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The Role of Artificial Intelligence in Enhancing Academic Performance among University Students

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ABSTRACT

In recent year,Artificial Intelligence (AI) has become a crucial component in higher education, reshaping how students study, access information, and complete assignments.AI-powered tools, including chatbots, plagiarism detection software, and adaptive learning systems, enable more efficient, interactive, and personalised learning experiences. With increasing AI adoption in universities, understanding how these technologies affect students' academic performance and learning behaviour is crucial. This study aims to examine the role of AI in enhancing academic performance among university students by focusing on perceived usefulness, ease of use, trust, risk, and learning engagement. Our findings indicate that Personalised Learning, Intelligent Feedback and AI-Driven Assessment & Learning Analytics significantly and positively affect university students academic performance. Among these, Personalised Learning and AI-Driven Assessment & Learning Analytics exerted the strongest influence on academic performance. These findings underscore the pivotal role of AI-driven tools in enhancing student behaviour and academic performance in higher education.

Keywords: Artificial Intelligence; Academic Performance; Learning Behavior; University

INTRODUCTION

The past few years have witnessed a rapid expansion of Artificial Intelligence (AI) applications in education, fundamentally transforming teaching and learning processes. AI has driven the development of personalised learning pathways, intelligent feedback systems, learning analytics, and AI-Driven assessment. These innovations offer substantial benefits by enabling more efficient instructional delivery, reducing cognitive and administrative burdens, and fostering adaptive, engaging, and learner-centred educational environments. As higher education institutions increasingly adopt AI-driven pedagogies, understanding how students interact with AI-supported learning tools and how these tools influence learning outcomes has become a critical concern in contemporary educational research (Sabeh et al., 2025; Ullah et al., 2022). Universities worldwide have increasingly integrated AI technologies into adaptive learning platforms, AI-Driven Assessment and learning analytics to enhance instructional effectiveness. However, empirical evidence examining the direct impact of specific AI features, such as personalised learning, AI-Driven assessment & learning analytics and intelligent feedback, on measurable academic outcomes remains limited. Most studies focus primarily on technology acceptance, user attitudes, or perceived usefulness rather than objective academic performance (Ravi et al., 2024; Ullah et al., 2022). Moreover, students' engagement and academic performance are affected not only by the design of AI tools but also by broader behavioural and lifestyle factors, such as smartphone usage and screen time, which can influence sleep quality, well-being, social behaviour, and learning outcomes (Kee et al., 2025).

From a psychosocial perspective, learning effectiveness in technology-enhanced environments is also influenced by psychological well-being, perceived safety, and supportive contexts. Negative digital and social experiences, such as bullying or toxic interactions, can impair engagement, motivation, and performance by increasing psychological strain and disengagement (Anwar et al., 2022; Rubel et al., 2025). Conversely, environments characterized by psychological safety and manageable demands foster engagement, satisfaction, and positive behavioral outcomes (Gan & Kee, 2024; Teoh & Kee, 2022). These findings suggest that students' engagement with AI-supported learning tools may similarly depend on whether such technologies are experienced as supportive, fair, and conducive to learning rather than stressful or alienating.

This research gap is particularly evident in the Malaysian higher education context, where the adoption of AI-supported educational tools is still at a relatively early stage. Malaysian universities are gradually incorporating AI into teaching and learning practices, yet systematic and comprehensive evaluations of AI effectiveness remain scarce. Without robust empirical evidence, institutions may struggle to design AI-enhanced learning systems that genuinely support student engagement, well-being, and academic success. Insights from organizational and educational psychology indicate that individual motivation and proactive engagement play a crucial mediating role in translating system features into performance outcomes (Zahra & Kee, 2022; You et al., 2025).

Against this backdrop, the primary objective of this study is to examine university students' acceptance, usage, and interaction with AI-supported academic tools and to investigate how these tools influence academic performance, as reflected in students' grades. Specifically, this study focuses on key AI features, personalised learning, AI-Driven assessment & learning analytics, and intelligent feedback, within a unified analytical framework. By examining these features both individually and collectively, the

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study aims to clarify how AI-supported learning environments shape student engagement, well-being, and academic outcomes.

