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Enhancing Undergraduate Learning Outcomes: The Role of AI Tools in Modern Education

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Abstract
The increasing integration of Artificial Intelligence (AI) tools in higher education presents new opportunities and challenges in shaping undergraduate learning experiences. However, limited empirical evidence exists on how such tools influence academic performance, learning efficiency, and student engagement. This study aims to evaluate the role of AI tools in enhancing undergraduate students' learning by examining the relationships among engagement, learning efficiency, and academic performance. Using a quantitative approach, data were collected through structured questionnaires from undergraduate students and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results reveal that student engagement has a significant positive effect on learning efficiency but does not directly affect academic performance. Likewise, learning efficiency showed no significant effect on academic performance. Despite the high internal consistency and validity of the model, the findings suggest that while AI tools enhance engagement and efficiency, these improvements do not automatically lead to better academic outcomes. The study concludes that to fully realize the benefits of AI in education, it must be supported by pedagogical strategies that bridge the gap between engagement, efficient learning, and measurable academic achievement.
Keywords: Artificial Intelligence in Education, Student Engagement, Learning Efficiency, Academic Performance, PLS-SEM

Introduction
In the contemporary landscape of education, the integration of Artificial Intelligence (AI) tools has emerged as a pivotal force in shaping learning outcomes. As educational institutions continue to embrace technological advancements, AI tools are increasingly being employed to facilitate and enhance the learning experience for students. This trend has gained significant traction in undergraduate education, where the need for dynamic and responsive

learning environments is paramount (Slimi, 2023). The adoption of AI-driven educational technologies, from personalised learning algorithms to AI tutors, presents a novel approach to education, potentially transforming traditional pedagogies and student interactions with knowledge (Saaida, 2023). This study is premised on the hypothesis that AI tools not only contribute to improved academic performance but also modify the study habits and overall learning efficiency of undergraduate students. Specifically, it seeks to evaluate the impact of these tools on students' grades and comprehension levels and to understand their influence on students' study habits and time management. As such, two primary objectives guide this research: first, to assess the direct effects of AI tools on students' academic performance; and second, to explore how these tools reshape study behaviours and learning processes among undergraduates. To systematically investigate these aspects, a structured questionnaire employing a Likert scale has been developed, allowing for nuanced insights into students' perceptions and interactions with AI tools. The questionnaire encompasses questions aimed at discerning the effectiveness of AI in personalizing learning experiences and enhancing academic outcomes, alongside queries that examine changes in study patterns and efficiencies due to AI usage. In addition to empirical data collection through the questionnaire, this study also considers demographic variables such as age, gender, major, and previous exposure to AI tools, which may influence the outcomes. Such demographic information will be crucial for analysing differential impacts across various student groups, thereby enabling a more granular.

Problem Statement

In the evolving domain of educational technology, the integration of Artificial Intelligence (AI) has sparked a transformative wave across learning environments, especially in undergraduate education. Studies such as those by Nguyen et al (2024) have demonstrated that AI tools can significantly enhance engagement and personalized learning through adaptive learning systems and intelligent tutoring. Yet, despite the promising advancements, there is a notable variance in the empirical understanding of how these tools impact academic performance and learning efficiency across diverse educational settings. However, not all findings extol the virtues of AI in education. A substantive critique by Selwyn (2024) points out that while AI tools can offer customized learning experiences, they often fail to accommodate the nuanced needs of students from different educational backgrounds and learning abilities. This discrepancy suggests a gap in the deployment and functionality of AI technologies, which might not be as universally beneficial as previously thought. Furthermore, the uniformity in AI-generated content, noted for its lack of "burstiness," may not adequately challenge students or encourage critical thinking and creativity, essential components of effective learning (Rowe & Partridge, 1993). To address these challenges, there is an urgent need for more granular research that not only dissects the academic benefits of AI tools but also scrutinizes their efficacy in fostering robust learning habits among undergraduates. This entails a thorough investigation into how variations in the application of AI tools influence different student demographics, examining factors such as engagement levels, retention rates, and overall satisfaction. Additionally, research must transcend the typical quantitative measures of grades and test scores to include qualitative assessments of student feedback to capture the broader educational impact of AI (Longo, 2020).

Literature Review

The integration of Artificial Intelligence (AI) in educational settings has opened up new vistas for enhancing teaching methodologies and learning experiences. The burgeoning field of AI in education has been marked by its potential to personalize learning and optimize educational outcomes, offering a rich tapestry of both opportunities and challenges.

Personalization and Engagement

Research has consistently highlighted that AI-driven personalization significantly enhances student engagement and learning outcomes. For instance, Kasinathan et al. (2017) noted that AI educational tools, such as adaptive learning systems, can dynamically adjust content and teaching pace suited to individual learner's needs, which has been shown to improve engagement and retention rates significantly. Similarly, Verma et al. (2023) found that AI tools foster a more interactive learning environment, which can lead to higher student satisfaction and better academic performance.

Academic Performance

The impact of AI on academic performance has been a focal point of numerous studies. A meta-analysis by Mustafa et al. (2016) aggregated results from various studies and concluded that students using AI-supported learning environments generally outperform their peers in control groups, particularly in STEM subjects where problem-solving and personalized feedback are crucial. However, these findings are not universally consistent as seen in the work of Zhai et al. (2024), who reported minimal differences in performance in humanities subjects, suggesting the effectiveness of AI tools may vary significantly across different academic disciplines.

