTU) significantly influence Learning Engagement (LE).
4. Assess the extent to which Learning Engagement (LE) significantly influence Academic Performance (AP).
5. Test whether Learning Engagement (LE) Significantly mediates the relationship between AI Learning Tool Use (AILTU) and Academic Performance (AP).

Research Hypotheses:
The following hypotheses are tested in this study:
H^1. AI Learning Tool Use (AILTU) significantly influences Academic Performance (AP).
H^2. AI Learning Tool Use (AILTU) significantly influences Learning Engagement (LE).
H^3. Learning Engagement (LE) significantly influences Academic Performance (AP).
H^4. Learning Engagement (LE) significantly mediates the relationship between AI Learning Tool Use (AILTU) and Academic Performance (AP).

The hypothesized framework illustrating the relationships among the variables is presented in Figure 1.

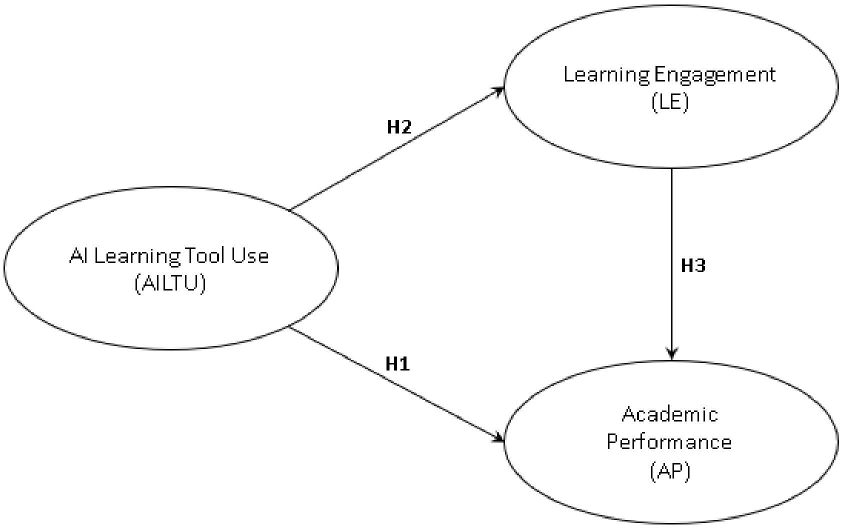

FIGURE 1. Hypothesized Framework of the Study

METHODOLOGY

RESEARCH DESIGN

This research implements a quantitative approach through Structural Equation Modeling (SEM) to analyze the AILTU, Learning Engagement (LE) as a mediating variable, and Academic Performance (AP) of college students from the State Universities and Colleges (SUCs) in Region 10, Philippines. The study combines descriptive and correlational research designs. The descriptive design aims to capture the frequency and contexts in which students utilize AI Learning Tools in educational settings.

The correlational design examines the magnitude and direction of the relationship AILTU shares with other variables such as LE and AP. More importantly, this study uses SEM to evaluate the direct and indirect relationships (through mediation) among the variables. SEM is fit for the focus of this study as it enables simultaneous testing of several relationships and mediation paths, which is appropriate for intricate structures with latent variables like engagement and performance.

Structural Equation Modeling (SEM) was utilized to statistically confirm the suggested mode, particularly regarding how Learning Engagement (LE) functions as a mediator between the AI Learning Tool Use (AILTU) and the Academic Performance (AP). This corresponds with the study's aim to evaluate both the direct effect of AILTU on academic performance and to investigate how this effect functions through student involvement.

This approach is closely aligned with practices in educational technology and behavioral research, where multivariate modeling and theory testing are crucial. Hence, applying SEM acts as a holistic analytical approach that improves the reliability, validity, and explanatory efficacy of the study's results in the context of SUCs in Region 10, Philippines.

PARTICIPANTS OF THE STUDY

The respondents of this research were university college students attending the State Universities and Colleges (SUCs) in Region 10, Philippines. Inclusion was restricted to students who had previous experience with AI learning tools which was confirmed through a screening question, a convenience sampling approach was utilized and information was gathered through google form. Only those who selected "Yes" were qualified to proceed, indicating both their eligibility and acknowledgement of the informed consent, privacy terms, and confidentiality of their responses. The questionnaire was distributed via institutional group chats, academic networks and student discussion platforms. Out of the total participants, 156 filled out the forms accurately which was then used for the analysis.

Since students are the main users of AI learning tools in educational settings, they were chosen as the exclusive respondents to guarantee that the data represented first and user experience. Their viewpoints offered essential insights into the use of AI Learning Tools, Learning Engagement (LE), and Academic Performance (AP). Choosing only students as respondents guarantees that the data has been drawn transparently from experiences of interacting with AI tools for learning which ensures reliability and validity pertaining to the value and effectiveness of the technology.

Study subjects were briefed regarding the aim of the study, the voluntary nature of their participation, and confidentiality. Informed consent was collected prior to the commencement of the survey which takes into account ethical standards. The information provided from this group would help achieve the objective of exploring the mediating effect of Learning Engagement on AI Learning Tool Use (AILTU) and Academic Performance.

POPULATION SAMPLING

In this study, participants were selected using convenience-voluntary sampling. The respondents were the students who are enrolled in the different State Universities and Colleges (SUCs) in Region 10, Philippines. This sample method was preferred because it is easy as well as practical in terms of quantitative data collection in the SUCs setting.

Assessment regarding sample size adequacy was done through statistical power and minimum sample size estimation feature available in WarpPLS 8.0. The calculated minimum absolute significance path coefficient of 0.414 at a 0.05 significance level and 0.80 strength of statistical power indicated that the sample size minimum had to be at least 23-37 according to the Gamma-exponential method and inverse square root method. The number of respondents which was 156 was already above this limit, thus guaranteeing adequate statistical power for the PLS-SEM analysis.

