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The Impact of an Ai-Based Dynamic Feedback System on Student Academic Performance in Higher Education

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Abstract

This study has delved into exploring the impact of an AI-based dynamic feedback system on student academic performance in higher education, particularly in the context of China. Accordingly, this research is carried out with the integration of “perceived ease of use”, “perceived usefulness”, “feedback”, and “motivation”, on “student academic performance”, which are grounded in the Technology Acceptance Model (TAM), Self-Regulated Learning Theory, and Constructivist Learning Theory. The integration of these constructs has encouraged the progress of the research in a systematic manner by developing relevant objectives, questions, and hypotheses employing the same. A quantitative research design has been adopted, with data collected from 420 undergraduate and postgraduate students in Guangdong, China, using a structured questionnaire based on a five-point Likert scale. The findings underscore that AI-based feedback systems positively influence student academic performance by providing timely, personalised, and actionable insights that foster engagement, motivation, and self-regulated learning, ultimately enhancing their academic performance. The outcomes from the descriptive analysis revealed a higher degree of agreement regarding the significance of the constructs on perceptions of usefulness, ease of use, feedback, and motivation. Reliability and validity tests have further added to the conformity of strong internal consistency and significant positive correlations between all independent variables and student academic performance.

Keywords: Perceived Usefulness, Perceived Ease of Use, Motivation, Feedback, Student Academic Performance

Introduction

Learners at higher education levels are often confronted by accumulating workloads, expectations and competition. The lack of teachers is usually a limiting factor in individualized academic instruction (Kozikoğlu & Albayrak, 2022). Such lapses in feedback are associated with poor performance and reduce motivation in students. Studies show that feedback not only influence grades, but is also a critical factor in influencing self-regulated learning and confidence among students.

One of the major issues in modern education is how students can use AI-based feedback and how this affects their academic performance. The quality and timeliness of the feedback that students get is often a contributor to academic success (Fisher et al., 2025). More traditional feedback systems that operate within universities are likely to be slow and indirect. Lack of personal guidance makes many students unable to know what their weaknesses and strengths are (Katajisto, Uusiautti & Hyvärinen, 2023). Delivering feedback in a timely and dynamic way has been demonstrated in several studies to substantially impact the learning outcomes in higher education. Implementation of AI-based feedback-generation systems has attracted interest due to their flexibility to deliver timely and responsive comments to students based on their needs.

It has also altered how students undertake their academic activities due to the rising use of technology in higher education. Artificial intelligence tools are finding their place in many institutions, particularly by enhancing performance in teaching and assessment (Gardner, O'Leary & Yuan, 2021). But questions still exist as to whether these systems are effective in terms of actually enhancing student performance (Mosqueira-Rey et al., 2023). The recommendations can be instantiated in an AI system, but it remains to be seen what the students think and do regarding such feedback. The students can also react to AI-generated suggestions depending on their cultural and contextual factors. None of these systems can address the academic needs of different learners unless it is properly integrated.

Lack of support and a poor feedback system have been reducing the performance of students in higher education in many regions. The mismatch between what students learn and what they can learn through instructional materials is increasing. This renders the process of seeking new solutions an urgency in itself (Garbuio & Lin, 2021). Artificial intelligence-based dynamic feedback systems can lead to academic performance improvement, and additional research is required to identify how effective such systems are. One should also know whether these systems are capable of delivering more meaningful, timely, and customized advice than the old systems (Saleela et al., 2025). This project will attempt to answer these questions by evaluating the AI-based dynamic feedback systems that can be used to improve the academic performance of higher education students.

RO1: To examine the impact of perceived ease of use of an AI-based dynamic feedback system on student academic performance in higher education.
RO2: To analyze the influence of perceived usefulness of an AI-based dynamic feedback system on student academic performance in higher education.
RO3: To investigate the effect of AI-generated feedback on student academic performance in higher education.
RO4: To assess the role of motivation driven by the AI-based dynamic feedback system in enhancing student academic performance in higher education.

Higher education is increasingly shaped by digital transformation, where both students and institutions are seeking innovative ways to improve learning effectiveness and academic performance. Traditional feedback mechanisms, often delayed, generic, and resourcedependent, no longer align with the fast-paced and personalized learning expectations of today's students. In this context, AI-based dynamic feedback systems present a breakthrough, offering timely, individualized, and actionable insights that can significantly influence student outcomes.