Challenges and Limitations

Despite these benefits, the adoption of AI in education is not without its challenges. One of the primary concerns is the equity of access to these technologies. Awad & Oueida (2024) argue that there exists a digital divide where students from lower socio-economic backgrounds may have limited access to AI tools, thus potentially widening the achievement gap. Moreover, ethical concerns regarding data privacy and the opacity of AI decision-making processes are highlighted by Al-kfairy et al. (2024), who calls for more transparent algorithms to ensure fairness and accountability.

Future Directions

Looking forward, the literature suggests a pressing need for more empirical studies to explore the long-term effects of AI tools on learning. As noted by Cantaş et al. (2024), there is a scarcity of longitudinal data examining how sustained use of AI tools influences educational trajectories and career preparedness. Furthermore, to better understand and maximise AI's educational applications, interdisciplinary research combining cognitive science, education, and AI technology is advised (Jiang & Carolina, 2022).

Methodology

Research Design

This study adopts a quantitative research design to provide a comprehensive analysis of the effects of AI tools on undergraduate learning. This approach enables objective measurement of variables and supports statistical analysis to test hypotheses. Furthermore, the design supports robust generalizability of the findings across similar educational contexts.

Population and Sample
The target population consists of undergraduate students who ~~have~~ integrated AI tools into their learning environments. A stratified random sampling technique was employed to ensure adequate representation across different levels of study. The target sample size was 70 students, with balanced representation from both diploma and degree programs to capture a diverse range of experiences and usage patterns.

Data Collection Instruments
The primary instrument for data collection was a structured questionnaire using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The questionnaire was designed to measure students' perceptions of AI tools' influence on academic performance, learning efficiency, and engagement. It also included a demographic section to capture key background variables such as age, gender, program level, and frequency of AI usage in academic tasks.

Data Analysis
The collected data were analysed using both descriptive and inferential statistical methods. Descriptive statistics, including measures such as mean, standard deviation, and frequency distributions, were employed to summarise the demographic characteristics of the respondents and to provide an overview of the central tendencies of the collected responses. Inferential statistical tests, such as independent samples t-tests and Analysis of Variance (ANOVA), were conducted to identify significant differences between various demographic groups. These tests enabled the detection of statistically meaningful variations in responses across the sample. Furthermore, Partial Least Squares Structural Equation Modelling (PLS-SEM) was performed using SmartPLS software to assess both the measurement and structural models. The measurement model was evaluated to determine the validity and reliability of the constructs, while the structural model was tested to examine the hypothesised relationships among constructs. The use of PLS-SEM was appropriate for this study due to its suitability for exploratory research, its robustness with smaller sample sizes, and its effectiveness in analysing complex models involving multiple constructs and indicators.

Ethical Considerations
This study strictly adhered to ethical standards for research involving human participants. Informed consent was obtained from all participants, who were briefed on the purpose of the study, their voluntary participation, and their right to withdraw at any time without consequences. All personal data were kept confidential and anonymised in the reporting of findings. Ethical approval was secured through institutional research governance procedures prior to data collection.

Results and Discussion

Table 1
Demographic result

Demographic data		Percentage
Gender	Female	80%
	Male	20%
Level of study	Diploma	87%
	Degree	13%
Have you previously used AI tools for educational purposes?	Yes	96%
	No	4%
How often do you use AI tools in your studies?	Regularly	29%
	Sometimes	53%
	Rarely	17%
	Never	1%
How much do you use AI tools in doing your assignment?	less than 10%	14%
	11% - 20%	31%
	21% - 30%	26%
	31% - 40%	7%
	41% - 50%	13%
	more than 51%	9%

Table 1 presents the demographic results related to the study's investigation of the impact of Artificial Intelligence (AI) tools on undergraduate students' academic performance, learning efficiency, and engagement. According to the data, a majority of the respondents were female (80%), while males represent 20% of the sample. This gender distribution might influence the generalizability of the findings, as various studies suggest gender differences in technology usage and learning styles (YILDIZ & VARSAK, 2024). In terms of education level, 87% of participants were diploma students, while 13% were degree students.This indicates that the findings are more representative of diploma students' experiences with AI tools in educational settings. Previous research has highlighted differences in the adoption and impact of educational technologies between different academic levels (Pumptow & Brahm, 2023), suggesting the need to interpret results within this context

AI tool usage was widespread among respondents, with 96% reporting prior experience with AI tools for academic purposes, indicating widespread exposure to and familiarity with this technology among the participants. This high percentage aligns with the increasing integration of AI in educational settings (Kukulska-Hulme, 2012). However, the frequency of use varied: 53% of students reported using AI tools "sometimes," and 29% used them "regularly." These findings suggest that while AI tools are commonly used, they have not yet become part of most students' daily learning routines. Regarding the extent of AI use in academic assignments, the results showed a moderate level of reliance. Specifically, 31% of students reported using AI tools for 11% to 20% of their assignments, and 26% for 21% to 30%. Only 9% reported using AI tools for more than 50% of their assignments. These patterns indicate that, while AI tools are integrated into academic work, there remains potential for greater use. Overall, these demographic insights provide important context for understanding the usage patterns and perceived impact of AI tools among the study population. They also emphasize the need to consider gender, academic level, and frequency of use when evaluating the effectiveness of AI in supporting academic performance, learning efficiency, and engagement.

