International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2025: 7.089

Beyond Feedback: The Role of AI-Assisted Feedback in Shaping Student Engagement and Academic Performance in Marketing Education

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Abstract: ***This study examines the impact of AI-assisted feedback on student engagement and academic performance in marketing education, with student engagement as a mediating variable. A quantitative cross-sectional survey design was employed, and data were collected from 260 undergraduate students enrolled in the Faculty of Business and Management at Universiti Sains Malaysia. Data were analyzed using SPSS and SmartPLS 4 through structural equation modeling. The findings indicate that AI-assisted feedback significantly enhances student engagement and directly improves academic performance. Student engagement also demonstrates a significant positive effect on academic performance and partially mediates the relationship between AI-assisted feedback and academic outcomes. The results suggest that timely, adaptive, and personalized AI-driven feedback can improve both learning participation and academic success in higher education marketing courses. The study contributes to the growing literature on AI in education by clarifying the psychological pathway linking AI-supported feedback and academic achievement.***

Keywords: AI-assisted feedback; artificial intelligence in education; student engagement; academic performance; marketing education; higher education; educational technology

1. Introduction

Artificial Intelligence (AI) has become a significant technological advancement in education, particularly in higher education. Institutions increasingly adopt AI technologies such as machine learning, natural language processing, and intelligent tutoring systems to enhance teaching, learning, and assessment processes. These tools support personalized learning, automated administration, and adaptive assessment, ultimately improving teaching effectiveness and student outcomes. Ayeni et al. (2024) highlight that AI has the potential to make education more accessible, efficient, and personalized. Holmes et al. (2019) show that AI-driven systems can enhance learning outcomes through data-informed insight.

Feedback is a central element of higher education as it helps students identify strengths and weaknesses, improve understanding, and support self-regulated learning. However, traditional feedback methods often rely on manual grading and written comments, which may be delayed or limited due to increasing class sizes and workload constraints. Insufficient or delayed feedback can negatively affect student motivation and learning progress (Fakhri et al., 2024). In response, AI-assisted feedback systems have been introduced to provide timely, scalable, and personalized feedback to students.

AI-assisted feedback refers to the use of intelligent systems to analyze student performance and generate automated, real-time feedback and assessments (Zhao, 2024). These systems enhance feedback quality and consistency while supporting continuous learning. Zawacki-Richter et al. (2019) indicate that AI-based feedback can improve student motivation, satisfaction, and academic performance by offering continuous and adaptive guidance throughout the learning process. This is particularly relevant in marketing education, where students are required to develop analytical, creative, and decision-making skills through activities such as case analysis, presentations, and project-based learning, all of which depend on timely feedback.

Student engagement is also a critical factor influencing academic success. It refers to students' behavioral, emotional, and cognitive participation in learning activities (Joshi et al., 2023). Engaged students are more likely to actively participate, interact with learning materials, and achieve better academic outcomes. Bond et al. (2021) suggest that AI-based learning tools can enhance engagement by providing interactive and personalized learning experiences. Therefore, understanding the role of AI-assisted feedback in promoting student engagement is essential for improving teaching practices in higher education.

Despite growing adoption of AI in education, several gaps remain in the literature. Most existing studies focus on STEM disciplines, with limited attention given to business and marketing education. In addition, while prior research has examined AI's impact on learning outcomes, fewer studies have investigated the mediating role of student engagement between AI-assisted feedback and academic performance. These limits understanding of how AI-driven educational tools influence learning processes and outcomes in marketing education contexts.

To address these gaps, this study examines the effects of AI-assisted feedback on student engagement and academic performance among undergraduate marketing students. It also investigates whether student engagement mediates the relationship between AI-assisted feedback and academic performance. By focusing on marketing education, this study contributes to expanding the literature on AI in higher education and provides a clearer understanding of how AI-supported feedback influences learning outcomes.

Theoretically, this study contributes to educational technology research by developing a framework linking AI-

assisted feedback, student engagement, and academic performance. It also extends mediation-based research in AI-enhanced learning contexts. Practically, the findings may assist universities and educators in designing effective AI-supported feedback systems to enhance student learning, engagement, and performance. The study also provides insights for policymakers seeking to integrate AI technologies effectively into higher education systems.