The importance of studying this topic stems from several critical gaps in higher education. First, despite the proven role of feedback in enhancing self-regulated learning and motivation, students often experience delays or a lack of meaningful input due to faculty workload and limited institutional resources. Second, higher education institutions are under increasing pressure to adopt AI-driven solutions, yet empirical evidence about their actual utility and effectiveness in improving academic performance remains limited. Without systematic investigation, educators and policymakers may risk investing in tools that do not address learners' real needs.

This study is therefore necessary to assess the practical effectiveness and educational value of AI-based dynamic feedback systems. By examining factors such as perceived usefulness, ease of use, feedback quality, and motivation, the research provides a structured understanding of how students interact with such systems and how these interactions translate into measurable academic improvements.

Research Framework

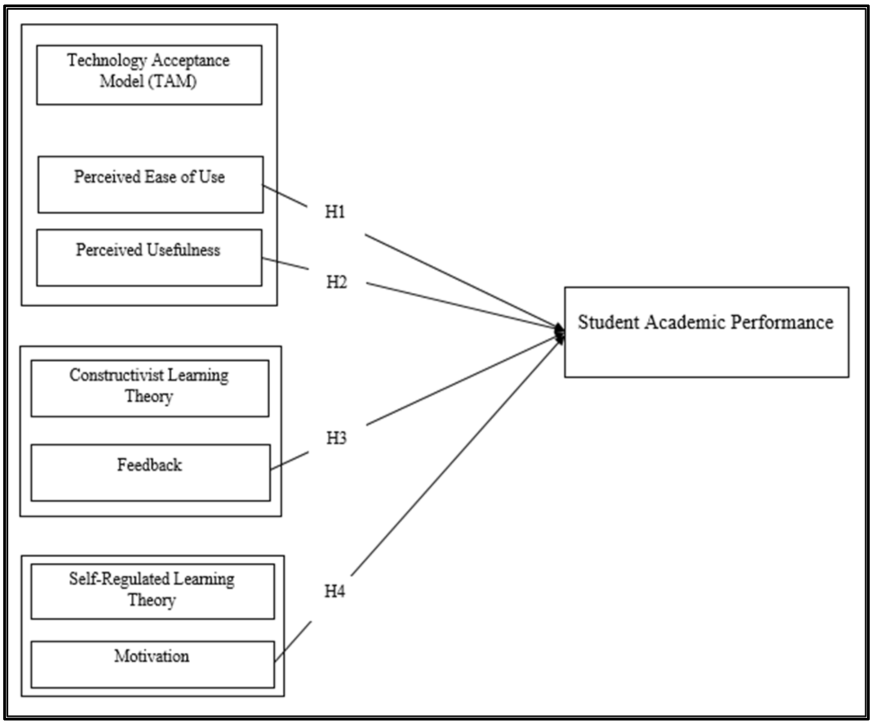

Figure 1: Research Framework

The study is focused on examining the impact of an AI-based dynamic feedback system on student academic performance in higher education. However, the studies are limited to 4 main variables, such as perceived ease of use, perceived usefulness, feedback, and motivation, as they directly influence students' learning outcomes. Here, the dependent variable is student academic performance, which is measured through learning improvement and academic achievement. The study is conducted among the higher education institutions by particularly targeting undergraduate and postgraduate students who have experience using AI-based feedback systems in their learning process to using a survey method. However, the scope is limited to selected universities, ensuring that the findings remain relevant within the context of technology-enabled higher education. The study does not explore other factors like prior academic standing and socioeconomic background, focusing on the role of AI based dynamic feedback systems. Thus, the outcome aims to provide insights for educators, policymakers, and institutions in enhancing student performance.

The study contributes to the theory by integrating the TAM, Self-Regulated Learning Theory, and Constructivist Learning Theory to explain how AI-based dynamic feedback systems influence student academic performance. Through TAM, the study advances understanding of how perceived ease of use and usefulness drive student engagement with AI systems. The self-regulated learning theory highlights the motivational dimension by clarifying how AI feedback fosters self-directed learning. In the context of constructivist learning theory, it emphasizes the role of feedback in knowledge construction, demonstrating the interactive process between learners and technology. Thus, this research strengthens the theoretical framework linking motivation, technological adoption, and active learning outcomes.