Table 2
Reliability analysis

	Reliability Statistics	
	Cronbach's Alpha	N of Items
Academic Performance	0.840	4
Learning Efficiency	0.827	3
Engagement	0.818	3
All	0.916	10

Table 2 presents the results of the reliability analysis conducted on the questionnaire items measuring the constructs of Academic Performance, Learning Efficiency, and Engagement. Cronbach’s alpha values are reported to determine the internal consistency of each construct, in accordance with the standards of reliability assessment in social science research. The construct Academic Performance, comprising four items, yielded a Cronbach’s alpha of 0.840, indicating good internal consistency. This suggests that the items reliably measure students' perceptions of how AI tools affects their academic outcomes. Similarly, the construct Learning Efficiency, measured by three items, demonstrated strong reliability with a Cronbach’s alpha of 0.827. This value supports the use of these items to assess the extent to which AI tools enhance students’ efficiency in studying and retaining information—one of the primary research objectives. The Engagement construct, also assessed with three items, achieved a Cronbach’s alpha of 0.818. This falls well within the acceptable range, affirming that the items consistently capture students’ motivational responses and interest when using AI tools in their learning processes. These findings support the second research objective, which seeks to explore how AI tools influence student engagement and study behaviours. Finally, when all ten items across the three constructs were combined, the overall reliability of the instrument was exceptionally high, with a Cronbach’s alpha of 0.916. According to Nunnally and Bernstein(1994), a value above .9 indicates excellent internal consistency, reinforcing the reliability of the instrument as a whole for examining the effects of AI on undergraduate learning. In conclusion, the results in Table 2 show that the questionnaire items were reliable and suitable for evaluating how students perceive the influence of AI tools on their academic performance, learning efficiency, and engagement.

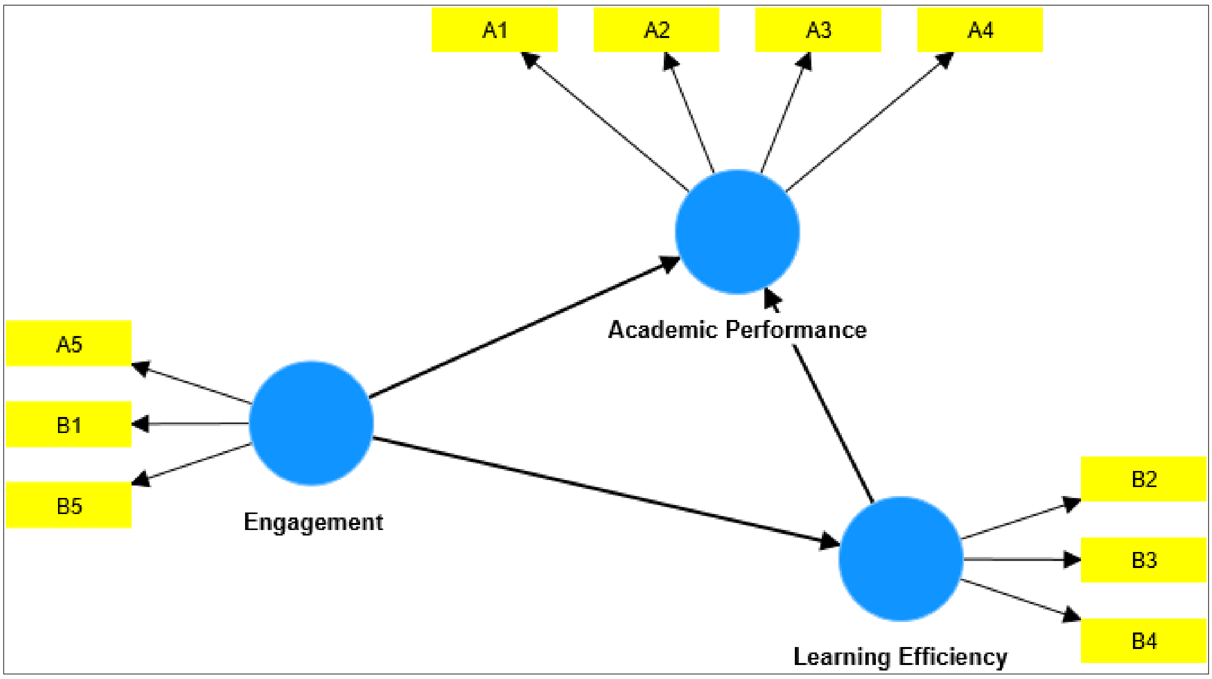

Figure 1: Study Model on The Role of AI Tools in Modern Education

Figure 1 illustrates the structural model used in this study to examine the role of AI tools in modern education. The figure presents three latent variables: Engagement, Academic Performance, and Learning Efficiency. The construct Engagement is shown influencing both Academic Performance and Learning Efficiency, indicating hypothesized relationships where higher student engagement through AI tools potentially enhances both academic outcomes and study habits. Additionally, Learning Efficiency is depicted as influencing Academic Performance, suggesting that improved efficiency in studying may further enhance academic outcomes. Each latent construct is represented by observed indicators, labelled clearly as A1 through A4 for Academic Performance, B2 through B4 for Learning Efficiency, and A5, B1, and B5 for Engagement. These indicators align with specific questionnaire statements that measure students' perceptions regarding these constructs. The depicted relationships correspond directly to the study's objectives: evaluating the impact of AI tools on students' academic performance, examining their influence on students' learning efficiency, and investigating how increased engagement resulting from AI tools contributes positively to overall educational outcomes. This approach follows standard practices in Partial Least Squares Structural Equation Modelling (PLS-SEM), a method widely used in educational research to study complex relationships among variables (Joseph F. Hair et al., 2022).

