MALAYSIA

SUMMARY:

STUDENT PERCEPTIONS OF AN AI-POWERED FEEDBACK SYSTEM IN ACADEMIC WRITING: A STUDY ON INTENTION, SATISFACTION, TRUST, AND REACTIONS TO NEGATIVE FEEDBACK.

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Key findings:

- Students acknowledged the system's helpfulness and expressed strong willingness to adopt it for future assignments, reflecting high acceptance and alignment with their learning needs.
- Positive reception of Studiosity among students, particularly in terms of intention to use and satisfaction.
- "High mean scores for intention-related items suggest that students not only value the system's contribution to their assignment work but are also willing to continue using it in future courses. This reflects a strong sense of technology acceptance, consistent with the Technology Acceptance Model (TAM) framework."
- The findings also demonstrate that students' perceptions of the AI-based feedback system - intention to use, satisfaction, and trust - have broad acceptance and perceived value regardless of demographic differences.

FINAL REPORT

Student Perceptions of an AI-Powered Feedback System in Academic Writing: A Study on Intention, Satisfaction, Trust, and Reactions to Negative Feedback

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ABSTRACT

The integration of Artificial Intelligence (AI) into higher education is redefining formative assessment practices, particularly through automated feedback systems. This study investigates student perceptions of *Writing Feedback Plus* (WF+), an AI-powered academic writing support tool implemented at Open University Malaysia (OUM). The research explores students' behavioural intention to use the system, satisfaction with its performance, trust in its feedback, and reactions to negative or critical feedback. Using a survey-based quantitative design, data were collected from 435 students who used the system during the January 2025 semester. Of these, 211 students responded to a specific section focused on negative feedback experiences. Descriptive statistics revealed high levels of student intention to continue using the system (M = 4.16), satisfaction (M = 4.20), and trust (M = 4.03). However, emotional responses to negative feedback were more variable (M = 3.45–3.80), indicating cognitive appreciation but inconsistent motivational impact. Independent samples t-tests showed no statistically significant differences in perceptions based on gender or level of study (undergraduate vs. postgraduate), suggesting the system's general acceptability across diverse learner demographics. The findings underscore the value of AI-assisted feedback in promoting self-directed learning and improving academic writing in open and distance learning (ODL) contexts. However, the results also highlight the importance of designing emotionally sensitive feedback mechanisms. To optimize impact, AI systems must balance clarity with motivational tone, trust-building transparency, and educator-guided interpretation. These insights inform future development of emotionally intelligent, adaptive AI feedback tools for inclusive and effective digital learning environments.

Keywords
AI in education, automated feedback, formative assessment

INTRODUCTION

Artificial Intelligence (AI) is increasingly becoming a transformative force in higher education. Its integration into teaching and learning processes is enabling more personalized, scalable, and data-driven instructional approaches. Among the most promising applications of AI is its role in formative assessment—especially through the generation of automated feedback. This report presents the findings of a study conducted at Open University Malaysia (OUM), focusing on an AI-powered feedback system known as Writing Feedback Plus (WF+), offered through Studiosity. The system was piloted during the January 2025 semester to support students' academic writing by delivering timely and constructive feedback.

This research was conducted to explore how automated AI-based feedback system for formative assessment such as WF+ s influences students' behavioural intention to use the system, satisfaction with the system, trust in the system and its feedback, and perceptions of receiving negative feedback. These factors are increasingly acknowledged in educational research as critical determinants for the successful adoption of AI technologies in learning environments.

AI-BASED FEEDBACK SYSTEMS IN FORMATIVE ASSESSMENT

Recent innovations demonstrate the potential of AI-powered systems in enhancing the formative assessment process. For instance, FlowHunt (2024) illustrates how AI feedback tools can offer real-time, individualized insights to learners, thereby improving engagement and learning outcomes across diverse educational settings. Analytikus (2024) highlights the efficiency of AI in automating assessment workflows, allowing educators to manage large volumes of student submissions while maintaining a degree of personalization in feedback. Additionally, the EvaluMate project demonstrates the integration of ChatGPT into peer-review systems, enabling learners to provide and receive constructive, scaffolded feedback in academic writing tasks (Guo, 2024). These examples underscore a growing shift toward the adoption of AI technologies to address the limitations of traditional feedback methods and support more adaptive, learner-cantered instructional strategies.