The significance of this study is threefold:

1. **For Students:** It highlights how AI-driven feedback systems can empower learners to take control of their academic journey by receiving personalized guidance, improving self-regulation, and fostering motivation. This has direct implications for learning efficiency, confidence, and performance outcomes.
2. **For Educators and Institutions:** The findings will assist teachers and administrators in integrating AI-based feedback tools more effectively into curricula, ensuring that these systems are both user-friendly and pedagogically valuable. Institutions can design targeted interventions to close performance gaps and enhance teaching quality.
3. **For Policymakers and Developers:** The results offer evidence-based insights into the utility and scalability of AI-driven educational technologies. Policymakers can make informed decisions about funding and adoption strategies, while developers can refine AI platforms to better meet the learning needs of diverse student populations.

Ultimately, this research strengthens the case for **AI as a transformative force in higher education** by demonstrating its practical impact on academic success. It underscores not only the technological promise of such systems but also their broader educational utility, ensuring that future learning environments are equitable, engaging, and effective.

Practically, this study provides a valuable understanding for higher education institutions seeking to enhance academic performance through AI-based feedback systems. By recognising the impact of usefulness, ease of use, feedback, and motivation, the findings can guide policymakers and educators in adopting AI Technology that supports student learning. This study provides practical evidence for designing effective and user-friendly AI platforms, which deliver timely feedback for boosting self-regulation and student motivation. It also informs administrators and curriculum developers about the potential AI tools to personalize learning experience, improve learning outcomes, and foster deeper engagement in higher education systems.

Literature Review

As per the figure 1, the relationship between the research variables has been explained below as per the works of other scholars -

Perceived Ease of use and Student Academic Performance

According to the findings of the study conducted by Lin & Yu (2023), whenever students perceive an AI-based feedback system to be easy to use, they are more likely to engage with it consistently. This further leads to increased exposure to formative feedback as well as improved academic outcomes. Systems that are known to be intuitive and user friendly as per the study conducted by Al-Abdullatif & Gameil (2021), often minimise the cognitive effort needed for navigating the same. As further mentioned in the study conducted by Al-Bashayreh et al. (2022), students are better able to engage independently whenever they find the tools to be accessible. In cases when feedback systems are easy to operate, students are better able to act on the feedback provided.

Alam et al. (2021) and Muñoz-Carril et al. (2021) further also mentioned how perceived ease of use is known to contribute to intrinsic motivation of learners. This is because the same reduces frustration and increases confidence among them to use the system more effectively. Moreover, an easy to use system, as per the study conducted by Romero-Rodríguez et al. (2023), also ensures that students with differing levels of digital literacy can benefit equally from AI-driven feedback. Students are also more likely to retrieve and review feedback promptly when the systems are straightforward. This, as per the study conducted by Malureanu, Panisoara & Lazar (2021), helps in real-time corrections and learning reinforcement among the students as well. The technology acceptance model explains how perceived ease of use is directly related to the intention to use a specific system among a student. Al-Abdullatif & Gameil (2021) also explained that, in the context of the current study, the intention translates into constant engagement and academic benefit drawn from AI-based feedback.

The theory also posits that ease of use indirectly affects the adoption of systems by improving perceived usefulness. This, as per the study conducted by Zou & Huang (2023), indicates that when students find the feedback system easy to navigate, they are more likely to view it to be beneficial for their academic performance. TAM also focuses that systems perceived as easy to use often face less resistance from the students. In the context of higher education, as mentioned in the study conducted by Fülöp et al. (2023), the same facilitates smoother integration of AI tools into existing learning environments. This further improves their impact on student outcomes as well.
H1: Perceived ease of use has a significant impact on student academic performance.

Perceived Usefulness and Student Academic Performance

Perceived usefulness of technology has a strong relation with academic performance of higher education students. Perceived usefulness is a personal attitude that the utilization of a system will result in positive academic outcomes and learning outcomes. Perceived usefulness is listed in the Technology Acceptance Model (TAM) as one of the aspects that influence student acceptance and uptake of new learning technologies. Students tend to be more encouraged to use a system when they are convinced that the system directly benefits their process of studying (Al-Mamary, 2022). This is the belief that promotes regular involvement in academic activities and good performance.