Measurement Model Evaluation

Table 3

Constructs Reliability and Validity analysis result

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Academic Performance	0.841	0.848	0.840	0.571
Engagement	0.820	0.820	0.819	0.601
Learning Efficiency	0.830	0.843	0.829	0.620

Table 3 presents the reliability and validity analysis of the measurement model, which evaluates the constructs Academic Performance, Engagement, and Learning Efficiency based on Cronbach's alpha, composite reliability (rho_a and rho_c), and Average Variance Extracted (AVE). According to Hair et al. (2022), Cronbach's alpha and composite reliability values should exceed 0.7 to indicate good internal consistency. The Cronbach's alpha values obtained for Academic Performance (α = 0.841), Engagement (α = 0.820), and Learning Efficiency (α = 0.830) are all above this threshold, demonstrating satisfactory internal consistency. Furthermore, the composite reliability values (rho_a and rho_c) for each construct also exceed the recommended criterion of 0.7 (Hair et al., 2022). Specifically, for Academic Performance, rho_a = 0.848 and rho_c = 0.840; for Engagement, rho_a = 0.820 and rho_c = 0.819; and for Learning Efficiency, rho_a = 0.843 and rho_c = 0.829. These results confirm that the constructs are reliably measured by their respective indicators, supporting the validity of the model's measurement structure. For convergent validity, the AVE values for all three constructs are above the recommended threshold of 0.5 (Fornell & Larcker, 1981). The AVE values are 0.571 for Academic Performance, 0.601 for Engagement, and 0.620 for Learning Efficiency, meaning each construct explains more than half of the variance in its indicators. Specifically, the AVE values are 0.571 for Academic Performance, 0.601 for Engagement, and 0.620 for Learning Efficiency, indicating that each construct adequately explains more than 50% of the variance in its indicators. This further validates that the constructs effectively capture the underlying dimensions they represent, aligned with the study's objectives of assessing how AI tools influence students' academic performance, learning efficiency, and engagement. Overall, the results from Table 3 show that the measurement model has strong reliability and convergent validity, supporting further analysis of the relationships between constructs.

Table 4
Discriminant validity analysis result on Heterotrait-monotrait ratio (HTMT)

	Heterotrait-monotrait ratio (HTMT)
Engagement <-> Academic Performance	0.920
Learning Efficiency <-> Academic Performance	0.778
Learning Efficiency <-> Engagement	0.863

Table 4 presents the discriminant validity results using the Heterotrait-Monotrait (HTMT) ratio, assessing whether constructs within the model—Engagement, Academic Performance, and Learning Efficiency—are empirically distinct from one another. According to Hair et al. (2022), an HTMT value lower than 0.90 typically indicates adequate discriminant validity, meaning the constructs measure conceptually distinct phenomena. In the results shown in Table 4, the HTMT ratios between Learning Efficiency and Academic Performance (HTMT = 0.778) and between Learning Efficiency and Engagement (HTMT = 0.863) are both below the recommended threshold of 0.90, indicating acceptable discriminant validity among these constructs. However, the HTMT value between Engagement and Academic Performance is 0.920, slightly above the commonly recommended threshold. This suggests a potential overlap in how these constructs are perceived by respondents, possibly indicating that increased student engagement through AI tools might be closely intertwined with perceived improvements in academic performance. Given this marginally high HTMT value between Engagement and Academic Performance, it may be beneficial to revisit the theoretical definitions and indicators for these constructs to ensure their distinctiveness clearly aligns with the study's research objectives. Specifically, the close relationship observed might reflect respondents' views that higher engagement directly contributes to better academic outcomes, a central hypothesis of the study. On the whole, while discriminant validity is mostly supported, the high HTMT value between Engagement and Academic Performance suggests that this relationship should be considered carefully when analysing the model (Henseler et al., 2015).