The integration of AI in education has introduced powerful tools that can significantly enhance formative assessment practices, particularly through the automation and personalization of feedback. Traditional feedback mechanisms, while valuable, often suffer from delays, inconsistencies, and scalability issues—especially in large, open and distance learning environments. These limitations can negatively affect student engagement, motivation, and the overall quality of learning (Luckin et al., 2016; Choy & Quek, 2016). In contrast, AI-based feedback systems provide a scalable solution by delivering automated, context-aware, and timely responses that promote conceptual understanding, support self-regulated learning, and sustain learner motivation (Zawacki-Richter et al., 2019).

In technology-enhanced environments, especially those involving distance education, AI-driven formative feedback systems can play a pivotal role in ensuring inclusivity, adaptability, and sustainability in the learning process (Nguyen & Tuamsuk, 2022).

The growing incorporation of artificial intelligence (AI) in education, particularly through AI-powered feedback mechanisms, offers scalable, real-time, and personalized learning support. Nevertheless, empirical studies on how students perceive and respond to these systems remain limited, especially concerning their behavioural intention, satisfaction, trust in the system and its feedback, and responses to negative feedback. While previous research has investigated AI adoption and trust in broader contexts—identifying trust as a key predictor of use and highlighting diverse trust dimensions in educational AI deployments (Choung et al., 2022; Zhang et al., 2025)—the specific application to formative assessment in academic writing lacks robust evidence. Furthermore, behavioural intention and satisfaction are well-established constructs in the Information Systems (IS) Success Model proposed by DeLone and McLean (2003), which emphasizes these factors as critical to evaluating system use and user acceptance. Although this model has been extensively applied in various educational technology studies (Alamäki et al., 2024; Valle et al., 2024), its application to AI-based feedback tools in higher education contexts remains underexplored. Similarly, trust dimensions (e.g., functionality vs. human-like trust) have been examined in AI voice assistants and other domains (Choung et al., 2022; Zhang et al., 2025), but not fully contextualized for educational feedback systems. While AI-generated feedback has potential to enhance learning, evidence shows that negative self-referential feedback from AI can "bruise one's ego," reduce state self-

5. To explore whether students' perceptions of the AI-based feedback system—measured through Intention to Use, Satisfaction, Trust, and Perception of Negative Feedback—differ significantly by gender and study level (postgraduate vs. undergraduate).

METHODOLOGY

This chapter outlines the research methodology used to investigate student perceptions of the Writing Feedback Plus (WF+) system at Open University Malaysia (OUM). It details the study context, implementation procedures, instrument design, data collection, and analysis methods employed to address the research objectives.

Overview of the WF+ System

Writing Feedback Plus (WF+), developed by Studiosity Pty Ltd (https://www.studiosity.com/), is an AI-powered feedback system designed to support academic writing by providing instant, formative feedback on student draft submissions. Integrated into OUM's Learning Management System (LMS), WF+ analyses student writing and delivers two types of automated feedback:

- Summaries: "Summaries" provides explanations and condense the information, offering a clearer understanding or reference for the key points highlighted (see Figure 1).
- Highlight: "Highlight" identifies key points in the text, drawing attention to specific ideas or details (see Figure 2).

Figure 1. A Randomly Selected Example of Feedback in the Form of "Summaries" Provided on a Learner's Draft Assignment Through the WF+ Platform