To promote full participation by students from diverse academic programs and levels, an open Google Form survey was shared, which facilitated the sampling process. This method provided a representative sample of students and an understanding of their experience with AI Learning Tool Use (AILTU) and its impact on Learning Engagement (LE) and Academic Performance (AP).

DATA ANALYSIS

Students' AI Learning Tool Use (AILTU) affects their academic performance (AP) directly and indirectly through Learning Engagement (LE) and for trying out predictive hypotheses correlational design of this study is for quantitative reasoning.

Descriptive statistics were computed for the participants' self-reported responses using means and standard deviations. These initial analyses provided a baseline understanding of AI Learning Tool Use (AILTU), Learning Engagement (LE), and Academic Performance (AP). Following this, both the measurement and structural models were evaluated in accordance to the guidance of WarpPLS 8.0 (Kock, 2020) with PLS-SEM. As a method of choice, PLS-SEM was selected for its suitability in handling complex models with latent variables and at the same time being fit for research with moderate to small sample sizes (Hair et al., 2021).
The criteria for measurement model evaluation includes:
[1] Internal consistency reliability calculated by means and composite reliability value with acceptance benchmarks of minimum ≥70, through Cronbach's alpha. [2] Convergent validity which can be controlled on the mean variance extracted presented with values adequate ≥.50. [3] Discriminant was determined through the ratio of Heterotrait-Monotrait (HTMT), with benchmark acceptable values between ≤ 85.

For the structural model explanation, included is the [1] estimation of path coefficients and along with the level of significance (p-values) and size effects (Cohen's f^2) to determine both direct effects (AP, AILTU → LE; AILTU → AP; LE → AP) and indirect (mediated) effects. [2] Model evaluation of goodness fit employed as a measure of multicollinearity include Average Path Coefficient (APC), Average R-squared (ARS), Adjusted R-squared (AARS), Tenenhaus' Gof, and Average Variance Inflation Factor (AVIF). [3] Evaluation of the mediating role of Learning Engagement on the relationship between AILTU and Academic Performance was carried out by evaluating direct and indirect effects.

RESEARCH INSTRUMENT

The survey instrument for this study was developed based on previous works concerning AI Learning Tool Use (AILTU), Learning Engagement (LE), and Educational Performance (EP) within the academic context. The primary constructs were sourced from the Technology Acceptance Model (TAM) (Davis, 1989), Self Determination Theory (SDT) (Deci & Ryan, 1985), and other relevant literature regarding student engagement and academic performance. These constructs were adapted from Smutny and Schreiberova's (2020) educational chatbot scale, Chen, Chen, and Lin's (2020) AI in education instrument, and Labadze et al.'s (2023) measures of AI impact on learning outcomes, and modified to suit the context of State Universities and Colleges in Region 10 to fit the higher education context considering the application of AI learning tools by students in the Region 10 State Universities and Colleges (SUCs).

The instrument was subdivided into three latent constructs, which are: [1] AI Learning Tool Use (AILTU); [2] Learning Engagement (LE); and [3] Academic Performance (AP). The respondents were provided with a four-point Likert scale for each statement to quantify their level of agreement with the given items, which was tailored to students. In addition, several questions focused on the perceived influence of AI learning tools on academic performance and engagement were included.

A validation process was conducted to guarantee the validity and reliability of the instrument. Even the internal consistency measures using Cronbach's Alpha (CA) and Composite Reliability (CR) achieved the recommended level of 0.70 for all constructs. Convergent validity was confirmed through average variance extracted (AVE) values which were all above the accepted level of 0.50. In addition, discriminant validity through the Fornell-Larcker Criterion and the Heterotrait-Monotrait (HTMT) ratio was confirmed which means that the constructs were not overly correlated and were indeed distinct.

Within the context of Partial Least Squares – Structural Equation Modeling (PLS-SEM) with WarpPLS 8.0 (Kock, 2020; Hair et al., 2021), a Confirmatory Factor Analysis (CFA) was conducted. Supporting the convergent validity of the measurement model, all item factor loadings were above the minimum threshold of 0.70.

To be appropriate for the educational context of the university, the expertise of the domain in technology-enhanced education and academic achievement were engaged to review the questionnaire for conceptual clarity and contextual relevance. Their input led to better item formulation for the respondents targeted that was correct and unambiguous.

DATA COLLECTION

The survey was conducted using Google Forms which allowed for convenient and anonymous participation. Clear guidelines were provided, detailing the study's goal, defining important concepts, and explaining the significance of each section from the respondents' perspective. Following RA 10173 (the Data Privacy Act of 2012), the survey also contained a confidentiality clause stating that the information collected would be for strict research purposes only and that the responses would be handled confidentially.

This questionnaire was adapted from Smutny and Schreiberova's (2020) educational chatbot scale, Chen, Chen, and Lin's (2020) AI in education instrument, and Labadze et al.'s (2023) measures of AI impact on learning outcomes, and modified to suit the context of State Universities and Colleges in Region 10, Philippines.

ETHICAL CONSIDERATIONS

The informed consent of the participants was provided with a clear information about the purpose of the study, procedures and the right to withdraw at any time if the respondents felt uncomfortable about the questionnaires. There was a written informed consent obtained or stated from all the respondents of the study before they completed the survey. A Statement included in the questionnaire emphasized that participation was voluntary and the respondents could withdraw anytime. The confidentiality of the responses from respondents were strictly kept confidential. Identifiable information was removed to protect the respondents' privacy. The data was securely stored with the password-protected files and only accessible only to authorized person. In compliance with the RA 10173 or the Data Privacy Act of 2012, respondents were informed that the data would be used solely for the purpose of research and handled in strict confidentiality. The survey questionnaire was designated to be non-invasive and respectful to the respondents' time and perspectives.