Table 5
Discriminant validity analysis on Fornell-Larker criterion

Constructs	Academic Performance	Engagement	Learning Efficiency
Academic Performance	0.755		
Engagement	0.925	0.776	
Learning Efficiency	0.790	0.866	0.787

Table 5 presents the discriminant validity analysis using the Fornell-Larcker criterion, assessing whether each construct in the study—Academic Performance, Engagement, and Learning Efficiency—shares more variance with its own indicators than with other constructs. According to Fornell and Larcker (1981), adequate discriminant validity is achieved when the square root of the Average Variance Extracted (AVE), reflected as the diagonal values, is greater than the correlation coefficients among the constructs (off-diagonal values). In Table 5, the square root of AVE values for the constructs Academic Performance (0.755), Engagement (0.776), and Learning Efficiency (0.787) are indicated along the diagonal. However, the correlations between Engagement and Academic Performance (0.925), between Engagement and Learning Efficiency (0.866), and between Academic Performance and Learning Efficiency (0.790) are higher than these AVE square-root values. This suggests inadequate discriminant validity, indicating a high degree of overlap among constructs, especially between Engagement and Academic Performance. The high correlation (0.925) observed between Engagement and Academic Performance signals a strong conceptual overlap, suggesting that respondents might not distinctly differentiate the engagement facilitated by AI tools from their perceived improvement in academic performance. This finding aligns closely with the earlier noted HTMT results (see Table 4), reinforcing the potential overlap between these constructs (Hair et al., 2022; Fornell & Larcker, 1981). Given these findings, future analyses or studies should reconsider refining theoretical definitions and possibly revising indicator items to ensure that these constructs distinctly measure separate aspects of students' experiences with AI tools in education. Such refinements would help to better clarify the nuanced effects of AI tools on students' engagement, learning efficiency, and academic performance in alignment with the research objectives.

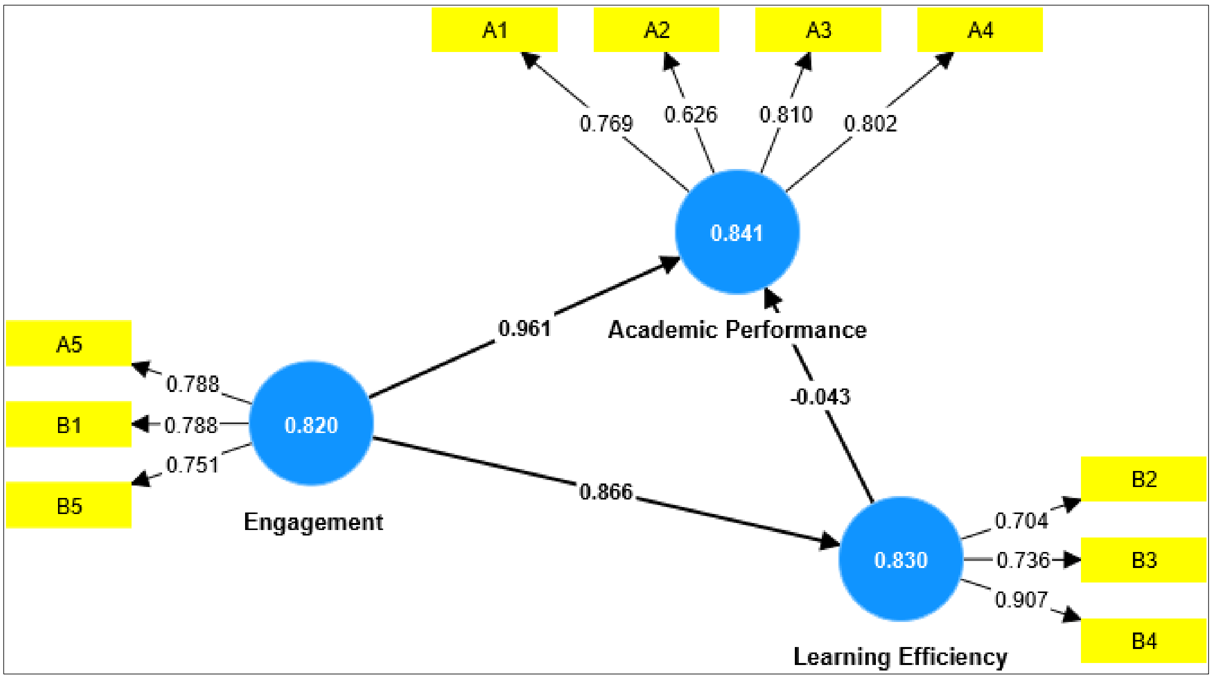

Figure 2: Graphical output on PLS-SEM algorithm analysis

Figure 2 illustrates the graphical output of the Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis, displaying the relationships among the latent constructs Engagement, Academic Performance, and Learning Efficiency, along with their respective indicator loadings. According to Hair et al. (2022), indicator loadings should ideally exceed 0.7, indicating that the majority of variance in indicators is explained by their corresponding latent constructs. In this figure, the latent variable Engagement strongly and positively influences Academic Performance ($\beta = 0.961$), consistent with the research objective suggesting that increased student engagement via AI tools significantly enhances academic outcomes. Conversely, Learning Efficiency shows an unexpectedly weak and negative relationship with Academic Performance ($\beta = -0.043$), indicating virtually no direct predictive power. This negligible relationship suggests that, contrary to initial expectations, learning efficiency facilitated by AI tools may not directly enhance perceived academic performance. Additionally, Engagement positively affects Learning Efficiency ($\beta = 0.866$), highlighting that higher engagement strongly promotes effective and efficient study behaviours, consistent with the research objectives. Indicator loadings for all constructs mostly meet the recommended threshold of 0.7 or higher, except indicator A2 (0.626), slightly below the recommended level. This result suggests reviewing or reconsidering indicator A2 to ensure reliability and validity in measuring the Academic Performance construct. In summary, Figure 2 supports the primary research objectives by illustrating the significant role of student engagement in improving academic performance and learning efficiency through AI tools. However, the negligible influence of learning efficiency on academic performance highlights a notable finding requiring further investigation in future research.