Based on the study objectives, the following research questions are proposed:

1) Does AI-assisted feedback influence student engagement in marketing courses?
2) Does AI-assisted feedback influence students' academic performance in marketing courses?
3) What is the relationship between student engagement and academic performance?
4) Does student engagement mediate the relationship between AI-assisted feedback and academic performance?

2. Literature Review and Hypothesis Development

2.1 AI-Assisted Feedback and Student Engagement

The rapid integration of artificial intelligence (AI) into higher education has transformed traditional pedagogical practices, particularly in assessment and feedback delivery. AI-assisted feedback refers to the use of intelligent systems capable of automatically analyzing student outputs and providing immediate, personalized, and adaptive feedback based on learner performance. These systems rely on machine learning and natural language processing techniques to evaluate assignments, detect patterns in student errors, and generate targeted improvement suggestions. Adayilo et al., (2025). AI has the potential to enhance learning environments by enabling personalized learning pathways and improving feedback efficiency, thereby strengthening student-centered education systems.

From a theoretical perspective, student engagement is a multidimensional construct that includes behavioral, emotional, and cognitive involvement in learning activities (Hasanov et al., 2021). Engagement theory suggests that students learn more effectively when they actively participate in meaningful learning processes rather than passively receiving information (Xu et al., 2023). In this context, timely and actionable feedback plays a critical role in sustaining engagement by guiding students' learning behaviors and reinforcing motivation.

Traditional feedback systems in higher education often suffer from delays, inconsistency, and limited personalization due to instructor workload and large class sizes. These limitations reduce the effectiveness of feedback in promoting continuous engagement. In contrast, AI-assisted feedback provides immediate responses, continuous monitoring, and adaptive suggestions, thereby enhancing students' sense of progress and control over their learning. Hattie and Timperley (2007) emphasize that effective feedback must answer three key questions: "Where am I going?", "How am I going?", and "Where to next?", all of which can be supported more efficiently through AI-based systems.

Furthermore, self-determination theory (Deci & Ryan, 2000) suggests that autonomy, competence, and relatedness are essential psychological needs that drive student motivation and engagement. AI-assisted feedback enhances perceived competence by helping students identify strengths and weaknesses in real time, thereby fostering intrinsic motivation and engagement. Empirical studies also show that digital feedback systems increase participation, interaction, and persistence in learning tasks (Zawacki-Richter et al., 2019). Based on these theoretical and empirical arguments, AI-assisted feedback is expected to play a significant role in enhancing student engagement in academic settings.

H1: AI-assisted f*eedback has a positive and significant effect on student engagement.*

2.2 AI-Assisted Feedback and Academic Performance

Academic performance is widely recognized as a key indicator of educational effectiveness, typically measured through grades, assignment scores, and overall course achievement. In marketing education, academic performance is particularly important because students are required to apply theoretical frameworks to real-world business cases, requiring continuous reflection, analytical thinking, and iterative improvement.

Constructivist learning theory posits that knowledge is actively constructed by learners through interaction with content, feedback, and experience rather than passively absorbed (Vygotsky, 1978). Within this framework, feedback is a crucial mechanism that supports learning development by helping students identify gaps between current and desired performance levels. However, traditional instructor-based feedback is often limited in frequency and specificity, reducing its impact on academic improvement.

AI-assisted feedback systems overcome these limitations by offering scalable, consistent, and data-driven evaluation of student performance. These systems provide instant corrective guidance, highlight conceptual misunderstandings, and suggest targeted improvements, which enhance students' ability to refine their academic work continuously. According to Holmes et al. (2019), AI-based educational tools can significantly improve learning outcomes by enabling adaptive and personalized learning support.

Additionally, from a cognitive load theory perspective (Sweller, 1988), timely and structured feedback reduces extraneous cognitive load by helping students focus on relevant learning tasks rather than struggling to interpret vague or delayed feedback. This allows students to allocate more cognitive resources to higher-order thinking processes, which ultimately improves academic performance.

Empirical evidence also supports the positive role of technology-enhanced feedback systems in improving academic achievement, particularly in higher education contexts where self-directed learning is essential (Urbina et

al., 2021). Therefore, AI-assisted feedback is expected to have a direct positive influence on academic performance.