This study is significant because it highlights the potential of AI to transform learning processes while recognizing that technological effectiveness is closely intertwined with psychological and contextual factors. Evidence from leadership, engagement, and technology adoption research suggests that supportive systems and meaningful engagement mechanisms are critical for sustaining positive behaviours and performance outcomes (Gan & Kee, 2024; You et al., 2025). Accordingly, the findings of this study are expected to provide valuable insights for educators, curriculum designers, and university administrators seeking to implement AI tools in ways that enhance learning effectiveness and student success. Finally, this study offers both theoretical and practical contributions. Theoretically, it extends the literature on AI-driven learning by integrating insights from engagement, psycho-social safety, and behavioral research to explain how students interact with AI-supported tools and how such interactions influence academic performance. Practically, the findings may assist higher education institutions in developing evidence-based strategies for the thoughtful design, implementation, and management of AI educational tools that promote student engagement, well-being, and overall learning quality.

LITERATURE REVIEW

Personalised learning and academic performance

Recent research indicates that the use of artificial intelligence in learning environments has a positive influence on the students' academic performance as it lets them interact with the learning content in a more flexible and interest-driven way. The personalized interaction allows the students to delve into the topics more which in turn their understanding is deeper and they are more engaged in academics for a longer time. These kinds of individualized learning experiences have been linked with higher academic results like better exam scores and more academic success in general (Nurtayeva et al., 2023). Artificial Intelligence has been integrated into education which is altering the traditional teaching styles by the way it provides the learners with the personalisation of education. The main factor for this change is the AI-powered learning paths that change according to the individual student's characteristics, preferences, and learning needs (Kicken et al., 2008). Data analytics and adaptive algorithms are used by the systems to customize the educational content, provide real-time feedback, and create individual learning trajectories, thereby aiming to optimize the learning process (Maghsudi et al., 2021; Chen et al., 2022).

The existing literature is in favor of personalisation being a major factor in enhancing the student engagement. It is believed that by changing the content and activities according to the learners' interests and proficiency levels, the AI-powered paths will lead to increased motivation, enhanced focus, and a more active interaction with the learning material (Koenka & Anderman, 2019; Hwang et al., 2020). Furthermore, this personalised teaching approach is considered a factor in improving academic performance. Timely support and targeted resources are expected to help students fill knowledge gaps, thereby maximizing their potential (Klašnja-Milićević & Ivanović, 2021). However, despite the well-developed theoretical advantages, empirical research from cases such as the University of Ilorin remains limited, thus requiring further research to validate these claims. Based on the above discussion, this study proposes that personalised learning has a positive effect on students' academic performance.

H1: Personalised Learning positively affects academic performance

Intelligent feedback and academic performance
One of the numerous things that teachers do to lead their students to better student learning and performance is giving feedback, and it is considered to be one of the most powerful practices for improving student learning effectively. (Henderson et al., 2019). However, when there are many students in a class, as is often the case in higher education, it becomes very challenging for teachers to provide all students with effective guidance individually. Moreover, it is challenging for teachers to understand which course activities and resources should be delivered as action recommendations that could help students to improve their learning and performance (Winstone and Carless 2019). Moreover, it has been demonstrated that constructive feedback and action suggestions are vital to self-regulated learning (SRL) and are closely linked to students' learning and performance. (Algayres and Triantafyllou 2020).

The latest progress in artificial intelligence has made it possible to incorporate smart feedback systems in digital learning environments, hence providing more accessible and individualised learning support to learners. Such systems offer customised feedback in accordance with students' learning styles and their progress thus improving, the students' motivation, self-control, and academic performance. Research findings have revealed that personalised and intelligent feedback mechanisms have a great impact on the students' learning outcomes by fostering deeper involvement and better learning regulation.（Zhongxu, 2023)

In higher education contexts, the integration of artificial intelligence has contributed to a shift toward more individualised learning approaches by enabling learning experiences that better align with students' needs and learning behaviors. At the forefront of this change are smart feedback systems that offer timely and accurate assistance, enabling more personalized support for students' learning processes (Maghsudi et al., 2021; Chen et al., 2022).These technologies powered by AI have the ability to improve students' academic performance by customising learning content, feedback, and assessment according to individual needs and learning speed.