RESULTS AND DISCUSSION

This subsection provides a detailed explanation of the analysis and its results, starting with the descriptive statistics and subsequently PLS-SEM using WarpPLS 8.0 (Kock, 2020) for estimating the measurement and structural models (Hair et al., 2021).

Assessment of internal consistency (Cronbach's alpha, composite reliability ≥ 0.70) and convergent validity (AVE≥0.50) alongside the discriminant validity using the HTMT ratio and Fornell–Larcker criterion were included as part of the measuring model.

The assessment of the structural model was done using path coefficients (AILTU→ LE, LE → AP, AILTU → AP), p-values, standard errors, effect sizes to assess both direct and indirect (mediated) effects. Additionally, model fit and quality indices−Average Path Coefficient (APC) Average R-Squared (ARS), Adjusted ARS (AARS), Tenenhaus Goodness-of-Fit, and Average Variance Inflation Factor (AVIF)—were calculated to determine the overall strength, adequacy, and trustworthiness of the proposed mediation model.

DESCRIPTIVE STATISTICS

The mean scores of the demographic profile and the three constructs, [1] AI Learning Tool Use (AILTU); [2] Learning Engagement (LE); and [3] Academic Performance (AP), were calculated to assess the overall levels. The results for each construct are further interpreted to provide a detailed understanding of the data results. The research by Labadze et al.'s (2023) emphasizes the importance of integrating effective learning tools in the educational framework, which is similar to the strategies employed in the AI Learning Tool Use (AILTU) framework. The findings support that student engagement with AI tools enhances learning outcomes, which aligns with the study's goal of assessing the effectiveness of AILTU in improving academic performance. The summary of student responses regarding AI Learning Tool Use (AILTU) is presented in Table 1.

TABLE 1. Descriptive Statistics for AI Learning Tool Use (AILTU)

Construct / Item	N	Mean	Std. Deviation	Interpretation
1. I regularly use AI tools (ChatGPT, Grammarly, Quillbot, etc.) for academic purposes.	156	3.083	.5675	High
2. AI tools help me better understand difficult topics.	156	3.282	.5180	Very High
3. I feel confident in using AI tools to assist my learning.	156	2.955	.6559	High
4. I find AI tools helpful in completing assignments or projects.	156	3.064	.5976	High
5. I use AI tools when preparing for exams or quizzes.	156	2.590	.7609	High
6. I think AI tools improve the way I study.	156	2.859	.6763	High
Overall AI Learning Tool Use	**156**	**2.972**	**.4763**	**High**

Note(s): AILTU = Artificial Intelligence Learning Tool Use

With an average mean score of 2.972, students showed a strong level of engagement with AI Learning Tools. Students frequently utilize platforms like ChatGPT, Grammarly, and Quillbot to assist with academic work such as assignments, study preparation and assessments. Among the items, the most highly rated use was for improving comprehension of difficult topics (M=3.282), whereas the least favored was for exam preparation (M=590). These results suggest that students are strategically integrating AI tools into their study habits, especially to enhance conceptual comprehension and support coursework. This aligns with research conducted by Amzat et al. (2022) and Labadze et al.'s (2023), which emphasize that students utilizing AI tools for learning often demonstrate enhanced comprehension and efficiency in completing tasks. Following this, the descriptive statistics for Learning Engagement (LE) are shown in table 2.

TABLE 2. Descriptive Statistics for Learning Engagement (LE)

Construct / Item	N	Mean	Std. Deviation	Interpretation
1.AI tools make learning more engaging for me.	156	2.968	.6664	High
2.I feel more motivated to study when I use AI tools.	156	2.679	.7448	High
3.I stay focused longer when studying with AI support.	156	2.654	.7419	High
4.I am more active in learning activities when AI tools are involved.	156	2.635	.7102	High
5.AI tools encourage me to put more effort into my schoolwork.	156	2.737	.7879	High
6.I enjoy studying more when AI tools are part of the process.	156	2.731	.7215	High
Overall Learning Engagement	**156**	**2.734**	**.6201**	**High**

Note(s): LE = Learning Engagement; AI = Artificial Intelligence

All respondents showed high levels of Learning Engagement (LE) as indicated with individual item mean scores between 2.635 to 2.968 and an overall mean score of 2.734. These findings support that AI tools help sustain student interest and involvement in learning activities. The highest-rated item which is "AI tools make learning more engaging for me", aligns with findings by Chaudhary et al. (2024), who emphasized that AI integration fosters learner motivation and deeper cognitive participation. Other items showed increased motivation, focus, enjoyment, and effort towards schoolwork with the use of AI tools which reinforces the mediating influence of Learning Engagement in the study. The consistently "High" rating interpretation across all items indicates that AI tools enhance students' active participation as well as their emotional engagement in academic tasks. This supports Aquino and Arboleda's (2022) view that engagement is shaped by context, tool interactivity, and perceived learning value. As such, these results are consistent with the study's hypothesis that Learning Engagement is fundamental in mediating the AI tool use and academic performance relationship. Subsequently, the students' self-reported Academic Performance (AP) is summarized in Table 3.