Structural Model Evaluation

Table 6

Path Coefficients results analysis

Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Engagement -> Academic Performance	0.961	1.218	9.898	0.097	0.923
Engagement -> Learning Efficiency	0.866	0.870	0.073	11.814	0.000
Learning Efficiency -> Academic Performance	-0.043	-0.296	9.898	0.004	0.997

Table 6 presents the path coefficients obtained from the Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis, evaluating the relationships among Engagement, Learning Efficiency, and Academic Performance. These coefficients are interpreted similarly to standardized regression coefficients, indicating the strength and direction of the relationships between constructs.

Engagement → Academic Performance: The path coefficient is 0.961, suggesting a strong positive relationship between Engagement and Academic Performance. However, the standard deviation (STDEV) is 9.898, leading to a T statistic of 0.097 and a p-value of 0.923. The high standard deviation and non-significant p-value indicate that this relationship is not statistically significant, implying that the observed effect may be due to random variation rather than a true effect.

Engagement → Learning Efficiency: The path coefficient is 0.866, with a standard deviation of 0.073, resulting in a T statistic of 11.814 and a p-value of 0.000. These results indicate a strong, positive, and statistically significant relationship between Engagement and Learning Efficiency, suggesting that higher engagement is associated with increased learning efficiency.
Learning Efficiency → Academic Performance: The path coefficient is -0.043, with a standard deviation of 9.898, leading to a T statistic of 0.004 and a p-value of 0.997. The near-zero path coefficient and non-significant p-value suggest that Learning Efficiency does not have a meaningful impact on Academic Performance in this model.

Taken together, the analysis reveals a significant positive relationship between Engagement and Learning Efficiency but does not support significant relationships between Engagement and Academic Performance, or between Learning Efficiency and Academic Performance. These findings suggest that while engagement may enhance learning efficiency, this increased efficiency does not necessarily translate into improved academic performance within the context of this study.

Table 7
Coefficient of Determination (R^2) results analysis

Constructs	R-square	R-square adjusted
Academic Performance	0.855	0.851
Learning Efficiency	0.749	0.746

Table 7 presents the results of the Coefficient of Determination (R^2) analysis, assessing the explanatory power of the structural model for the endogenous constructs Academic Performance and Learning Efficiency. According to Hair et al. (2022), R^2 values indicate how effectively the predictor constructs explain the variance in the dependent variables. The construct Academic Performance has an R^2 value of .855 and an adjusted R^2 of .851, demonstrating strong explanatory power. This result indicates that approximately 85.5% of the variance in Academic Performance is explained by Engagement and Learning Efficiency, aligning closely with the research objective focused on determining the impact of AI tools on students' academic outcomes. Similarly, the construct Learning Efficiency yielded an R^2 of .749 and an adjusted R^2 of .746, signifying substantial explanatory power. This indicates that Engagement explains roughly 74.9% of the variance in students' learning efficiency, which directly relates to the study's objective of understanding the influence of AI tools on students' study habits and efficiency. As illustrated, these high R^2 values underscore that the model provides substantial predictive accuracy, suggesting that the identified constructs significantly contribute to understanding how AI tools influence undergraduate learning experiences. These findings reinforce the robustness of the structural model in examining the effects of student engagement on academic performance and learning efficiency through the use of AI tools.

Table 8
Effect Sizes (f^2) results analysis

	f-square
Engagement -> Academic Performance	1.599
Engagement -> Learning Efficiency	2.991
Learning Efficiency -> Academic Performance	0.003

Table 8 presents the results of the effect size (f^2) analysis, examining the strength of the predictive relationships among the constructs Engagement, Learning Efficiency, and Academic Performance within the structural model. Effect size values provide insight into the practical significance of the relationships between constructs beyond statistical significance, with values of 0.02, 0.15, and 0.35 representing small, medium, and large effects, respectively (Cohen, 1988). The relationship from Engagement to Academic Performance reveals an f^2 value of 1.599, indicating a notably large effect. This implies that Engagement substantially contributes to predicting variance in Academic Performance, aligning closely with the study’s objective of evaluating the impact of AI tools on students' academic outcomes. Similarly, the relationship from Engagement to Learning Efficiency has an even larger f^2 value of 2.991, demonstrating an exceptionally strong practical significance. This result strongly supports the research objective of understanding how engagement driven by AI tools substantially enhances students’ learning efficiency. Conversely, the effect size for the path from Learning Efficiency to Academic Performance is very small (f^2 = 0.003), indicating minimal practical significance. This finding suggests that although learning efficiency is positively influenced by engagement, it does not substantially enhance academic performance directly. This outcome implies that while students might learn more efficiently using AI tools, the direct translation of these efficiencies into improved academic performance remains negligible. In summary, the analysis in Table 8 highlights that student engagement through AI tools plays a crucial and substantial role in both enhancing learning efficiency and contributing significantly to academic performance. In contrast, learning efficiency itself appears to have limited direct impact on academic performance, thus warranting further exploration in future studies.