H2: *AI-assisted feedback has a positive and significant effect on academic performance.*

2.3 Student Engagement and Academic Performance

Student engagement has been consistently identified as one of the strongest predictors of academic success across educational contexts. Engagement reflects the degree to which students are actively involved in learning activities, both behaviorally (participation), emotionally (interest and motivation), and cognitively (investment in understanding) (Hasanov et al., 2021).

Theoretical foundations from the engagement-performance model suggest that engaged students are more likely to persist in academic tasks, apply deeper learning strategies, and achieve higher levels of understanding. Kahu (2013) further argues that engagement acts as a psychosocial process that directly influences academic outcomes by enhancing motivation, self-efficacy, and learning persistence.

In marketing education, engagement is particularly critical because students are required to analyze complex case studies, collaborate in group projects, and apply theoretical models to dynamic market conditions. More engaged students are better able to integrate theoretical knowledge with practical applications, resulting in improved academic performance.

Empirical studies have repeatedly demonstrated a positive relationship between engagement and academic achievement in higher education settings. For example, active participation in learning activities and strong cognitive engagement have been linked to higher grades and improved retention rates (Tshering et al., 2024). Therefore, student engagement is expected positive influence on academic performance.

H3: *Student engagement positively influences academic performance.*

2.4 Mediating Role of Student Engagement

While AI-assisted feedback may directly enhance academic performance, its effect is also likely to occur indirectly through student engagement. This suggests a mediation mechanism in which engagement acts as a psychological and behavioral pathway linking feedback systems to academic outcomes.

Self-regulated learning theory provides a strong foundation for this relationship. According to Chou & Zou (2020), self-regulated learners actively monitor their performance, evaluate feedback, and adjust their learning strategies accordingly. AI-assisted feedback enhances this process by providing continuous, structured, and personalized performance information, which encourages students to engage more deeply with learning tasks.

Moreover, engagement theory suggests that learning outcomes are maximized when students are actively involved in meaningful learning experiences (Andrews et al., 2023). AI-assisted feedback increases engagement by making learning more interactive, responsive, and personalized, which subsequently improves academic performance.

Empirical research also supports the mediating role of engagement in educational technology contexts. Studies have shown that digital learning tools improve academic performance primarily through increasing student engagement and motivation rather than direct cognitive effects alone (Joshi et al., 2023). Therefore, student engagement is expected to serve as a key mediating mechanism in the relationship between AI-assisted feedback and academic performance.

H4*: Student engagement mediates the relationship between AI-assisted feedback and academic performance.*

The conceptual model illustrating the direct and mediating relationships among AI-assisted feedback, student engagement, and academic performance is presented in Figure 1. Therefore, the following hypotheses are proposed:

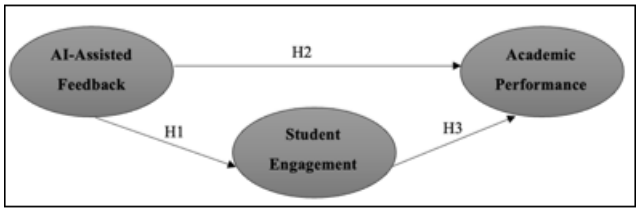

Figure 1: Conceptual Model

3. Methodology

3.1 Research Design and Approach

This study employed a quantitative research approach to examine the influence of AI-assisted feedback on student engagement and academic performance in marketing courses. A cross-sectional survey design was adopted to collect data from undergraduate students at a single point in time. The quantitative approach was considered appropriate because it allows the researcher to statistically examine relationships among variables and test the proposed hypotheses objectively. Ethical approval for this study was obtained from the relevant institutional review board of Universiti Sains Malaysia (USM), and informed consent was obtained from all participants before data collection. Participation was voluntary, and respondents were assured of confidentiality and anonymity.

3.2 Sampling Strategy and Participant Selection

The target population of this study comprised undergraduate students enrolled in marketing courses within the Faculty of Business and Management at Universiti Sains Malaysia (USM). A total of 260 students participated in the study. The sample was selected using a convenience sampling technique due to the accessibility of respondents within the academic environment and time constraints in reaching the full population. While this approach is practical and commonly used in educational research, it may introduce sampling bias and limit the generalizability of the findings, as the sample may not fully represent all marketing students across

different institutions. Participants were required to have experience with AI-assisted feedback or digital learning systems used in marketing education.