Students that find the use of technology helpful, tend to devote more time to learning activities. Whenever they are tackling tasks and tests, they undertake them confidently when they have academic tools to assist them. According to Conrad et al. (2022), students who perceive technology as working in their favor also learn to devise more effective ways of coping with workloads and comprehending tricky ideas. This feeling also helps in minimizing the opposition to learning new ways of doing things. Conversely, unless students find the obvious advantages, they will utilize technology minimally, and performance levels will be limited (Al Rawashdeh et al., 2021). Perceived usefulness is hence a direct driving force to successful adoption of technology. The TAM framework also points out that usefulness is more instrumental in terms of student behavior than ease of use. Although a system may be complex, students will persist in using a system as long as they believe that they are able to achieve a better result.

Within the realm of higher education, much of the learning technology, A.I. tools and feedback systems are judged by this perception of utility. Students relate technology to good grades, on time task accomplishment and knowledge (Badr et al., 2024). This brings a sense of intent to the utilization of educational technology. The greater this perception the better chance of great performance in school. The perception of usefulness is an important factor in the development of the relationship between technology and scholastic achievement (Klein et al., 2021). Motivation, persistence, and satisfaction in the learning process are promoted by the belief that technology has a direct and positive relationship with performance. In the absence of this belief, students will either dismiss technology or use less of its functionality (Hanham, Lee & Teo, 2021). TAM theory demonstrates that usefulness not only relates to system efficiency, but also academic value. It establishes the level of integration of technology in the learning activities of students.
H2: Perceived usefulness has a significant impact on student academic performance.

Feedback and Student Academic Performance

Scholars such as Deng et al. (2025) have pointed out how AI-driven feedback systems provide immediate responses to student inputs. This is further needed for allowing learners to correct their misconceptions as well as reinforce understanding in real time. All of this, as per the study conducted by Morris, Perry & Wardle (2021), is needed for improving academic performance. As further seen in the study conducted by Albreiki, Zaki & Alashwal (2021), dynamic feedback, tailored to the student responses helps in fostering deeper engagement. This mainly happens due to learners perceiving the feedback to be relevant and supportive of their unique learning trajectory.

Along with this, as mentioned in the study conducted by García-Martínez et al. (2023), continuous formative feedback is also needed for helping students monitor their progress, set goals and adjust strategies. These are crucial components of self-regulated learning which are interconnected with improved academic achievement. Constructivist theory has also explained that learners actively construct ideas and knowledge with the help of constant interaction and reflection. AI-based feedback systems as per the study conducted by Tan et al. (2021), support the same by providing iterative dialogue feedback. These help improve students' understanding as well.

Feedback is a key factor in Constructive Learning Theory and student academic performance is strongly modulated by feedback. The theory further asserts that learning is not in isolation and that students interact with one another to create constructions of knowledge through interaction and thinking (Ahmed, Thomas & Farooq, 2021). Feedback also gives relevant advice that assists the learners to relate the new information to what they have already learned. It also allows them to identify mistakes, correct mistakes and support learning mechanisms (Mackinney, Kelly & Pulling, 2021). When academic feedback is provided to students in a constructive manner, the students are more actively involved with school work and become more responsible with their own learning. The feedback should be timely and clear enough to allow the facilities to improve and increase the overall performance level.

Constructive Learning Theory is based on the idea that knowledge is not conveyed but is built up as a result of participatory processes. Feedback can assist this process by being an intermediary between the actual results and the desired results (Morris, Perry & Wardle, 2021). It provides the learners with guidance on the way they should sharpen their abilities and attain academic targets. Students tend to implement efficient learning strategies and remain motivated when they receive high-quality feedback in an actionable way (Lim et al., 2021). Conversely, there is a risk of misunderstanding, lack of self-confidence and performance due to lack of valuable feedback. Constructive feedback is, therefore, both an assessment and evaluation tool and a strong mechanism of enhancing academic performance in a higher institution.
H3: Feedback has a significant impact on student academic performance.