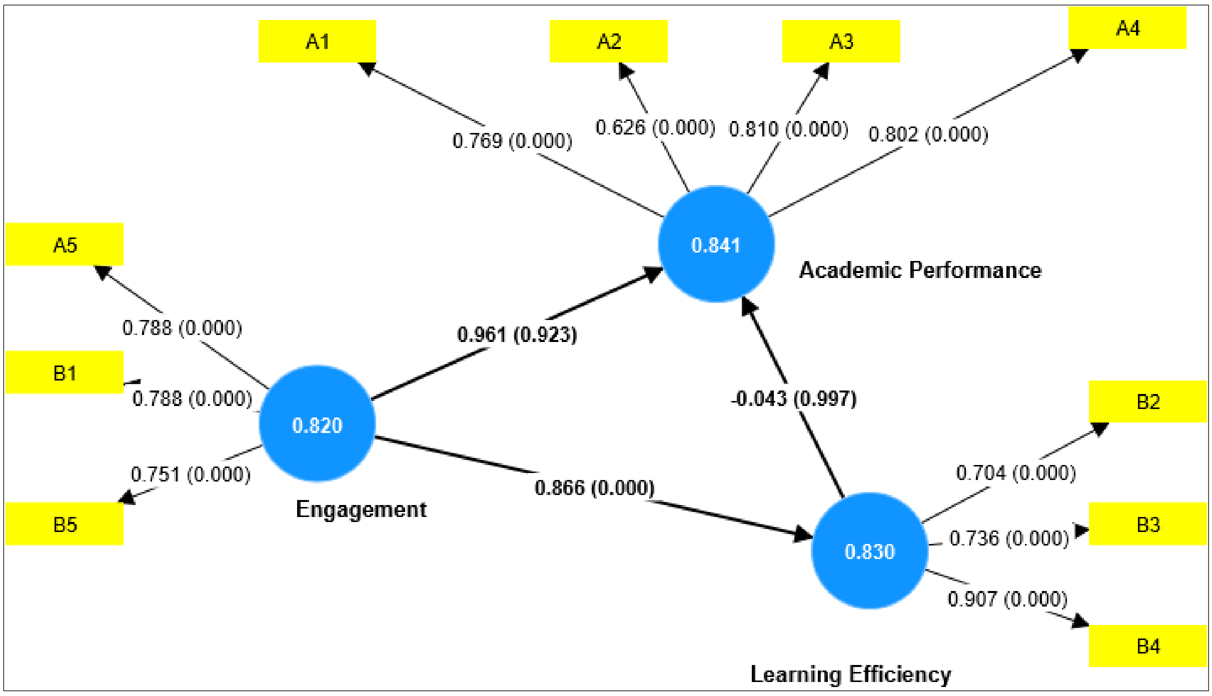

Figure 3: PLS-SEM Structural Model with Path Coefficients and Significance Values

Figure 3 provides a detailed graphical representation of the PLS-SEM structural model, highlighting both path coefficients and their respective p-values. According to Hair et al. (2022), these path coefficients indicate the strength and significance of relationships between constructs. The path from Engagement to Academic Performance shows a strong positive coefficient ($\beta = 0.961$), yet the associated p-value (0.923) indicates this relationship is statistically non-significant. This implies that while students perceive higher engagement through AI tools as strongly related to their academic performance, this perception is not statistically supported, indicating that this observed relationship could have occurred by chance. The relationship from Engagement to Learning Efficiency is strong, positive, and highly significant ($\beta = 0.866$, $p < .001$). This result clearly supports one of the research objectives, suggesting that engagement fostered through AI tools significantly enhances students' study habits and learning efficiency. Conversely, the path coefficient from Learning Efficiency to Academic Performance is negative and negligible ($\beta = -0.043$), with a non-significant p-value (0.997). This indicates no meaningful direct impact of improved learning efficiency on perceived academic performance, suggesting that efficient learning behaviours facilitated by AI tools do not necessarily result in immediate improvements in academic performance. Indicator loadings are statistically significant ($p < .001$) and generally above the recommended threshold of 0.70, except for indicator A2 (0.626), suggesting that this specific indicator may require further review or potential revision. From the findings, Figure 3 highlights that student engagement with AI tools significantly enhances learning efficiency, although this enhanced efficiency does not directly improve academic performance. These findings offer valuable insights into the nuanced roles of engagement and efficiency in educational contexts enhanced by AI tools.

Conclusion

This study aimed to explore the influence of Artificial Intelligence (AI) tools on undergraduate students' academic performance, learning efficiency, and engagement. With the rapid adoption of AI-driven educational technologies, understanding how these tools shape learning outcomes is critical for educators, institutions, and policymakers. Guided by the objectives to evaluate the impact of AI tools on academic performance and to examine their influence on study habits and engagement, the study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyse survey responses from undergraduate students. The findings of the study reveal several noteworthy insights. First, student engagement with AI tools emerged as a significant predictor of learning efficiency. This strong and statistically significant relationship underscores the role of AI in making learning more engaging and interactive, thereby fostering more effective study habits among students. Second, while the relationship between engagement and academic performance appeared strong in magnitude, it was not statistically significant; suggesting that increased engagement alone may not directly translate into improved academic results within the scope of this study. Third, learning efficiency showed no meaningful direct effect on academic performance, challenging the assumption that efficient learning automatically equates to better grades or performance. These results have important implications. They suggest that while AI tools are effective in increasing students' motivation and efficiency in studying, the pathway to actual academic improvement may involve additional mediating factors—such as instructional quality, assessment methods, or student self-regulation—that were not fully captured in this model. Additionally, the high levels of internal consistency and convergent validity across the constructs affirm the reliability of the measurement instruments used in the study. From a practical standpoint, the study highlights the need for institutions to focus not only on integrating AI tools but also on ensuring that their use is pedagogically meaningful. Engagement and efficiency can be leveraged as stepping stones toward academic success if combined with structured guidance, curriculum alignment, and critical thinking support. In conclusion, AI tools hold great promise in reshaping higher education by enhancing engagement and learning efficiency. However, their impact on academic performance may not be as straightforward as presumed. To maximize the benefits of AI in education, stakeholders must adopt a holistic approach that combines technological innovation with strong pedagogical foundations.