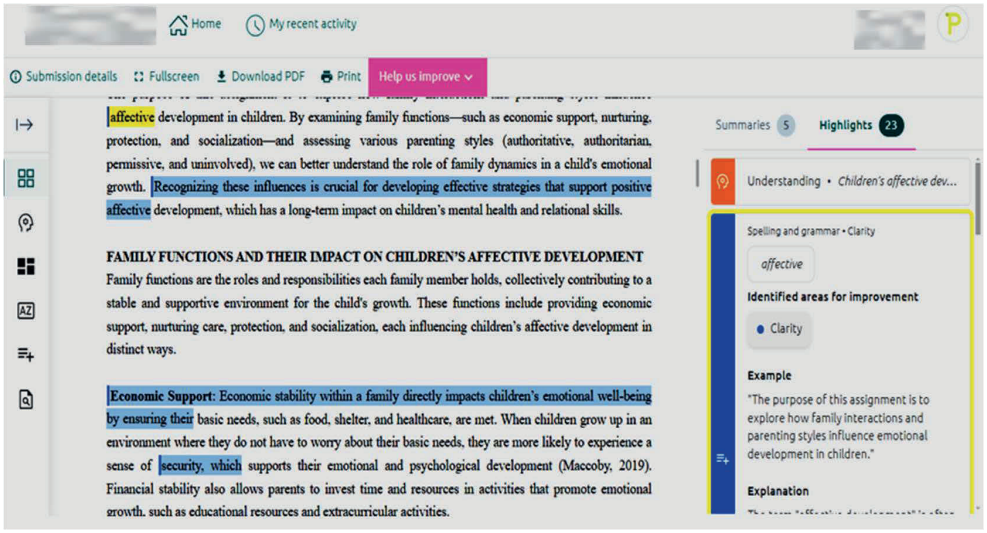

Figure 2. A Randomly Selected Example of Feedback in the Form of "Highlight" Provided on a Learner's Draft Assignment Through the WF+ Platform

WF+ evaluates student submissions across five key dimensions:

- Structure: Assessment of document organization, logical flow, and coherence.
- Language Choice: Evaluation of word selection, tone, and appropriateness for the audience.
- Argument/Idea Development: Review of idea clarity and support with evidence.

- Referencing: Assessment of reference accuracy, formatting, and relevance.
- Spelling and Grammar: Detection of common language errors and suggestions for correction.

AI-assisted feedback is provided through in-text annotations and related comments, supplemented by a comprehensive feedback summary. This system does not directly edit or change the content of student scripts. Instead, it highlights and discusses commonly made mistakes, incorporating examples to help students understand and address these issues. This approach empowers students to apply the feedback to their current and future writing tasks, fostering long-term critical-thinking skill development. Feedback on spelling and grammar emphasises patterns of errors within the document, allowing students to recognise systemic and syntax issues in their writing. Identified errors are highlighted and thoroughly explained, with relevant examples provided for clearer understanding.

Study Context and Implementation

The WF+ system was piloted during the January 2025 semester across 12 first-semester part-time courses, engaging a total of 1243 Open and Distance Learning (ODL) students at Open University Malaysia (refer to Table 1). The assignments for the subjects listed in Table 1 carry a weightage of between 50% and 60% of the overall course grade.

Table 1. Courses with WF+ Access

	Subject Code	Subject Name
1	BBPP1103	Principles of Management
2	OUMH1603	Learning Skills for 21st Century
3	SBFS1103	Thinking Skills and Problem Solving
4	ABCC1103	Introduction to Communication
5	CBCT2203	Basic Concepts of Information Technology
6	MPU3412	Community Service
7	BBPB2103	Human Resource Management
8	HPGD2203	Educational Management
9	HPGD3503	Inclusive Education
10	HPGD1103	Curriculum Development
11	HPGD1203	Theories and Practices of Teaching and Learning
12	HMEC5213	Early Childhood Curriculum

Students accessed the tool through the LMS, where they submitted their draft essay-type assignments for automated review. Upon receiving feedback, they were given the opportunity to revise and resubmit their assignments. This iterative cycle was designed to promote self-directed learning and improve academic writing through formative assessment.

Following their engagement with the WF+ system, students were invited to participate in a structured survey designed to evaluate their perceptions across several key constructs.

Research Design

A quantitative research design was employed to measure student perceptions of the WF+ system based on four research objectives:

1. Intention to use the AI-based feedback system
2. Satisfaction with the AI-based feedback system
3. Trust in the system and its feedback
4. Perception and response to negative feedback

Each construct in the study was measured using three survey items. The alignment between the research objectives and their corresponding survey items is presented in Table 2. Items for the constructs **Intention to Use** and **Satisfaction** were adapted from Mathur, Anand, Sharma, and Vishnoi (2025), as well as Ojo (2017). The items measuring **Trust** were developed based on Ghazizadeh et al. (2012), while those related to the **Perception of Negative Feedback** were adapted from Li et al. (2025), Adanyin (2024), Sadeghi (2024), and Piispanen and Rousi (2024).