TABLE 3. Descriptive Statistics for Academic Performance (AP)

Construct / Item	N	Mean	Std. Deviation	Interpretation
1.My academic performance has improved since I started using AI tools.	156	2.910	.6463	High
2.I can finish academic tasks faster with the help of AI tools.	156	3.141	.5382	High
3.I get better results in quizzes and assignments when I use AI tools.	156	2.782	.6937	High

4.AI tools help me achieve higher grades.	156	2.731	.7125	High
5.I feel more prepared in class when I use AI tools for review.	156	2.795	.7159	High
6.My confidence in performing well academically has increased because of AI tools.	156	2.827	.7017	High
Overall Academic Performance	**156**	**2.864**	**.5381**	**High**

Note(s): AP = Academic Performance; AI = Artificial Intelligence

All aspects of Academic Performance (AP) evaluated AI tools between 2.731 and 3.141, with an overall mean score of 2.864. As per the responses, AI tools significantly aided respondents in achieving desired academic outcomes. The highest-rated item which is "I can finish academic tasks faster with the help of AI tools" (M=3.141) supports findings by Amzat et al. (2022), who noted that AI integration can enhance time efficiency and academic outcomes, especially in an open and distance learning contexts.

Furthermore, students indicated enhancements in quiz and assignment scores, readiness for class, and self-assurance in academics when they use AI learning tools. This is consistent with Strzelecki (2023), who found that AI tools can greatly enhance students' self-regulation and academic performance in eLearning settings. These results highlight that the use of AI Learning Tools (AILTU) positively influences students perceived academic performance, affirming the validity of the construct within the model. Additionally, the consistent "High" perception across all items indicates a shared conviction among students that AI boosts both their performance and self-assurance, reinforcing the beneficial impact of AI-enhanced learning settings (Alzahrani, 2023). These results confirm the proposed connection between AILTU and AP, further framing AI tools as beneficial educational interventions in higher education.

MEASUREMENT VALIDITY AND RELIABILITY

The measurement model's reliability and validity were evaluated considering item loadings, Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (CA). Each construct must achieve a minimum value of 0.70 for both Composite Reliability (CR) and Cronbach's Alpha (CA), as well as a value over 0.50 for Average Variance Extracted (AVE) (Fornell & Larcker, 1981; Nunnally 1978; Nunnally & Bernstein, 1994; Kock, 2017; Kock & Lynn, 2012). Meeting these thresholds confirms high reliability, internal consistency, and validity of the measurement model. In continuation, the reliability and validity results from the Confirmatory Factor Analysis are displayed in Table 4.

TABLE 4. Confirmatory Factor Analysis (CFA) Showing Validity and Reliability of Constructs

Construct / Item	Item loading	AVE	CR	CA
AI Learning Tool Use		0.572	0.889	0.850
AILTU 1	0.751			
AILTU 2	0.764			
AILTU 3	0.841			
AILTU 4	0.706			
AILTU 5	0.742			
Learning Engagement		0.724	0.940	0.924

LE 1	0.809			
LE 2	0.868			
LE 3	0.866			
LE 4	0.874			
LE 5	0.823			
LE 6	0.863			
Academic Performance		0.644	0.915	0.887
AP 1	0.803			
AP 2	0.642			
AP 3	0.820			
AP 4	0.884			
AP 5	0.829			
AP 6	0.815			

Note(s): AILTU = Artificial Intelligence Learning Tool Use; LE = Learning Engagement; AP = Academic Performance; AVE = Average Variance Extracted; CR = Composite Reliability; CA = Cronbach's Alpha; CFA = Confirmatory Factor Analysis

Table 4 includes the output of the Confirmatory Factor Analysis (CFA) for the three constructs employed in the study, namely: AI Learning Tool Use (AILTU), Learning Engagement (LE), and Academic Performance (AP). CFA calculations involve item loadings together with the Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (CA) which evaluate validity and reliability of the constructs.

AILTU demonstrated measurement item loadings ranging from 0.706 to 0.841 with an AVE of 0.572, CR of 0.889 and CA of 0.850. All exceeded convergence validation thresholds (AVE > 0.50, CR > 0.70, CA > 0.70; a significant level of validity was AILTU's lower bounds confirming convergent validity and internal consistent reliability for the construct).

For Learning Engagement (LE), item loadings ranged from 0.809 to 0.874. The values of AVE were 0.724 while CR and CA was 0.940 and 0.924 respectively. The internal consistency and validity were remarkably strong and without question, LE's indicators upon review, were confirmed to effectively measure the latent construct of learning engagement.

The results of the AP construct show item loadings ranging from 0.642 to 0.884 and maintaining an AVE at 0.644, CR at 0.915 and a CA of 0.887. With such results the hypothesis can align positively as the results gathered were still within required margins thus supporting the construct's reliability and convergent validity.

In general, all three constructs studied: AI Learning Tool Use, Learning Engagement, and Academic Performance are found to be valid and reliable. The instrument's effectiveness in capturing the intended variables is greatly supported by high item loadings of AVE, CR, CA values, confirming the extent of the structural model and hypotheses validity as supported. To examine further, the discriminant validity assessed using the Fornell and Larcker Criterion is shown in Table 5.

TABLE 5. Discriminant Validity Using Fornell and Larcker Criterion (Square Roots of AVE Coefficients and Correlation Coefficients)

	AILTU	LE	AP
AILTU	**0.757**		
LE	0.648	**0.851**	
AP	0.738	0.726	**0.802**

AILTU = Artificial Intelligence Learning Tool Use; LE = Learning Engagement; AP = Academic Performance. Diagonal elements are the square root of AVE of constructs, whereas the off-diagonal elements are the correlation between constructs.

Table 5 illustrates the results from the evaluation of discriminant validity using the Fornell and Larcker Criterion. The diagonal entries of the matrix are the square roots of the Average Variance Extracted (AVE) for the constructs: AI Learning Tool Use (AILTU) = 0.757, Learning Engagement (LE) = 0.851, and Academic Performance (AP) = 0.802. The off-diagonal elements represent the correlation coefficients between the constructs.