Theoretical perspectives suggest that AI-supported learning tools may enhance academic performance by increasing student engagement. By making learning more relevant, interactive, and responsive, intelligent feedback, can encourage greater attention, effort, and motivation, which are closely associated with improved academic performance (Fredricks et al., 2004). Therefore, it is reasonable to expect that the use of intelligent feedback supported by artificial intelligence can lead to improved academic performance among university students.

H2: Intelligent feedback positively affects academic performance

AI-Driven assessment & learning analytics and academic performance
In traditional teaching methods, the results of learning are frequently organized according to a set of taxonomies defined in advance which highlight the achievement in specific domains. While such approaches provide clear outcome measures, they offer limited insight into students' ongoing learning processes. In response to this limitation, the integration of artificial intelligence and learning analytics enables more adaptive instructional support by combining data-driven performance indicators with contextual feedback from educators. This integration allows learning processes to be monitored and adjusted more effectively, thereby supporting improved academic performance and deeper learning engagement (Luckin & Cukurova, 2019). According to Rincón-Flores The (2020), AI-Driven Assessment & Learning Analytics is one of the possible

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applications of data science in the field of education. It facilitates the process of measuring, collecting, analyzing, and reporting data about learners and their context. AI-Driven Assessment & Learning Analytics is usually described as "the measurement, collection, analysis and reporting of data about learners and their contexts, for understanding and optimising learning and the environments in which it occurs" (Siemens & Gašević, 2012). Nevertheless, the majority of the recent LA applications have not taken students' opinions into account on a proper basis; this has resulted in a mismatch between the students' hopes and the services offered by the schools. Such misalignment may limit the effectiveness of learning analytics in supporting students' learning outcomes and academic performance. (Ferguson et al., 2014).

AI-powered evaluation together with learning analytics has been linked to improved academic performance more and more due to their capabilities to provide quick feedback, assist in personalized learning paths, and detect individual learning gaps. These systems, through the use of data-driven insights, prompt the application of learning interventions that are very effective in uplifting students' engagement, motivation, and learning accuracy, at the same time slicing off the possibility of assessment bias. The support provided to students based on the above-mentioned capabilities of technology is also not limited to learning progression but includes academic persistence too. A considerable number of studies conducted in higher education contexts have pointed out the positive influence of AI-powered evaluation and learning analytics on the academic outcomes of students (Garcia, 2018; Igwe & Okeke, 2020; Oyekunle & Adekunle, 2022; Nwosu & Okoro, 2022). Therefore, it is reasonable to hypothesis that AI-driven assessment and learning analytics have a positive effect on students' academic performance.

H3: AI-Driven assessment and learning analytics positively affect academic performance.

Conceptual Framework
Figure 1 illustrates the conceptual framework developed for this study, highlighting the relationships between the independent and dependent variables.