Motivation and Student Academic Performance

Previous studies like Wei (2023) have pointed out how motivated students engage more actively with learning materials. They are the ones who also participate in feedback cycles and are persistent through academic challenges. Students who are intrinsically motivated, as per the study conducted by Acosta-Gonzaga & Ramirez-Arellano (2021), also tend to seek understanding rather than surface level completion. Along with this, as mentioned in the study conducted by Smith et al. (2021), dynamic feedback systems which can recognise effort, progress and achievement can better reinforce the sense of competence among students. Highly motivated learners, as mentioned in the study conducted by Urhahne & Wijnia (2023), are better able to adopt mastery-oriented goals. These are correlated with sustained effort, strategic learning behaviours as well as better academic outcomes.

Acosta-Gonzaga (2023) and Leitão et al. (2022) also explained that AI systems which can deliver constructive feedback to students can strengthen their beliefs in their own capabilities. This is a crucial motivational driver of academic success among learners as well. Moreover, as seen in the study conducted by Gan, An & Liu (2021), motivated students are more likely to reflect on and apply feedback. This transforms the feedback into actionable learning which further improves their academic performance. As further mentioned in the study conducted by Ismail et al. (2022) and Chiu et al. (2024), students with higher motivation levels also tend to allocate time more effectively. They are the ones who prioritise academic tasks and avoid procrastination as well. These are the common behaviours linked to better academic outcomes.

Furthermore, as seen in the study conducted by Hsiao & Su (2021), motivated learners are also better able to perceive setbacks with the use of feedback. They are the ones who use feedback as a tool for recovery and growth rather than discouragement. The theory of self-regulated learning has identified motivation to be a foundational component in goal initiation as well as strategic planning. These are some of the core components of academic success as mentioned in the study conducted by Acosta-Gonzaga & Ramirez-Arellano (2021). Wei (2023) explained that students with strong motivational profiles have spread. This theory explains that motivated students are better able to monitor their progress and adapt strategies as well as reflect on outcomes. Educational institutions, which provide timely, personalised and goal relevant feedback can support the development of different self-regulated learning skills. This, as per Hongsuchon et al. (2022) and Chiu et al. (2024) reinforces motivational beliefs like self-efficacy or task value among the students.
H4: Motivation has a significant impact on student academic performance.

Research Methodology
Sample

The research focuses on investigating the influence of AI-based dynamic feedback systems on the improvement of the academic performance of students. The quantitative research is conducted by considering the Guangdong region of China; thus, definition of the target population can as it is identified that Guangdong province of China, has a significant number of students in the field of higher education. It is not possible to consider students belonging to different parts of China, thus, focusing on the specific region can be beneficial to get a significant number of learners as the number of students in higher education fields is quite high. The number is identified near about 1.41 million in that case Text or, (2024), thus, it is necessary to draw a proper subset, which can be utilizable for continuing the survey as well as easily represent the opinion of the target audiences. Therefore, a sample size should be determined here first through the help of the “Krejcie & Morgan” table.

The population is greater than 100,000. Thus, considering the table above, it is better to consider a sample size above 384 (which is suitable while the population size is near about 100,000). Therefore, taking a slightly larger population size, like 420, can be suitable to conduct the entire survey process (Muchai & Ng’asike, 2021). The sampling method that seems suitable in this study is the simple random sampling method, which may be supportive in optimising the time needed to complete sampling. Furthermore, the simple random sampling is associated with reducing the chances of sampling bias in the research. Therefore, simple random sampling can allow or provide equal chances to all of the target respondents to be included as respondents for the study. Additionally, the simple random sampling procedure is closely associated with the selection of respondents from such a population, which is very much homogenous by nature. As identified from the study, all of the respondents are pursuing their higher education (whether undergraduate or graduate), and the institutional setting seems almost the same for them.

Study Instrument

In the study, the primary data collection method is conducted through a structured questionnaire that is mainly designed to capture the perception of the respondents regarding the impact of an AI-based dynamic feedback system on student academic performance in higher education. The questionnaire serves as the main instrument as it allows for the systematic collection of data from a large group of respondents in a cost-effective and time-efficient manner (Taherdoost, 2022). All the items in the questionnaire are developed based on the established theories, ensuring the alignment and validity with the objectives of the study. In order to measure the construct including the variables, the study has also employed a five-point Likert scale, ranging from (1) strongly disagree to (5) strongly agree (Tanujaya, Prahmana & Mumu, 2022). This scale has been widely identified in social science and educational research as it enables the qualification of subjective perceptions, attitudes, and opinions. However, the Likert scale facilitates statistical analysis by converting the quantitative response into measurable data by supporting the use of inferential techniques to test hypotheses. This questionnaire is divided into different sections corresponding to independent and dependent variables. Each section contains multiple items designed to assess various dimensions of the construct. For example, items related to ease of use may focus on the simplicity of using an Internet-based learning platform, which enhances students' drive to learn. Therefore, by using a well-structured questionnaire and Likert scale, the survey ensures reliability, consistency, and compatibility of the. This approach can help to collect robust data, which can be analyzed to determine the relationship between student academic performance and AI-based feedback systems in higher education.