Table 2. Mapping of Research Objectives to Corresponding Survey Items Used in Evaluating the WF+ System

Research Objective	Survey Items
To examine students' **intention to use** an AI-based feedback system for academic writing support	1. I believe it is worthwhile for me to use the AI-assisted System for Assignment 2. Based on my experience, I am very likely to use the AI-assisted System for Assignment 3. I plan to use the AI-assisted System for Assignment very often in future courses if given the access to this system
To evaluate students' **satisfaction** with the AI-based feedback system	1. I think the AI-assisted System for Assignment is very helpful 2. I am satisfied with the performance of the AI-assisted System for Assignment 3. Overall, I am pleased with the experience of using AI-assisted System for Assignment
To investigate students' **trust** in the AI-based feedback system	1. I will trust the feedback provided by the AI-assisted system to improve the academic writing of my assignment 2. I think I can depend on the AI-assisted System for Assignment 3. I will feel more comfortable exploring and completing various tasks with the support of the AI-assisted system for my assignment
To explore the **impact of negative feedback** from the AI-based feedback system on students' motivation, perception, and willingness to improve	1. I felt demotivated after receiving negative feedback from the AI system 2. The AI system's negative feedback helped me identify my weaknesses in the assignment 3. I used the negative feedback from the AI system to revise and improve my assignment Note: Negative feedback refers to constructive input that points out errors or areas needing improvement, such as issues with language structure, writing style, critical thinking, language use, spelling and grammar)

Data Collection Procedure

Data was collected through an online survey administered at the end of the semester. Participation was voluntary, and informed consent was obtained. The survey was made accessible via the university's LMS to students who had used the WF+ system during their course. The items were structured using a five-point Likert scale ranging from "1 -Strongly Disagree" to "5 -Strongly Agree".

Summary of the methodology is given in Figure 3.

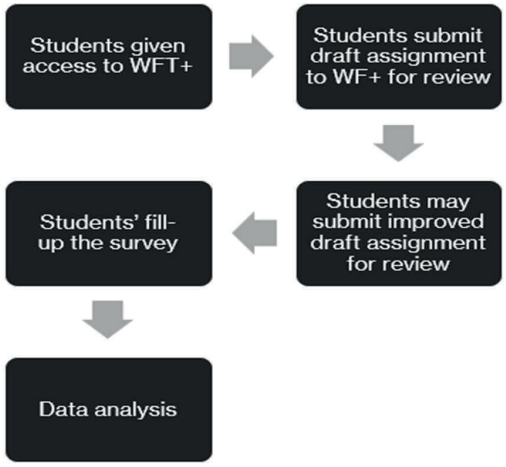

Figure 3. The summary of methodology adopted in this study

RESULTS & ANALYSIS

A total of 435 students participated in the survey, representing approximately 35% of those who used the Writing Feedback Plus (WF+) system during the January 2025 semester. Among the respondents, 60% were postgraduate students and 40% were undergraduates, with an average age of 31.1 years. The majority were female (77%), while 23% were male. Each student interacted with the WF+ system approximately twice, indicating sustained engagement with the feedback process. Of the 435 students who responded to the survey (N = 435), a subset of 211 students completed the section on negative feedback experiences. This section was conditionally displayed only to respondents who had received negative or critical feedback from the AI-based system. As such, analyses related to perceptions and reactions to negative feedback were based on this subgroup (n = 211). The remaining respondents (n = 224) did not receive negative feedback from the system, and thus were excluded from the analysis related to negative feedback response.

Reliability and Reverse-Coding

To assess the internal consistency of the survey constructs, **Cronbach's alpha** was calculated for each and given in Table 3.

Table 3. Reliability Coefficients (Cronbach's Alpha) for Each Construct

Construct	Cronbach's Alpha
Intention to Use	0.96
Satisfaction	0.97
Trust	0.93
Perception of Negative Feedback	0.40

The constructs *Intention to Use*, *Satisfaction*, and *Trust* exhibited excellent internal reliability ($\alpha > 0.90$), supporting the calculation of consolidated means. The *Perception of Negative Feedback* construct yielded low reliability ($\alpha = 0.40$), suggesting conceptual divergence among its items. Accordingly, responses to this construct were analysed at the item level rather than as a composite. One item in this construct was originally phrased negatively: *"I felt demotivated after receiving negative feedback from the AI system."* For analytical consistency, this item was reverse-coded and reworded as *"I felt motivated after receiving negative feedback from the AI system"*

Descriptive Statistical Analysis

Descriptive statistics were applied to evaluate students' perceptions across four constructs: Intention to Use, Satisfaction, Trust, and Perception of Negative Feedback. Mean scores and standard deviations for individual items are presented in Table 4 which presents the full breakdown of survey items, mean scores, and standard deviations. Scores for *Intention to Use* and *Satisfaction* were consistently high, reflecting strong student acceptance and positive experiences. *Trust* in the AI system was also high but with slightly more variability, suggesting moderate reservations among some students. For *Perception of Negative Feedback*, the highest item mean related to students using the feedback to revise their work (M = 3.80), while the affective item (reworded *I felt motivated after receiving negative feedback from the AI system*) received the lowest score (M = 3.45), indicating mixed emotional responses.