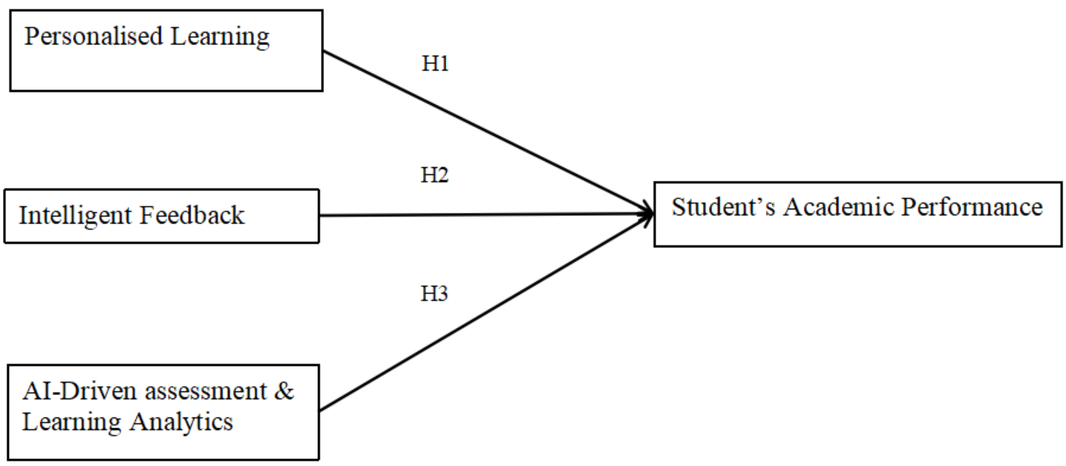

Figure 1. Research Framework

RESEARCH METHOD

The study applied a quantitative approach in assessing the engagement of university students with AI-based educational tools. The chosen population consisted of university students who were frequent users of AI technology, and out of these, 130 volunteers

participated in this study. A convenience sampling method was employed, which was based on the indirect and constant contact of the students with AI technologies. This guaranteed that the analyzing units were significant to the research aims and could give valuable views about the impact of AI-assisted learning on academic performance.
Data collection utilizes an online questionnaire developed and managed by Google Forms. The questionnaire was widely distributed to student groups across universities, allowing students to participate regardless of location or time constraints. Respondents were informed that participation was entirely voluntary, for academic purposes only, and their responses would be anonymous and confidential. The entire data collection process adhered to ethical guidelines, ensuring transparency and respect for participants' rights. The tool for measurement included items of a questionnaire from earlier studies with certain adaptations to ensure validity and reliability. All items were organized with a 5-point Likert-scale to evaluate core constructions such as personalised learning, intelligent feedback, AI-Driven assessment & learning analysis and academic performance, to mention a few. Moreover, demographic information like gender, age, year of study, type of university, name of university, AI tools most often used, and frequency of AI tool usage, were collected to aid in the more detailed analysis of patterns and correlations. This method ensured that the data was strong enough and up to date for answering the research questions.

Data Analysis
All completed responses were initially checked and coded before analysis. The dataset was analyzed by using SPSS statistical software. Descriptive statistics were used to summarize respondents' demographic and usage profiles. Pearson correlation analyses were first conducted to assess the relationships among the study variables and to evaluate potential multicollinearity. Multiple regression analyses were then employed to test the hypothesized relationships between the independent variables and customer satisfaction and loyalty.

Measures
All constructs used in this study were measured using a five-point Likert scale ranging from 1 (Strongly disagree) to 5 (Strongly Agree). The survey consisted of four sub-sections which are academic performance, personalised learning, intelligent feedback and AI-Driven assessment & learning analytics. Each sub-section contained 4 to 6 statements that respondents rated based on their experience using AI tools.

Personalised Learning: Six items measured how people perceive or experience personalized learning of AI (e.g., "I believe that personalised learning paths have improved my overall interest in the course material."). Cronbach's Alpha was 0.883.
Intelligent Feedback: The three items that were used to measure the AI feedback's utility for improvement, the helpfulness of its suggestions, and the overall value of receiving smart feedback were the three items that were used.(e.g., "The AI tools provide timely feedback tailored to my specific learning activities."). Cronbach's Alpha was 0.870.

AI-Driven Assessment *& Learning Analytics:* Five items were used to measure learners' perceptions of the usefulness and impact of AI-driven assessment and learning analytics. The items assessed the system's ability to evaluate students' performance through automated, AI-based assessment, provide clear and timely assessment feedback, generate understandable performance summaries, track learning progress over time, and offer data-driven recommendations for skill development and learning improvement. (e.g., The AI learning analytics system provides me with a clear summary of my learning performance across all my courses."). Cronbach's Alpha was 0.862.

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Academic Performance: Four items measured the useful of AI tools that help university student enhance their academic achievement (e.g., I feel the AI tools help me improve my knowledge and information”). Cronbach's Alpha was 0.862.