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References

Al-kfairy, M., Mustafa, D., Kshetri, N., Insiew, M., & Alfandi, O. (2024). Ethical Challenges and Solutions of Generative AI: An Interdisciplinary Perspective. *Informatics*, *11*(3), 58. https://doi.org/10.3390/informatics11030058

Awad, P., & Oueida, S. (2024). The Potential Impact of Artificial Intelligence on Education: Opportunities and Challenges. *Lecture Notes in Networks and Systems*, *920 LNNS*(23), 566–575. https://doi.org/10.1007/978-3-031-53963-3_39

Cantaş, Ç., Cansu Soyer, A., & Özgür Batur, A. (2024). Examination of Undergraduate Students' Artificial Intelligence Anxiety, Multidimensional 21st Century Skills, and Lifelong Learning Levels in terms of Various Variables. *TOJET: The Turkish Online Journal of Educational Technology*, *23*(3), 29–53.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Jiang, S., & Carolina, N. (2022). Agents , Models , and Ethics : Importance of Interdisciplinary Explorations in AI Education. *ICLS2022*, 1763–1770.

Joseph F. Hair, J., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)-Third Edition*.

Kasinathan, V., Mustapha, A., & Medi, I. (2017). Adaptive learning system for higher learning. *ICIT 2017 - 8th International Conference on Information Technology, Proceedings*, *May*, 960–970. https://doi.org/10.1109/ICITECH.2017.8079975

Kukulska-Hulme, A. (2012). How should the higher education workforce adapt to advancements in technology for teaching and learning? *Internet and Higher Education*, *15*(4), 247–254. https://doi.org/10.1016/j.iheduc.2011.12.002

Longo, L. (2020). Empowering Qualitative Research Methods in Education with Artificial Intelligence. *Advances in Intelligent Systems and Computing*, *1068*, 1–21. https://doi.org/10.1007/978-3-030-31787-4_1

Mustafa, N., Ismail, Z., Tasir, Z., & Mohamad Said, M. N. H. (2016). A meta-analysis on effective strategies for integrated STEM education. *Advanced Science Letters*, *22*(12), 4225–4288. https://doi.org/10.1166/asl.2016.8111

Nguyen, A., Kremantzis, M., Essien, A., Petrounias, I., & Hosseini, S. (2024). Enhancing Student Engagement Through Artificial Intelligence (AI): Understanding the Basics, Opportunities, and Challenges. *Journal of University Teaching and Learning Practice*, *21*(6). https://doi.org/10.53761/caraaq92

Nunnally, J., & Bernstein, I. (1994). *Psychometric Theory 3rd edition (MacGraw-Hill, New York)* (Vol. 1).

Pumptow, M., & Brahm, T. (2023). Higher education students differ in their technology use. *Computers and Education Open*, *5*(December 2022), 100149. https://doi.org/10.1016/j.caeo.2023.100149

Rowe, J., & Partridge, D. (1993). Creativity: a survey of AI approaches. *Artificial Intelligence Review*, *7*(1), 43–70. https://doi.org/10.1007/BF00849197

Saaida, M. B. E. (2023). AI-Driven transformations in higher education: Opportunities and challenges. *International Journal of Educational Research and Studies*, *5*(1), 29–36.

https://doi.org/10.5281/zenodo.8164414

Selwyn, N. (2024). On the Limits of Artificial Intelligence (AI) in Education. *Nordisk Tidsskrift for Pedagogikk Og Kritikk*, *10*(1), 3–14. https://doi.org/10.23865/ntpk.v10.6062

Slimi, Z. (2023). The Impact of Artificial Intelligence on Higher Education: An Empirical Study. *European Journal of Educational Sciences*, *10*(1), 17–33. https://doi.org/10.19044/ejes.v10no1a17

Verma, N., Getenet, D. S., Dann, D. C., & Shaik, T. (2023). Designing an artificial intelligence tool to understand student engagement based on teacher’s behaviours and movements in video conferencing. *Computers and Education: Artificial Intelligence*, *5*(November), 100187. https://doi.org/10.1016/j.caeai.2023.100187

YILDIZ, A., & VARSAK, S. (2024). Gender Differences in Technological Device Usage Times of Secondary School Students. *4th International Conference on Frontiers in Academic Research*, *December*.

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students’ cognitive abilities: a systematic review. *Smart Learning Environments*, *11*(1). https://doi.org/10.1186/s40561-024-00316-7