Data Collection Procedure

Based on the entire research plan, it can be mentioned that a primary data collection method should be employed for the study to generate unique as well as exclusive insight about the topic. In addition, the collection of primary data can be supportive in providing an idea about what students think about the effectiveness of AI technology and AI-generated feedback in their performance improvement (Mazhar et al., 2021). Primary data collection can be supportive for collecting data based on the responses of survey participants; thus, it can be said that the data collected in this case is free of any kind of undesirable interpretation, hence, the collection of unstructured as well as raw data may take place in this case.

The research can be conducted through selecting research data by the help of survey methods. In addition, the selection of data through surveys is associated with covering various ideas regarding the study topic from a large number of respondents. Thus, the survey method is flexible to the size of the sample compared to the interview or focus group method. In addition, the survey data is considered supportive to provide ideas about different kinds of aspects of AI-based dynamic feedback systems and its impact on student performance (Ghanad, 2023). Thus, survey data is suitable to conduct data analysis to investigate the relationship between hypotheses that were developed at the initial phase of the study. All of the questions , which are to be used in this study, are collected or adapted from relevant articles, thus, these questionnaires seem reliable in terms of helping in gaining authentic response.The survey process can be effective for the research as it has close association with securing the privacy of the respondents. The survey process is closely associated with beneficial aspects like anonymity. Thus, in the context of the study, it can be said that there are high chances of gaining real and honest response from the students because the survey process is to be used for conducting the study. The opinions can be highly diverse as the sample size is significantly large. Therefore, it seems a suitable procedure for the study. However, all the relevant ethical guidelines as well as rule should be followed at the time of selection of data by surveying the target respondents

Data Analysis Procedure

The data analysis procedure for the study should be quantitative data analysis, as it is associated with using statistical techniques to convert raw data as meaningful information. Thus, the survey-based responses should be analysed through the help of IBM SPSS software. In addition, both the descriptive statistical analysis as well as inferential statistical analysis is to be covered under the study (Rahman & Muktadir, 2021). Furthermore, it should also be discussed in this context, the role of following both methods should be helpful to investigate the trends, patterns, standard deviations and correlations between the variables. The impact of independent variables on the dependent variable can be done through the help of multiple regression tests. The outcome of multiple regression tests can be supportive to test hypotheses developed at the initial phase of the research. It is expected that quantitative data analysis can be supportive to provide a detailed idea about the level of impact which can be generated by perceived usefulness, ease of use, feedback and motivation is associated with improving the academic performance of students. Thus, it can be helpful to fulfill the gaps which are existing in the previous research as identified at the initial stage of the study.

Findings

Demographic Profiling test

Table 1

Demographic Profiling Test

		Count	Column N %
Gender	Male	192	45.7%
	Female	228	54.3%
Age	18 to 21 years	125	29.8%
	22 to 24 years	206	49.0%
	Above 24 years	89	21.2%
Education	Undergraduate	201	47.9%
	Post-graduate	174	41.4%
	Doctoral	45	10.7%

As per the result of table 1, the background characteristics of selected respondents has been represented. It has been determined that a total of 228 (54.3%) females participated in the survey. On the other hand, the number of male respondents is slightly lower than female, which is 192 (45.7%). This gender based outcome has been represented that the researchers minimise the gender bias by allowing both female and male in this survey. On the other hand, a total of 206 (49.0%) belong from 22 to 24 years, while only 89 (21.2%) are above 24 years. There are also a few 125 (29.8%) respondents who are between 18 to 24 years. Hence, collecting data from most of the senior respondents assists the researcher to maintain the quality and accuracy of included information.

Based on the educational level of respondents, 201 (47.9%) are studying at undergraduate level, while only 45 (10.7%) have a doctoral degree. Some respondents 174 (41.4%) also participated in the survey from post-graduate level. This result of a descriptive statistical test has been denoted as allowing respondents from different demographic categories to help to ensure the reliability and validity of study findings.