RESULTS

Table 1: Summary of Respondents Demography (N=130)

Response	Frequency	Percentage （%）
Gender		
Male	76	58.5
Female	54	41.5
Age		
Below 18	3	2.3
19-25	115	88.5
26-30	12	9.2
Year of study		
Year 1	20	15.4
Year 2	62	47.7
Year 3	29	22.3
Year 4	19	14.6
Type of University		
Private University	33	25.4
Public University	97	74.6
Name of University		
USM	59	45.4
IIUM	4	3.1
INTI College	1	0.8
MSU	1	0.8
SUM	1	0.8
Sunway University	3	5.3
TARUMT	15	11.5
Taylor’s University	3	2.3
UITM	3	2.3
UKM	1	0.8
UM	3	2.3
UMP	1	0.8
UMS	1	0.8
UniKL	1	0.8
UNIMAP	4	3.1
UPM	5	3.8
UTAR	6	4.6
UTEM	3	2.3
UTHM	6	4.6
UTM	4	3.1
UUM	1	0.8
Have you used AI for Learning Purpose		
Yes	129	99.2
No	1	0.8
What Artificial Intelligence Tools do you use most often		
ChaGPT	104	80.0
Deepseek	15	11.5
Google Gemini	9	6.9
Microsoft Copilot	2	1.5

Frequency of AI Tools Usage		
Daily	67	51.5
Occasionally	16	12.3
Weekly	47	36.2

Table 1 presents the demographic profile of respondents. Most of the respondents (88.5%) fall within the age between 19-25 years, with no respondents above age 30. In terms of gender, most respondents are male (58.5%), while females make up a smaller proportion (41.5%). For the type of university, 33 out of 130 respondents, 25.4% are studying in private university whereas 97 respondents, 74.6% are studying in public university. The data indicates that almost all respondents had used AI for learning, with 129 of them (99.2%) answering in the affirmative and only 1 (0.8%) negating the usage. Among the most common AI applications, most of the responses were for ChatGPT (80%), followed by DeepSeek (11.5%), followed by Google Gemini (6.9%), and finally, Microsoft Copilot (1.5%). In terms of how often AI tools are used, many respondents (51.5%) stated that they use AI tools every day. Furthermore, there are 47 people (36.2%) who use them on a weekly basis and 16 (12.3%) who use them from time to time. This shows that AI tools have become a common and necessary part of the learning process for the participants.

Table 2. Descriptive statistics, Cronbach's Coefficients Alpha, and Zero-order Correlations for all study variables Note:

Variables	1	2	3	4
Personalised Learning	**0.862**			
Intelligent Feedback	0.674**	**0.883**		
AI-Driven assessment & Learning Analytics	0.603**	0.683**	**0.870**	
Academic Performance	0.615**	0.565**	0.604**	**0.862**
Number of items	4	6	5	6
Mean	4.778	4.145	3.971	4.250
Standard Deviation	0.664	0.628	0.614	0.620

N = 130; *p < .05, **p < .01, ***p < .001. The diagonal entries represent Cronbach's Coefficient Alpha.

Table 2 presents descriptive statistics, Cronbach's alpha reliability coefficients, and zero-order correlations for the study variables. All scales demonstrate good internal consistency: Personalised Learning (α = 0.862), Intelligent Feedback (α = 0.883), AI-Driven assessment & Learning Analytics (α = 0.870), and Academic Performance (α = 0.862). The mean is between 3.97 and 4.78 which indicates that most of the respondents were favorable towards the Personalised Learning, Intelligent Feedback, AI-Driven assessment & Learning Analytics, and Academic Performance features.

Table 3 presents the results of the regression analysis conducted to test the proposed hypotheses examining the effects of Artificial Intelligence based learning features on university students' academic performance. The hypotheses were evaluated based on the standardized beta coefficients and their corresponding significance levels. The overall regression model is statistically significant, with an R-square value of 0.469, indicating that 46.9 percent of the variance in academic performance is explained by personalised learning, intelligent feedback, and AI-Driven assessment & learning analytics. The F-value of 37.13 further confirms the adequacy of the model. In addition,

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the Durbin-Watson statistic of 2.063 indicates that there is no serious autocorrelation in the residuals.

Table 3. Summary of Regression Analysis

Variables	Academic Performance
Personalised Learning	0.346***
Intelligent Feedback	0.115
AI-Driven assessment & Learning Analytics	0.317***
R-Square	0.469
F-Value	37.13
Durbin-Watson Statistic	2.063

Note: N=130; *p < 0.05, **p < 0.01, ***p < 0.001. Standardized coefficients Beta are reported.