Table 4. Mean Scores of Survey Items Categorized by Construct for the AI-Assisted Feedback System

Construct	Survey Item	Number of Respondents	Mean Score	Standard Deviation
Intention to Use	I believe it is worthwhile for me to use the AI-assisted system for assignment	N=435	**4.19**	0.83
	Based on my experience, I am very likely to use the AI-assisted system for assignment		**4.13**	0.90
	I plan to use the AI-assisted system for assignment very often in future courses if given access		**4.17**	0.87
Satisfaction	I think the AI-assisted system is very helpful		**4.23**	0.84
	I am satisfied with the performance of the AI-assisted system		**4.18**	0.84
	Overall, I am pleased with the experience of using the AI-assisted system		**4.20**	0.84
Trust	I will trust the feedback provided by the AI-assisted system to improve my academic writing		**4.05**	0.84
	I think I can depend on the AI-assisted system for assignment		**3.93**	0.91
	I will feel more comfortable exploring tasks with support from the AI-assisted system		**4.11**	0.80
Perception of Negative Feedback	I felt motivated after receiving negative feedback from the AI system	n=211	**3.45**	1.18
	The AI system's negative feedback helped me identify my weaknesses		**3.67**	1.13
	I used the negative feedback to revise and improve my assignment		**3.80**	1.13

Interpretation Summary

Table 5 presents the descriptive analysis of mean scores across four key constructs measured in the study: intention to use, satisfaction, trust, and perception of negative feedback. These constructs reflect students' overall experience with the AI-based feedback system. The mean score ranges provide insight into general trends in student responses, while the interpretation summary highlights the overall sentiment for each construct. The results indicate generally positive perceptions of the system, with strong willingness to continue its use, high satisfaction, and moderate to high trust levels. Perceptions of negative feedback revealed recognition of its cognitive value, though emotional responses varied more widely.

Table 5. Descriptive Summary of Students' Perceptions Based on Key Constructs

Construct	**Mean Range**	**Interpretation Summary**
Intention to Use	4.13–4.19	Strong willingness to continue using the AI feedback system
Satisfaction	4.18–4.23	High satisfaction with the system's usefulness and performance
Trust	3.93–4.11	Generally positive, though some hesitance in full reliance on the system
Perception of Negative Feedback	3.45–3.80	Cognitive value recognized; emotional response to negative feedback was more variable

Figure 4 provides a graphical representation of the mean scores for each construct, underscoring the consistently positive reception of the system in terms of intention to use and satisfaction, while revealing comparatively greater variability in emotional responses to feedback.