As all diagonal values exceeded the corresponding off-diagonal values in both rows and columns, the Fornell and Larcker criterion is satisfied. This ascertains that all constructs in the study are separate and have sufficient discriminant validity. Thus, AI Learning Tool Use, Learning Engagement, and Academic Performance are statistically distinct from each other and effectively captured within the model. To further examine, the HTMT ratio results further confirming discriminant validity are presented in Table 6.

TABLE 6. Discriminant Validity using HTMT Ratio of correlations

	AILTU	LE	AP
AILTU	—	0.729	0.851
LE		—	0.800
AP			—

AILTU = Artificial Intelligence Learning Tool Use; LE = Learning Engagement; AP = Academic Performance. Values above 0.90 may indicate a lack of discriminant validity; HTMT = Heterotrait-Monotrait

Table 6 includes the Heterotrait-Monotrait (HTMT) ratio of correlations which measures discriminant validity across the constructs of the study. All HTMT values rest below the cutoff of 0.90 which is often cited as the maximum or upper bound of discriminant validity (Henseler et al., 2015). More specifically, the HTMT ratio of AI Learning Tool Use (AILTU) and Learning Engagement (LE) is 0.729, with AILTU and Academic Performance (AP) 0.851, and LE and AP 0.800.

This result indicates that the constructs; AI Learning Tool Use (AILTU), Learning Engagement, and Academic Performance (AP) are empirically different but adequately connected, offering satisfactory proof of discriminant validity within the framework. The observed correlations reflect strong construct validity, confirming that each latent variable measures its intended concept while maintaining theoretical coherence across structural model.

Detailed Hypotheses for Structural Model Analysis: H^1. AI Learning Tool Use (AILTU) significantly influences Academic Performance (AP); H^2. AI Learning Tool Use (AILTU) significantly influences Learning Engagement (LE); H^3. Learning Engagement (LE) significantly influences Academic

Performance (AP); and H[4]. Learning Engagement (LE) significantly mediates the relationship between AI Learning Tool Use (AILTU) and Academic Performance (AP). The structural model with the corresponding parameter estimates is presented in table 7 and illustrated in Figure 2.

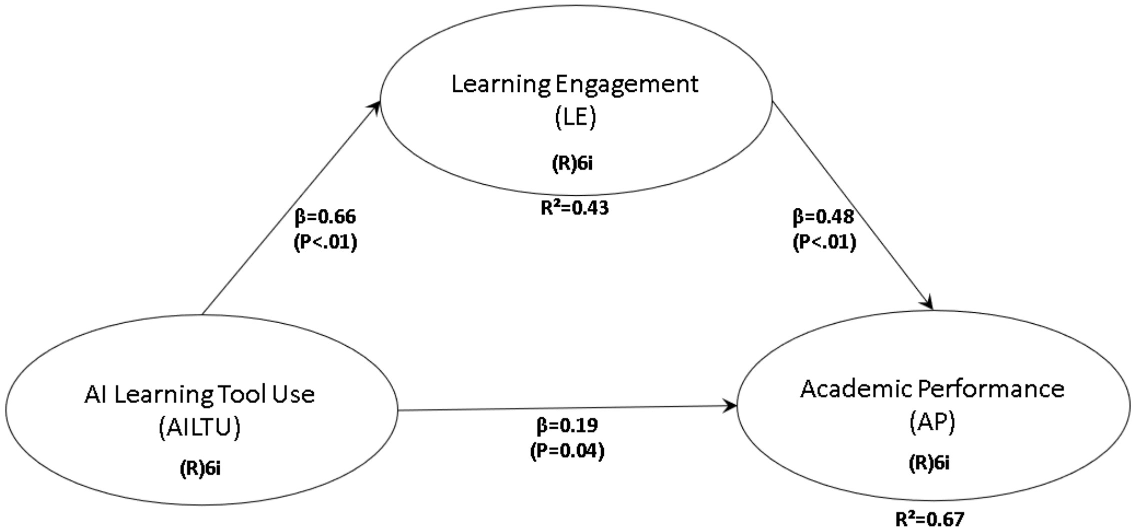

FIGURE 2. The Structural Model with Parameter Estimates

Partial Least Squares (PLS)-Path Model

TABLE Figure 2 and Table 7 show the structural model with significant path coefficients and parameter estimates from the Partial Least Squares (PLS) analysis performed with Warp-PLS. These findings demonstrate the tested correlations among the constructs using the hypothesized model.

TABLE 7. Parameter Estimates for Hypotheses Testing in the Structural Equation Model

Hypotheses	***β***	***P-value***	***SE***	***f^2***
H[1]. AILTU → AP	0.414	<0.001	0.073	0.307
H[2]. AILTU → LE	0.656	<0.001	0.069	0.430
H[3]. LE → AP	0.480	<0.001	0.072	0.367

Note(s): AILTU = Artificial Intelligence Learning Tool Use; LE = Learning Engagement; AP = Academic Performance; SE = Standard Error; f^2 is the effect size (Cohen. 1988) where 0.02 = small, 0.15 = medium, 0.35 = large

The result of hypothesis testing through structural equation modeling is provided in Table 7. All three relationships (H[1], H[2], and H[3]) remain within the bounds of the model at $p < .001$ level of significance, meaning they are all supported by the evidence and strongly support the model.