Descriptive Statistical Test
Table 2
Descriptive Statistical Test

Descriptive Statistics									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PEU	420	2.33	5.00	3.9837	.49440	-.291	.119	.287	.238
PU	420	2.33	5.00	3.9361	.54078	-.145	.119	-.268	.238
F	420	1.00	5.00	3.4488	.85897	-.457	.119	-.056	.238
M	420	2.33	5.00	3.9310	.50099	.045	.119	-.257	.238
SAP	420	2.33	5.00	4.0139	.54047	-.273	.119	-.252	.238
Valid N (listwise)	420								

The result of the descriptive statistical test offers valuable insights regarding student's perception of the AI based dynamic feedback system along with its impact on academic performance. As per Table 2, The mean value for Perceived Ease of Use (PEU) is 3.98 that indicates respondents strongly agree with the use of AI. On the other hand, the mean value for Perceived Usefulness (PU) and Motivation (M) is 3.93. It also refers to a strong significance of these constructs on student academic performance.

Additionally, it has been figured out that the skewness and kurtosis value for all of the variables are close to zero. Hence, the collected data are normally distributed and there is no existence of any normality issue. The minimum and maximum value for all variables is between 1.00 and 5.00. Hence, all of the respondents shared their opinion based on Five Point Likert scale. As per the result of table 2, it seems that the standard deviation value for all variables are below to 1.0. It means most of the respondents shared a moderate response and are effective for the improvement of student's academic performance by implementing AI-based dynamic feedback systems.

Reliability
Table 3
Cronbach Alpha

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.747	.793	5

As per Table 3, reliability analysis in statistics explains the internal consistency of the research items used for measuring the different constructs. The Cronbach Alpha test is used for measuring the reliability. A value more than 0.7 for Cronbach alpha shows high reliability of the research items. This means that whenever such value is obtained for Cronbach alpha, the research methods can be called highly generalisable for similar studies. It is seen in the above table that the calculated Cronbach alpha value for the current study's research items is 0.793 which is greater than the desired threshold. Hence, the research methods used for the current study's measurement are highly reliable. This indicates that these methods can be used in future similar studies for yielding similar results in similar circumstances. The research methods are all generalisable for similar studies as well as per these findings.

Validity

Table 4

Pearson's Correlation Coefficient

Correlations						
		PEU	PU	F	M	SAP
PEU	Pearson Correlation	1	.602**	.235**	.533**	.520**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	420	420	420	420	420
PU	Pearson Correlation	.602**	1	.261**	.529**	.614**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	420	420	420	420	420
F	Pearson Correlation	.235**	.261**	1	.191**	.298**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	420	420	420	420	420
M	Pearson Correlation	.533**	.529**	.191**	1	.561**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	420	420	420	420	420
SAP	Pearson Correlation	.520**	.614**	.298**	.561**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	420	420	420	420	420
****. Correlation is significant at the 0.01 level (2-tailed).**						

The overall correlation result as per table 4 has been indicated to a significant and strong relationship among the variables. Perceived Ease of Use (PEU) have a positive and strong correlation with Perceived Usefulness (PU) with the p value of less than 0.01 and r value of .602. On the other hand, PEU also has a moderate correlation with Student Academic Performance (SAP) as the r value is .520. Similarly, the correlation between PEU and Motivation (M) is also positive and moderate as the r value is .533. It indicates that user-friendly systems like AI-based dynamic feedback systems ensure student's learning outcome by enhancing the engagement.

The results of correlation analysis indicate that Perceived Ease of Use is positively and strongly associated with Perceived Usefulness. It is also moderately related to Student Academic Performance and Motivation. An implication of these findings is that easy to use systems are more helpful to and motivating to students. The system should be easy to use in order to improve academic performance through higher participation and learning efficiency. This demonstrates the need to create AI-based dynamic feedback systems which are convenient and easy to design. Through such systems, a better learning environment and better performance amongst the students can be realized through higher education.