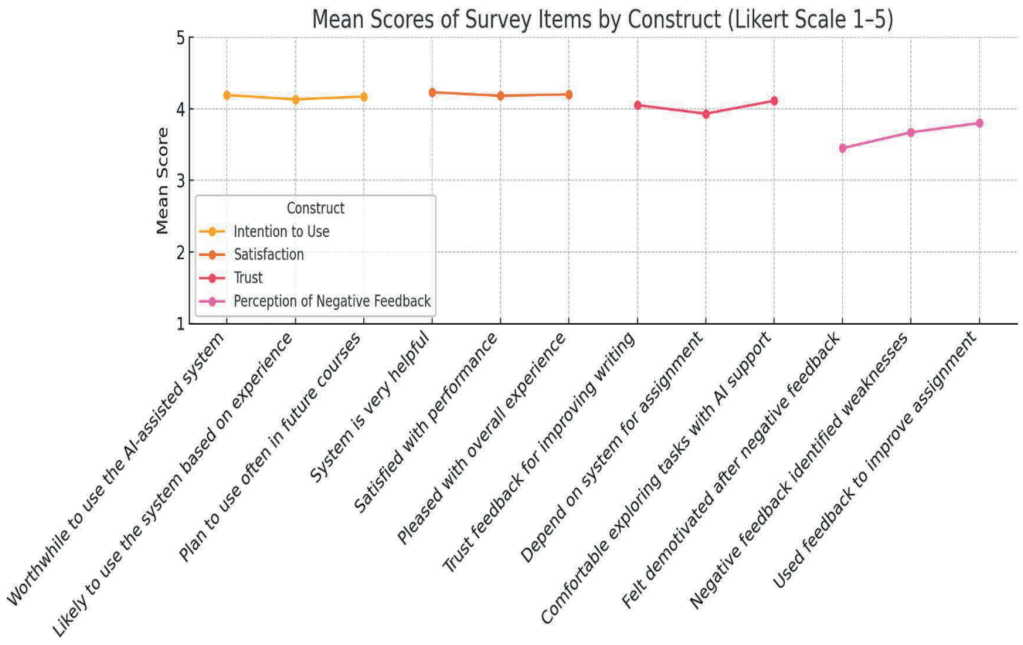

Figure 4. Mean Scores of Survey Items Categorized by Construct for the AI-Assisted Feedback System

Construct-Level Averages

For the three constructs with high reliability, the consolidated means were calculated as shown in Table 6.

Table 6. Consolidated means of the constructs

Construct	**Consolidated Mean**
Intention to Use	4.16
Satisfaction	4.20
Trust	4.03

These averages provide a summary indication of overall student perceptions in each area and are consistent with the interpretation of the individual item means.

Group Comparisons by Gender and Study Level

To address Research Objective 5, independent samples t-tests were conducted to compare students' perceptions based on gender (male vs female) and study level (undergraduate vs postgraduate). Composite scores were used for *Intention to Use*, *Satisfaction*, and *Trust.*

Study Level

An independent samples t-test was conducted to assess whether students' perceptions of the AI-based feedback system varied by level of study (undergraduate vs. postgraduate) across three constructs: intention to use, satisfaction, and trust. Levene's Test for Equality of Variances indicated that the assumption of equal variances was met for all three constructs (Intention: p = .372; Satisfaction: p = .684; Trust: p = .714), justifying the use of the equal variances assumed values in the t-tests.

For intention to use, no significant difference was found between undergraduate and postgraduate students, $t(433) = 0.380$, p = .704. The mean difference was minimal (0.031, 95% CI: [-0.130, 0.192]), suggesting both groups had similarly positive intentions to adopt the system.

In terms of satisfaction, the results also showed no statistically significant difference, $t(433) = 0.426$, p = .670. The mean difference of 0.034 (95% CI: [-0.123, 0.190]) indicates comparable levels of satisfaction between the two cohorts.

Finally, for trust, there was no significant difference between undergraduates and postgraduates, $t(433) = 0.005$, p = .996. The extremely small mean difference (0.00036, 95% CI: [-0.153, 0.154]) further confirms that both groups expressed nearly identical levels of trust in the AI system.

These findings collectively indicate that perceptions of the AI-based feedback system were consistent across levels of study, with no statistically meaningful differences in intention, satisfaction, or trust.

Gender

An independent samples t-test was conducted to examine whether students' perceptions of the AI-based feedback system differed significantly by gender across three constructs: intention to use, satisfaction, and trust. Levene's Test for Equality of Variances indicated that the assumption of equal variances was met for all three constructs (Intention: $p = .491$; Satisfaction: $p = .100$; Trust: $p = .397$).

For intention to use, there was no significant difference between male and female students, $t(433) = -1.398$, $p = .163$. The mean difference was -0.133 (95% CI: [-0.320, 0.054]), suggesting that both genders held similar intentions to adopt the system.

For satisfaction, the difference was also not statistically significant, though it approached marginal significance, $t(433) = -1.748$, $p = .081$. The observed mean difference of -0.162 (95% CI: [-0.344, 0.020]) suggests that female students may have reported slightly higher satisfaction than male students; however, the difference was insufficient to reach the conventional threshold of significance.

Lastly, for trust in the system, no significant gender difference was found, $t(433) = -0.782$, $p = .435$, with a mean difference of -0.071 (95% CI: [-0.250, 0.108]).

These findings indicate that male and female students generally perceived the AI-based feedback system similarly in terms of their satisfaction, intention to use the system and trust.