In the case of H[1], the AI Learning Tool Use (AILTU), positively and significantly influences Academic Performance (AP), with the standardized path coefficient $\beta = 0.414$, $p < .001$, and a medium effect size of $f^2 = 0.307$. This finding implies that students who utilize AI learning tools diligently and effectively tend to demonstrate better academic outcomes. This finding aligns with the prior study emphasizing that AI-driven platforms can improve student performance by providing personalized assistance, facilitating task execution and supporting understanding of complex content (Amzat et al., 2022; Alzahrani, 2023). The alignment of these results with the current research strengthens the case that AI tools significantly enhance academic success in higher education environments.

H^2 demonstrates that AI Learning Tool Use (AILTU) possesses a strong and statistically significant positive effect on Learning Engagement (LE) with a standardized coefficient of $\beta = 0.656$, $p < .001$, and a large effect size of $f^2 = 0.430$. This means that students who regularly incorporate AI tools into their educational practices are likely to show increased levels of engagement in learning activities. This outcome supports previous findings that AI-driven tools enhance student engagement, motivation and cognitive participation by providing adaptive feedback and personalized learning experience (Chaudhary et al., 2024; Heung & Chiu, 2025; Akgun & Greenhow, 2021). The significant level of engagement noted in this study emphasizes AILTU's crucial role in promoting active and meaningful student engagement in the educational experience.

H^3 indicates that Learning Engagement (LE) has a positive significant effect on the Academic Performance (AP) of a students with $\beta = 0.480$, $p < .001$, and large effect size of $f^2 = 0.367$. This affirms the hypothesis that learners who invest more effort into learning activities generally achieve higher academic results. This reinforces prior findings that emotional and cognitive engagement significantly enhances academic performance (Fredricks et al., 2004; Chaudhary et al., 2024). AI tools that foster engagement through interactive and personalized support have been shown to enhance both motivation and academic outcomes (Chen et al., 2020; Heung & Chiu, 2025).

Overall, the results support the hypothesis that Learning Engagement serve as a mediator in the relationship between AI Learning Tool Use (AILTU) and Academic Performance (AP) which suggests that both technology utilization and student engagement enhance academic results. The direct and indirect effects from mediation analysis are summarized in Table 8.

TABLE 8. Direct and Indirect (Mediating) Effects in the Structural Equation Model (Path coefficients, p-values, standard errors, effect sizes)

Hypotheses	***β***	***P-value***	***SE***	***f²***
H^1. AILTU → AP	0.414	<0.001	0.073	0.307
H^2. AILTU → LE	0.656	<0.001	0.069	0.430
H^3. LE → AP	0.480	<0.001	0.072	0.367
Indirect Effect				
H^4. AILTU → LE → AP	0.315	<0.001	0.005	0.158

Note(s): AILTU = Artificial Intelligence Learning Tool Use; LE = Learning Engagement; AP = Academic Performance; SE = Standard Error; f² is the effect size (Cohen. 1988) where 0.02 = small, 0.15 = medium, 0.35 = large

Table 8 presents the structural model's direct and indirect effects focusing on the impact of an AI Learning Tool Use (AILTU) on an Academic Performance (AP), considering Learning Engagement (LE) as a mediating variable. The findings confirm AILTU significantly predicts both Learning Engagement (LE) and Academic Performance (AP), and also that Learning Engagement (LE) exerts a strong positive influence on Academic Performance (AP), thus confirming the first three hypotheses.

Furthermore, mediation analysis (H^4) reveals a significant indirect effect of AILTU on AP through LE ($\beta = 0.315$, $p < .001$, $f^2 = 0.158$), thus confirming that LE partially mediates the effect of AILTU on AP. This supports the hypothesis regarding the model's premise that using AI tools enhances academic performance by improving engagement. Subsequently, the overall model fit and quality indices of the SEM analysis are displayed in Table 9.

TABLE 9. Model Fit and Quality Indices (APC, ARS, AARS, AVIF, AFVIF, Tenenhaus Goodness-of-fit)

Model fit and Quality indices	Coefficients
APC	0.517, $p < 0.001$
ARS	0.552, $p < 0.001$
AARS	0.548, $p < 0.001$
AVIF	1.873
AFVIF	2.479
Tenenhaus GoF	0.597

APC – average path coefficient; ARS – average r-squared; AARS – average adjusted r-squared; AVIF – average block variance inflation factor; AFVIF – average full collinearity VIF; Tenenhaus GoF – Tenenhaus goodness of fit.

Table 9 shows the results of the model fit and quality indices for the structural equation model within the scope of the study are included. The metrics mentioned above suggest that the Average Path Coefficient, Average R-Squared, and Average Adjusted R-Squared Tests: APC = 0.517, p value < 0.001, ARS = 0.552, p value < 0.001, AARS = 0.548, p value < 0.001 are above the accepted threshold of significance implying that the model fits the data considerably well; moreover, the remaining indices confirm the validity of the explanatory power of the model regarding the covariance of the independent variables in the dependent variables that explain the observed data.

The model is therefore useful given that the AVIF = 1.873 and AFVIF = 2.479, both below the widely accepted limit of 5.00 show that multicollinearity remains within reasonable tolerable limits meaning that the constructs within the model are not overly correlated, permitting the estimated path relationships to be strong and stable.

Moreover, Tenenhaus GoF indicates goodness of fit measuring with a limit of GoF = 0.597 gives low GoF range yielding profound insights into empirical data whilst basing the anchor on the provided theoretical outline reinforcing the overall strong fit of the model with provided metrics.

To sum up, the described fit indices verify the model's structure with respect to AI Learning Tool Use (AILTU), Learning Engagement (LE), and Academic Performance (AP), which appears to be in accordance with the initial expectations. The findings suggest that the model is valid in terms of the underlying framework and provides a useful assessment of the impacts of AI educational tools on academic metrics through the involvement level of the students as an engagement. Following this, the collinearity statistics, coefficient of determination (R^2), and predictive validity (Q^2) are shown in Table 10.