3.3 Data Collection Method and Questionnaire Development

Data were collected through an online questionnaire adapted from previously validated studies. The questionnaire consisted of two sections: demographic information and measurement items related to AI-assisted feedback, student engagement, and academic performance. Items of the questionnaire were adapted from scales that have been previously validated in the literature. The measurement of AI-assisted feedback was based on four items adapted from Mekheimer (2025). Eight items adapted from Oga-Baldwin and Nakata (2017) were used to measure student engagement, and four items adapted from Wut et al. (2023) were used for academic performance. The items were evaluated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

4. Data Analysis

Data were analyzed using IBM SPSS Statistics 25 for preliminary analysis and SmartPLS 4 for Structural Equation Modeling (SEM), including measurement model assessment, structural model analysis, and mediation testing. PLS-SEM was chosen due to its suitability for predictive modeling and complex relationships between latent constructs. The measurement model was evaluated using factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Discriminant validity was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. Bootstrapping with 5,000 resamples was used to assess the significance of path coefficients and mediation effects.

It is important to note that the path coefficient between AI-assisted feedback and student engagement ($\beta = 1.130$) reflects a standardized estimate produced by the PLS algorithm under the specific scaling of latent variables. Although this value appears unusually high compared to typical SEM ranges, it may occur in PLS-SEM when constructs are highly strongly related or when indicator scaling produces inflated standardized paths. Therefore, the interpretation is based on statistical significance and structural relationships rather than magnitude alone.

4.1 Demographic Profile

Table 1 shows the demographic data of the respondents. In terms of gender, the sample consists of 134 males (51.5%) and 126 females (48.5%), showing a nearly equal representation between both groups. Regarding age distribution, most respondents fall within the 18–20 age group (39.6%), followed by those aged 21–23 (31.9%) and 24–26 (28.5%). Academic year-wise distribution of students shows that second-year students are the largest group (34.2%), followed by third year (25.8%), first year (22.3%), and fourth year (17.7%). This means that there is a good spread of students studying at the various levels of undergraduate study. Lastly, the frequency of the use of AI-assisted learning tools reveals that most respondents used AI tools often, with (60.4%) reporting 'always, (23.1%) reporting occasionally, and (16.5%) reporting rarely. This highlights a high level of exposure to AI-assisted learning among participants overall.

Table 1: Demographic Profile of Respondents (N=260)

Demographic variable	Category	Frequency	Percentage
Gender	Female	126	48.50%
	Male	134	51.50%
Age	18–20	103	39.60%
	21–23	83	31.90%
	24–26	74	28.50%
Academic Year	First Year	58	22.30%
	Second Year	89	34.20%
	Third Year	67	25.80%
	Fourth Year	46	17.70%
Frequency of using AI-assisted learning tools	Always	157	60.40%
	Occasionally	60	23.10%
	Rarely	43	16.50%

Table 2 shows the KMO value was 0.915, which is considered excellent sampling adequacy. Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 1231$, df = 120, $p < 0.001$), which indicated that the correlations between the variables were adequate for the purpose of factor analysis.

Table 2: KMO and Bartlett's Test Results.

Kaiser-Meyer-Olkin (KMO) Measure		0.915
Bartlett's Test of Sphericity	Chi-Square (χ^2)	1231
	Degrees of Freedom (df)	120
	Significance (p-value)	< 0.001

4.2 Measurement Model Assessment

Table 3 presents the results of the measurement model assessment, including internal consistency reliability and convergent validity for all constructs. For AI-Assisted Feedback, the factor loadings are satisfactory, ranging from 0.625 to 0.995. The construct demonstrates good internal consistency, with Cronbach's alpha ($\alpha = 0.83$) and composite reliability (CR = 0.909) exceeding the recommended threshold of 0.70. The AVE value of 0.718 confirms adequate convergent validity.

Student Engagement shows strong measurement quality, with high factor loadings (0.867–0.938), Cronbach's alpha of 0.76, and excellent composite reliability (CR = 0.932). The AVE value of 0.819 indicates strong convergent validity and that the construct explains a substantial proportion of variance in its indicators. Academic Performance demonstrates acceptable internal consistency ($\alpha = 0.70$) and adequate factor loadings (0.642–0.746). However, composite reliability (CR = 0.745) is comparatively lower, and AVE (0.494) is slightly below the recommended threshold of 0.50, suggesting marginal convergent validity.