H1 proposed that personalised AI driven learning paths have a significant positive effect on student academic performance. The regression results show that personalised learning has a strong positive and statistically significant effect on academic performance with a standardized beta coefficient of 0.346 at p less than 0.001. This finding indicates that students who experience higher levels of AI driven personalised learning tend to achieve better academic performance. Therefore, H1 is supported. H2 proposed that direct positive relationship between intelligent feedback and academic performance. The regression results show that intelligent feedback has a positive but non-significant direct effect on academic performance with a standardised beta coefficient of 0.115. Therefore, H2 is not supported. H3 proposed that AI-Driven assessment & learning analytics have a positive and significant effect on academic performance. The findings demonstrate that AI-Driven assessment & learning analytics are positively and significantly related to academic performance, with a standardised beta coefficient of 0.317 at p less than 0.01. This result indicates that AI-Driven assessment and learning analytics contribute to better academic performance among university students. Therefore, the H3 is supported. Overall, the results provide empirical support for the roles of personalised learning and AI-Driven assessment & learning analytics in enhancing academic performance, while offering limited support for intelligent feedback. The summarised output of the hypothesised model is illustrated in Figure 2.

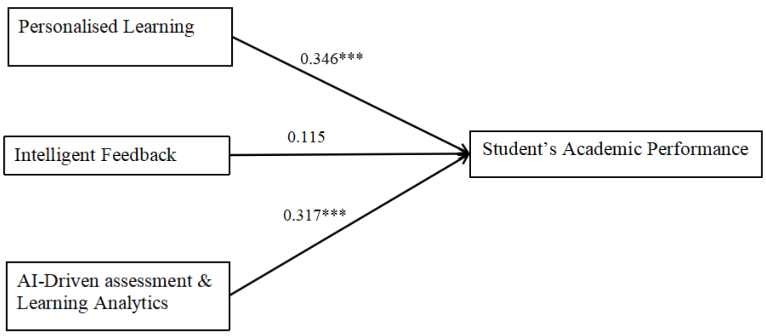

Figure 2. Hypothesized Model

DISCUSSION

Personalised Learning

The findings indicate that personalised learning has a significant positive effect on students' academic performance, supporting H1. AI-driven personalised learning paths allow instructional content, pacing, and difficulty levels to be tailored to individual learners, thereby enhancing relevance and reducing cognitive overload. This targeted learning approach increases motivation and sustained engagement, which in turn contributes to improved academic outcomes, as highlighted by Chen et al. (2022), Maghsudi et al. (2021), and Koenke and Anderman (2019). Consistent with prior studies, adaptive learning systems help students address knowledge gaps more efficiently and improve overall learning effectiveness in higher education settings.

Intelligent Feedback

The findings indicate that intelligent feedback show a positive effect, yet statistically non-significant, direct influence on students' academic performance, resulting in the rejection of H2. Although AI-generated feedback provides timely guidance and supports students in identifying errors and misconceptions, its impact on academic performance depends on how actively students apply the feedback during learning activities as noted by Hwang et al. (2020), and Nouri et al. (2021). Previous research suggests that feedback primarily enhances learning engagement and self-regulated study rather than directly improving academic outcomes, which may explain the weaker direct relationship observed in this study.

AI-Driven Assessment & Learning Analytics

The findings demonstrate that AI-driven assessment and learning analytics have a significant positive effect on students' academic performance, supporting H3. AI-Driven assessment and learning analytics systems provide continuous, data-driven insights into learning progress, enabling students to monitor performance, identify weaknesses, and adjust study strategies, accordingly, as discussed by Siemens and Gašević (2012) and Klašnja-Milićević and Ivanović (2021). Consistent with earlier studies, learning analytics enhances self-regulated learning and academic decision-making, making them a critical component in AI-supported learning environments.