TABLE 10. Full Collinearity Variance Inflation Factor (FCVIF), Coefficient of Determination (R2), and Predictive Validity (Q2)

Constructs	Full Collinearity VIF	R^2	Q^2
AILTU	2.330		
LE	2.246	0.430	0.434
AP	2.860	0.674	0.674

AILTU = Artificial Intelligence Learning Tool Use; LE = Learning Engagement; AP = Academic Performance.

Table 10 shows results of full collinearity variance inflation factor (FCVIF), R^2, and Q^2 to evaluate informational quality and value of the structural equation model as recommended by Kock (2015). The FCVIF values for AI Learning Tool Use (AILTU=2.330), Learning Engagement (LE=2.246), and Academic Performance (AP=2.860) were all below the threshold of 5.0, indicating multicollinearity is not an issue, common method bias does not exist, and there is no evidence of averted bias.

AILTU demonstrated explanatory power by accounting for 43% of the variance in LE (R^2 = 0.430). In addition, AILTU and LE together explain 67.4% of the variance in AP (R^2 = 0.674). These numbers in the context of behavioral research have been characterized as moderately to highly explanatory (Hair et al., 2019). From the perspective of predictive relevance, LE (Q^2 = 0.434) and AP (Q^2 = 0.674) both surpassed the threshold of 0.00, thus providing strong evidence for the model's predictive accuracy and theoretical plausibility. These outcomes further confirm the model's robustness in explaining and forecasting the academic performance results that are mediated by the learning engagement in AI-supported contexts.

Overall, the findings corroborate that the model is able to explain and predict behaviors with a high degree of accuracy. The AI Learning Tool Use (AILTU) adds value to comprehending the variance in the Academic Performance (AP) both directly and indirectly through mediation of Learning Engagement (LE), demonstrating the structural validity of the proposed model.

DISCUSSION

The outcomes of the structural equation model strongly validated the assumptions concerning the relationship between AI Learning Tool Use (AILTU), Learning Engagement (LE), and Academic Performing (AP). In particular, AILTU had a marked direct positive impact on AP (β = .414, $p < .001$, f^2 = .307) and on LE (β = .656, $p < .001$, f^2 = .430). Furthermore, LE also had a positive impact on AP, which was also significant (β = .480, $p < .001$, f^2 = .367). Additionally, the indirect impact of AILTU through LE on AP was also significant (β = .315, $p < .001$, f^2 = .158), which demonstrates that LE partially mediates the effect of AILTU on AP. These results support claims that suggest higher and more confident activity with AI learning tools contributes positively to students' academic performance directly applicable outcomes and indirectly through enhanced engagement with the process (Holstein et al., 2019).

With regards to State Universities and Colleges in Region 10, this trend seems to indicate attempts by institutions to incorporate AI training and support into the aids used for digital learning. Efforts such as dedicated workshops on ChatGPT best practices, Grammarly being assigned to writing labs, and the use of AI powered modules in learning management systems seem to have enabled students to use these tools automatically. The strong significant relationship between AI Learning Tool Use (AILTU) and Learning Engagement (LE) suggests that these initiatives are effective in turning technical training into meaningful learning experiences that promote active student participation (Sung et al., 2016; Zhai, 2023).

Prior studies validate the strongly asserted claims about the importance of perceived usefulness and ease of use in technology adoption. Students' beliefs concerning the AI tool's usefulness and ease of employing it guides the utilization behavior as per the Technology Acceptance Model (Davis, 1989). In this case, the findings help extend the model in question by illustrating that AILTU leads to greater engagement but also measurable performance improvement. This is consistent with Dwivedi et al. (2021) findings where positive perceptions of a technology were correlated with engagement and learning outcomes.

The mediated role of Learning Engagement (LE) in this study corresponds with the autonomy and competence dimensions of Self-Determination Theory (Ryan & Deci, 2000). Remotely guided feedback empowers learners with control over the pace of their learning while ensuring timely access to instructional input. This sense of autonomy and competence supports the fulfillment of basic psychological needs, which promotes engagement (Chaudhary et al., 2024; Chen et al., 2020). Increased engagement also leads to more profound cognitive processing which enhances the academic performance and achievement outcomes (Fredricks et al., 2016).

With 85% of respondents being undergraduates' students enrolled in AI-driven courses; their opinions reflect practical experiences of the implementation of AILTU practices. While this subset of perspectives represents students most immediately impacted by AI-driven tools, future research should purposefully involve faculty and administrative staff to broaden the understanding of AI adoption and its broader effects on institutional practices and outcomes.

These results support the continued investment towards more forms of systemic AILTU support and to professional development activities. Maintenance of high engagement and performance levels can be achieved through regular refresher trainings, peer mentoring focused on advanced prompt design, and curriculum redesign that incorporates the use of AI tools (Smutny & Schreiberova, 2020).

This study is based on self-reported AILTU, LE and AP by students. Holstein et al. (2019) and Labadze et al.'s (2023) suggest looking beyond these boundaries to explore other organizational elements like leadership dedication to digital innovation, resources, and level of technical infrastructure that can influence the existing relationships. Furthermore, more work is needed to understand the long-term effects of AILTU on learning and academic pathways with longitudinal studies.

CONCLUSION

The findings of this research suggest that AI Learning Tool Use (AILTU) has a direct effect on Learning Engagement (LE) and Academic Performance (AP) of the students. The research further shows that increased AILTU results in higher student engagement which positively affects the students' academic performance. This data highlights the importance of AI learning tools in the context of student participation as well as in achieving academic success. Additionally, the findings suggest that using AI learning tools enhances the students' learning experience during the class session and improves their academic performance in the long run.