Table 3: Measurement Model Assessment: Reliability and Convergent Validity Results

Factor	Indicator	Factor Loadings	Cronbach's alpha (a)	CR (Composite Reliability)	AVE
AI-Assisted Feedback	AI1	0.894	0.83	0.909	0.718
	AI2	0.625			
	AI3	0.831			
	AI4	0.995			
Student Engagement	SE2	0.909	0.76	0.932	0.819
	SE4	0.938			
	SE6	0.867			
Academic Performance	AP1	0.642	0.70	0.745	0.494
	AP3	0.716			
	AP4	0.746			

4.3 Discriminant Validity

Table 4 presents the results of discriminant validity assessment using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. Based on the Fornell–Larcker criterion, the square root of the Average Variance Extracted (AVE) for each construct (AI-Assisted Feedback = 0.847, Student Engagement = 0.905, Academic Performance = 0.703) is higher than the corresponding inter-construct correlations. Specifically, AI-Assisted Feedback shows a stronger association with itself (0.847) than with Student Engagement (0.738) and Academic Performance (0.684). Similarly, Student Engagement demonstrates a higher diagonal value (0.905) compared to its correlations with AI-Assisted Feedback (0.738) and Academic Performance (0.696). Academic Performance also meets the criterion, with its AVE square root (0.703) exceeding its correlations with AI-Assisted Feedback (0.684) and Student Engagement (0.696), although the margin is relatively small. These results indicate that each construct is empirically distinct, supporting discriminant validity.

The HTMT results further reinforce this conclusion, as all values are below the recommended threshold of 0.85. The HTMT ratios between AI-Assisted Feedback and Student Engagement (0.74), AI-Assisted Feedback and Academic Performance (0.69), and Student Engagement and Academic Performance (0.71) indicate acceptable levels of discriminant validity without evidence of multicollinearity or construct overlap.

Table 4: Discriminant Validity- Using Fornell–Larcker Criterion and Heterotrait–Monotrait Ratio (HTMT)

Fornell–Larcker Criterion				Heterotrait - Monotrait Ratio (HTMT)		
Construct	AI-Assisted Feedback	Student Engagement	Academic Performance	AI-Assisted Feedback	Student Engagement	Academic Performance
AI-Assisted Feedback	**0.847**			—		
Student Engagement	0.738	**0.905**		0.74	—	
Academic Performance	0.684	0.696	**0.703**	0.69	0.71	—

4.4 Mediation Results

Table 5 shows the path analysis results, indicating that all hypothesized relationships were statistically significant. AI-assisted feedback had a strong positive effect on student engagement (β = 1.130, p < .001), which in turn significantly influenced academic performance (β = 0.255, p < .001). In addition, AI-assisted feedback also had a significant direct effect on academic performance (β = 0.348, p < .001). Overall, the results indicate that student engagement partially mediates the relationship between AI-assisted feedback and academic performance.

Table 5: Path Estimates

Path				Estimate	SE	Z	p
H1	AI-Assisted Feedback	→	Student Engagement	1.130	0.0618	18.29	<.001
H2	AI-Assisted Feedback	→	Academic Performance	0.348	0.0550	6.33	<.001
H3	Student Engagement	→	Academic Performance	0.255	0.0402	6.35	<.001

Table 6 shows that the mediation analysis indicates that student engagement partially mediates the relationship between AI-assisted feedback and academic performance. The indirect effect was significant (β = 0.288, p < .001), indicating that AI-assisted feedback improves academic performance through its positive impact on student engagement. The direct effect remained significant (β = 0.348, p < .001), suggesting partial mediation. The total effect was also significant (β = 0.636, p < .001), confirming the overall strong influence of AI-assisted feedback on academic performance.

Table 6: Mediation Analysis Results

Effect	Estimate	SE	Z	p
Indirect	0.288	0.0485	5.94	<.001
Direct	0.348	0.0550	6.33	<.001
Total	0.636	0.0362	17.58	<.001

According to the path analysis findings, all path relationships between variables have been statistically significant (p < .001). AI-assisted feedback positively influenced student engagement (β = 1.130), while both AI-assisted feedback and student engagement significantly affected academic performance. In addition, mediation analysis indicated that academic performance was indirectly affected by AI-assisted

feedback through student engagement (β = 0.288, p < .001). Both indirect and direct effects proved to be important and resulted in part from mediation by student engagement between the effects of AI-assisted feedback and academic performance.