Students' Academic Performance

Overall, the findings indicate that students' academic performance is positively influenced by the integration of AI-supported learning tools in higher education. Personalised learning and AI-driven assessment & learning analytics emerge as the strongest contributors to academic performance, while intelligent feedback plays a complementary role in supporting the learning process, as reported by Alotaibi and Alshehri (2023) and Mahafdah et al. (2024).These results are in line with previous research, suggesting that AI tools can effectively enhance academic outcomes when applied to complement traditional teaching approaches and aligned with students' individual learning requirements.

Practical Implications

The study can serve as a benchmark for the university and education sector, as it spotlights some of the major factors that need to be taken into account for the successful use of AI in higher education. To start with, the digital learning aids that personalize the learning process have been proven to increase academic performance to a great extent and, therefore, should be considered as one of the digital teaching strategies and also mainstreamed into the instructional practices. Next, the intelligent feedback process needs a lot of upgrading before it can be said that the AI system is providing feedback that is detailed, actionable and closely matched with the learning needs of the students. Additionally, learning analytics dashboards should be recommended strongly to support students in tracking their academic progress and organizing their study rituals in a more effective way. On the other hand, the use of AI should be managed very cautiously, while students are being motivated to see AI as a support in their learning process and not a quick way out, thus the ability to think critically and solve problems will be enhanced.

CONCLUSION

This study presents the results of an exploration of the various AI-based academic support elements which includes personalised learning, AI-Driven assessment & learning analytics, and intelligent feedback. Since they positively impact the academic performance among university students to considerable degree. The cordiality of students toward and involvement in AI-assisted learning tools emphasized by the SPSS results implies that AI can be a strong vehicle for improving learning outcomes if properly sequenced in the instructional process.

Accompanying these findings, university students are advocated to make use of AI application software for their learning to the fullest to sustain and enhance their learning experiences. Nevertheless, teachers should make students aware that relying heavily on AI might deter the student from acquiring the vital skills of reasoning and problem-solving. Hence, coupling AI-assisted Learning and traditional ways of teaching in a well-thought-out manner is the way to go in order to reap the maximum educational benefits.

This research brings forth both theoretical and practical benefits. Theoretically, it adds to the topic of AI in higher education by showing through specific AI features that academic performance can be positively impacted and thus delivering clearer AI-assisted learning engagement insights. The practical aspect of it is the postulations that the educators and the university administrators would find very useful in the question of the efficient deployment of AI-based tools, particularly student engagement as the main point of allied learning strategies rather than the teaching methods being replaced. In brief, the study asserts that when the use of AI is carefully planned, monitored, and pedagogically guided it still shows strong potential for enhancing the teaching and learning processes.

LIMITATION

Using a cross-sectional, self-report approach for data collection is a major drawback of this study, and it also limits the extent of one's conclusions that can be drawn from the results. The research that relied on a single-time collection of data through a Google Form questionnaire from 130 university students could not demonstrate any definitive causal links among the measured variables. The relationships detected were purely correlational thereby allowing the researchers to just show an association, not that one variable directly brought about a change in another. Besides, the dependence on self-reported data increases the risk of common method bias where the influences on the participants' answers may include their most likely to be influence and thus the true relationship between constructs being inadvertently misrepresented or artificially inflated. The weaknesses of the methodology warrant careful reading of the findings, especially when their practical implication is being considered.

The second main constraint is associated with the generalization of the research, which is a result of the sampling method and the relatively narrow focus of the study. Though the number of subjects, 130, is enough for performing statistical analyses, the adoption of a non-probability online questionnaire implies that the respondents might be a selfchosen group, namely, university students who were present and ready to take an online survey during the two-month data collection period. Thus, sampling bias is introduced, as the results might not be able to appropriately mirror the opinions, habits, or experiences of the lying university students' continent, especially among those who are not easily accessible or not very familiar with online and digital platforms. To overcome these limitations in future studies, adopting a longitudinal approach would be one way to developments in the relationships and cause-effect links between events, whereas employing strict, diverse sampling methods would be another way to improve the external validity and applicability in different institutional and demographic contexts of the results.

DECLARATION OF CONFLICTING INTERESTS

The authors report that there are no conflicts of interest related to the conduct of this study, its authorship, or its publication.

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