The research emphasizes the need to integrate AI learning tools in teaching technology as they are capable of increasing students' engagement and performance, thus enabling success in the academic system. The recently conducted research provides insights about the development of AI learning systems in helping digitalized learning in students' performance, and productive growth to achieve a well-rounded development.

FINDINGS SUMMARY

This study received data indicating a positive relationship between AI Learning Tool Use (AILTU) and two factors: Learning Engagement (LE), and Academic Performance (AP). Moreover, the statistical analyses suggest AI learning tools enhances accessibility to learning resources, which in turn increase student engagement and leads to improve academic outcomes. LE play a significant mediating role, highlighting the importance of AI-driven tools in promoting engagement and academic success in higher education.

IMPLICATIONS FOR PRACTICE

The findings draw attention to the need for strengthening educational practices with AI learning tools to improve the learning outcomes. Adoption AI tools should be prioritized especially in ways that significantly enhance the engagement of learners to improve their overall performance even when there are adverse learning conditions. There are still some educational institutions that because of irregular updates and inadequate access to sufficient training resources face barriers in realizing the full benefits of AI learning tools within education system frameworks. Similar to other industries such as healthcare and corporate training (Almasri et al., 2024), this study shows that these institutions must eliminate barriers to the implementation of AI in education if they are to reap the benefits. Bozkurt et al. (2021) emphasized that such technologies can only retained their value in practice if academic programs are actively revised to integrate specialized AI training coupled with relevant professional development activities.

RECOMMENDATIONS FOR INSTITUTIONS

To fully take advantage of AI in higher education, institutions need to put in place specific strategies. These strategies should promote effective use, improve accessibility, and integrate AI learning tools throughout academic settings: [1] *Mandatory Training and Awareness.* Regular AI learning tool training should be embedded within institutional programs to ensure all stakeholders are proficient in using AI resources. [2] *Continuous Engagement with AI Tools.* Institutions should facilitate ongoing interaction with AI tools to encourage continuous learning and engagement among students. [3] *Leadership Commitment.* Academic leaders must actively promote and advocate for AI learning tool integration, demonstrating a commitment to technological advancement in education. [4] *Regular Updates and Evaluations.* AI tools should be regularly updated to ensure that they align with the latest educational needs and technological advancements. [5] *Incorporation of AI in Daily Learning.* Integrating AI tools into everyday learning practices can help make these technologies an integral part of the academic experience, ensuring long-term benefits for students.

These recommendations help institutions create a sustainable and effective AI-supported learning environment.

FUTURE RESEARCH DIRECTIONS

Advancing the role of AI in higher education requires continued research to reveal deeper insights and improve its implementation. Several areas need more exploration to support better decision-making and policy development: [1] *Leadership Support.* Future research should explore the role of leadership in driving AI tool adoption and its impact on student engagement and academic success. [2] *Availability of Resources.* Research could investigate how the availability of technological, human, and financial resources influences the effectiveness of AI tool integration in academic settings. [3] *Student and Faculty Perspectives.* Future studies should gather insights from both students and faculty to better understand how AI tools are perceived and utilized in the classroom. [4] *Long-Term Impacts of AI Learning Tools.* Analyzing the long-term effects of sustained AI tool use on academic performance could provide valuable insights into the enduring benefits of these technologies. [5] *Adaptation to External Challenges.* Research should examine how AI tools are adapted and utilized to overcome external challenges, such as pandemics or shifts in educational delivery modes like online learning during COVID-19.

These directions aim to expand the understanding of AI's evolving role in education and to inform more responsive, data-driven strategies. This study adds to the existing literature on AI in higher education. It shows how Structural Equation Modeling (SEM) can capture complex educational dynamics, providing implications not only for State Universities and Colleges in Region 10 but also for academic institutions globally.

HYPOTHESES TESTING RESULTS AND DECISIONS

H^1. AI Learning Tool Use (AILTU) significantly influences Academic Performance (AP). The direct effect of AILTU on AP was significant ($\beta = 0.414$, $p < .001$) with a medium effect size ($f^2 = 0.307$), indicating that greater use of AI learning tools is associated with higher academic performance. Decision: H^1 is accepted.

H^2. AI Learning Tool Use (AILTU) significantly influences Learning Engagement (LE). AILTU had a strong positive effect on LE ($\beta = 0.656$, $p < .001$) with a large effect size ($f^2 = 0.430$), demonstrating that students who use AI tools more frequently and confidently report higher engagement in their studies. Decision: H^2 is accepted.

H^3. Learning Engagement (LE) significantly influences Academic Performance (AP). LE showed a significant positive relationship with AP ($\beta = 0.480$, $p < .001$) and a large effect size ($f^2 = 0.367$), confirming that more engaged students tend to achieve better academic outcomes. Decision: H^3 is accepted.

H^4. Learning Engagement (LE) significantly mediates the relationship between AI Learning Tool Use (AILTU) and Academic Performance (AP). The indirect effect of AILTU on AP via LE was significant ($\beta = 0.315$, $p < .001$) with a medium effect size ($f^2 = 0.158$), indicating that part of AILTU's impact on academic performance operates through enhanced learning engagement. Decision: H^4 is accepted.

This study highlights the important role of AI Learning Tools in the Higher Education Institutions (HEIs) in improving student engagement and academic performance. The strong mediating effect of learning engagement shows the need to go beyond simple use and aim for thoughtful design and application of AI tools in education. These findings provide insights into how AI can influence student learning paths and results, calling for more research on their long-term effects.

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