DISCUSSION

The results of this study indicate a generally positive reception of the AI-assisted feedback system among students, particularly in terms of intention to use and satisfaction. This aligns with prior research highlighting the role of perceived usefulness and ease of use in shaping users' behavioural intentions to adopt educational technologies (Davis, 1989; Teo, 2011). High mean scores for intention-related items suggest that students not only value the system's contribution to their assignment work but are also willing to continue using it in future courses. This reflects a strong sense of technology acceptance, consistent with the Technology Acceptance Model (TAM) framework.

In terms of satisfaction, students found the system helpful and effective in enhancing their academic writing. This echoes findings by Winstone et al. (2017), who emphasized that students are more satisfied with feedback that is actionable and timely. The integration of the AI system within the Learning Management System (LMS) appears to support the timely provision of formative feedback, a critical factor for student satisfaction in online learning environments (Espasa & Meneses, 2010).

Regarding trust, although students generally trusted the AI-generated feedback, there was some hesitation about fully depending on the system. This finding mirrors concerns raised in the literature about the credibility and perceived authority of AI-generated content, especially in higher education contexts (Popenici & Kerr, 2017). Trust in AI systems is often shaped not only by system accuracy but also by the perceived fairness, transparency, and emotional intelligence of the tool (Shin, 2020). Hence, fostering trust may require enhancements in both the interpretability and personalization of feedback.

A more nuanced picture emerged in the perception of negative feedback. While many students used the AI's feedback to improve their assignments and identified areas of weakness, a portion still felt demotivated after receiving such feedback. This is consistent with research by Lipnevich and Smith (2009), who found that negative feedback, even if constructive, can impact learners' emotional states and motivation. The challenge in AI feedback systems is thus not only delivering accurate assessments but also doing so in a manner that is emotionally supportive. Feedback that is perceived as overly critical may reduce self-efficacy or increase anxiety, especially in formative stages of learning (Narciss, 2008).

The findings also demonstrate that students' perceptions of the AI-based feedback system—measured through intention to use, satisfaction, and trust—did not differ significantly across gender or study level, suggesting broad acceptance and perceived value of the tool regardless of demographic differences. This aligns with prior research indicating that when AI tools are perceived as useful and easy to use, demographic factors such as gender and academic level exert minimal influence on user acceptance (Davis, 1989; Teo, 2011). Such consistency in

perception reinforces the potential of AI-driven feedback systems to support inclusive digital learning environments across diverse learner groups.

These findings suggest that while AI-based feedback systems have strong potential to enhance learning, their effectiveness depends on the thoughtful design of feedback mechanisms that balance cognitive clarity with emotional sensitivity. Importantly, the absence of significant differences in perceptions across gender and study level underscores the inclusive nature of such systems, highlighting their capacity to support equitable learning experiences across diverse student populations. Future developments should consider integrating affective computing techniques to personalize not only the content but also the tone of feedback, ensuring it resonates effectively with learners from varied backgrounds and emotional dispositions.

CONCLUSION

The findings from this study indicate a generally positive perception of the AI-assisted feedback system among students, especially in terms of its perceived usefulness, satisfaction, and intention to use. Students acknowledged the system's helpfulness and expressed strong willingness to adopt it for future assignments, reflecting high acceptance and alignment with their learning needs. However, while trust in the system was moderately high, some students exhibited reservations about relying solely on AI-generated feedback. Notably, emotional responses to negative feedback revealed a gap between cognitive appreciation and affective impact, suggesting that even helpful feedback can demotivate if not appropriately framed.

These insights emphasize the dual importance of functional performance and emotional intelligence in AI-assisted learning tools. The value of such systems lies not only in delivering technically sound feedback but also in fostering motivation, trust, and student engagement through supportive and constructive feedback practices.

WAY FORWARD

To further enhance the effectiveness of AI-assisted feedback systems, three key strategies are recommended. First, the integration of emotion-aware feedback mechanisms is essential. While students cognitively value constructive criticism, emotional responses such as demotivation can hinder learning. Incorporating affective computing or sentiment-sensitive phrasing can help tailor feedback in ways that are both supportive and motivational. Second, improving the transparency and explainability of AI feedback can significantly build student trust. When students understand the rationale behind suggestions or corrections—especially with contextual examples—they are more likely to engage with and act upon the feedback. Third, empowering educators and students through training and guidance is vital. Educators can help mediate the AI-human interaction by contextualizing feedback and encouraging reflective practices, while students benefit from learning how to interpret and apply AI-generated insights effectively. Together, these approaches can foster a more adaptive, emotionally intelligent, and pedagogically sound AI-supported learning environment.

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