5. Discussion

This study confirms the importance of AI-assisted feedback for student engagement (SE) and academic performance (AP) in higher education. More significantly, it reveals the intermediate effect of student engagement, which is considered a pivotal psychological mechanism to explain how AI-based feedback can boost student performance. The significant path from AI-assisted feedback to student engagement (β = 1.130, p < .001) suggests that students who are provided immediate feedback, tailored to their individual needs, and adaptive based on AI systems are more likely to be engaged in learning activities. The findings are in line with previous studies that focused on the importance of providing feedback at the right time to provide the right feedback (Hattie & Timperley, 2007; Shute, 2008).

Besides, AI-driven feedback and academic performance are directly linked (β = 0.348, p < .001), suggesting that AI systems have a direct influence on learning outcomes besides engaging the learner. The advantage of AI-generated feedback is that learners have immediate feedback to discuss and correct their learning trajectory, thus reducing the processing load on the brain and improving learning understanding. This is consistent with the cognitive theory of multimedia learning, explaining that feedback is an effective stimulus to enhance the efficiency of learning (Mayer, 2009).

In addition, student engagement has a positive effect on academic performance (β = 0.255, p < .001), which indicates that being an engaged student is positively associated with academic success. This reinforces the strong consensus that engagement is a strong predictor of academic performance as it leads to persistence, attention, and increased cognitive processing (Xu et al., 2023).

The mediation analysis indicated that the direct association between AI-assisted feedback and academic performance was partially mediated by students' engagement. This suggests that AI-powered feedback may directly and indirectly influence the performance of their students by influencing student engagement. Hints of this partial mediation suggest that engagement has an important explanatory value, with the independent effect of AI systems on academic achievement. This aligns with the other studies, which emphasized the cognitive and motivational-learning dimensions of technologies for learning (Zawacki-Richter et al., 2019).

The results are related to the literature in two different aspects: first, the usage of AI for giving feedback can be a direct facilitator for studying and second, an indirect facilitator with the involvement of other academic processes of students. The study contributes to the growing body of research on AI in education by clarifying the psychological mechanisms through which AI improves learning outcomes.

6. Conclusion and Practical Implications

6.1 Conclusion

This study demonstrates that AI-assisted feedback can significantly improve student engagement and academic performance in higher education marketing courses. The findings confirm that AI-supported feedback contributes both directly to academic achievement and indirectly through enhanced student engagement, indicating a partial mediation effect. These results reinforce the educational value of timely, adaptive, and personalized AI-driven feedback systems. The study contributes theoretically by clarifying the psychological mechanism linking AI feedback and academic performance, while practically supporting the thoughtful integration of AI-based feedback tools in higher education teaching environments. Future research should validate these findings using longitudinal and multi-institutional designs.

6.2 Practical Implications

This study contributes to Student Engagement Theory and Self-Determination Theory by confirming the mediating role of student engagement in the relationship between AI-assisted feedback and academic performance. The findings show that AI-assisted feedback influences academic performance both directly and indirectly through enhancing student engagement, highlighting the importance of engagement in technology-supported learning. From a practical perspective, AI-assisted feedback should be integrated into formative assessment practices to improve learning effectiveness, reduce instructors' workload, and enhance student engagement. AI systems should provide timely, personalized, and adaptive feedback that actively supports student learning rather than delivering generic responses. Higher education institutions can use AI-driven feedback systems to manage large class sizes and improve feedback efficiency. However, successful implementation requires faculty training and attention to ethical issues such as data privacy, transparency, and responsible AI use.

7. Limitations and Future Research

Despite the theoretical and practical contributions of this study, several limitations should be acknowledged. First, the cross-sectional research design limits the ability to draw strong causal inferences regarding the relationships among AI-assisted feedback, student engagement, and academic outcomes, and the possibility of reverse causality cannot be fully excluded. Future studies are encouraged to adopt longitudinal or experimental designs to better establish causality and examine changes over time. Second, the study relies on self-reported data, which may introduce common method bias; therefore, future research should incorporate objective performance measures or multi-source data to enhance validity. Finally, the focus on a specific context may limit the generalizability of the findings, suggesting that future studies should replicate the model across different educational settings and populations to strengthen external validity.

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