Multiple Linear Regression

Table 5

Multiple Linear Regression

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.600	.181		3.314	.001	.244	.956
	PEU	.138	.051	.127	2.694	.007	.037	.239
	PU	.357	.047	.357	7.583	.000	.264	.449
	F	.076	.023	.121	3.284	.001	.031	.122
	M	.304	.048	.282	6.402	.000	.211	.397

a. Dependent Variable: SAP

As per Table 5, the first independent variable, “perceived ease of use,” exhibits a statistically significant positive effect on Student Academic Performance (SAP), with an unstandardized coefficient beta value of 0.138 and a standardized beta of 0.127. The sig value derived in this regard is .007, which reflects that the availability and accessibility of intuitive and accessible AI systems devoid of cognitive load can enhance student engagement and academic performance. Furthermore, concerning perceived usefulness, the results highlight that it is the most influential predictor of student academic performance in the regression model, with both the unstandardized and standardized coefficients at 0.357. It illustrates that when students believe that the system poses the potential to enhance their learning efficiency or academic outcomes, they are more likely to engage. The relevance of this construct is further demonstrated by the p-value achieved herein, which is .000, thus demonstrating a statistically significant relationship with SAP. Similarly, regarding the outcomes of feedback and motivation, the unstandardized beta values achieved in both cases are .076 and .304, along with the t values of 3.284 and 6.402, respectively, which highlight the viability of the interrelationship. Additionally, the sig values achieved herein are .001 and .000, which are well within the required threshold and further add to the conformity of the strength and significance of the correlation.

Hypothesis Test

Table 6

Hypothesis Test

Hypothesis	**Status**
H1: Perceived ease of use has a significant impact on student academic performance.	Satisfied
H2: Perceived usefulness has a significant impact on student academic performance.	Satisfied
H3: Feedback has a significant impact on student academic performance.	Satisfied
H4: Motivation has a significant impact on student academic performance.	Satisfied

From table 6, the outcomes of the various hypotheses developed in this research have been presented in the table provided above. The first hypothesis developed herein explores the interplay of perceived ease of use and student academic performance, regarding which the responses acquired have confirmed the validity of the assumption. It can be stated here that an intuitive and user-friendly feedback system can add to the improvement of the academic performance of the students. Furthermore, the assumption related to perceived usefulness has also been validated by the findings. It interprets that the elimination of technological novelty and a greater degree of understanding of the AI-based feedback system imparts a positive impact on the academic performance of the students. In addition to this, the third hypothesis in this regard delves into the exploration of feedback on student academic performance, wherein the responses have validated this assumption. It demonstrates that feedback functions as a form of communication that guides the pupils towards improvement, identification of knowledge gaps, and reinforces learning outcomes. Likewise, regarding the hypothesis developed, assessing the interplay of motivation and student academic performance, the results have supported it as well. It corresponds that when students are motivated to succeed, not only are they likely to employ formative feedback derived from AI-driven systems optimally, but they are also likely to incur the benefits in their academic achievement.

Discussion

The integration of AI-based dynamic feedback systems in higher education has the potential to revolutionise the teaching and learning process by offering timely, personalised guidance. Understanding the interplay of factors such as perceived usefulness, ease of use, feedback quality, and motivation is crucial in comprehending their collective influence on student academic performance. This research is therefore executed with the inclusion of 420 students hailing from a higher education background in Guangdong Province in China. The viewpoints derived from the respondents add to the conformity of the constructs in the research model, which suggests that there is a strong and statistically significant correlation between the perception of the pupils regarding the AI-based feedback system and their educational outcomes.

The results highlight that when students perceive the AI-based feedback system as beneficial to their learning process, they are more likely to engage with it actively, thereby enhancing their academic outcomes. Based on the analysis regarding perceived ease of use, the results underscore that with the absence of a learning curve, students are likely to be inclined towards using AI tools. The outcomes derived in this case are consistent with the assertion of Lin & Yu (2023), who have also elaborated that this positive perception drives their exposure to formative feedback, which further improves the academic outcomes. The perceived ease of use reduces their cognitive load, allowing students to focus more on learning content than on navigating the system. Likewise, the relevance of “feedback” has also been confirmed with the results from the correlation and the regression analysis, where the derived sig values further add to the conformity. The correlation between perceived usefulness and academic performance also indicates that students are more likely to value systems that offer actionable insights. Hence, it can be ascertained that the availability of timely and personalised feedback helps students identify their strengths and weaknesses, thus further encouraging continuous improvement.

“Motivation” is chosen as one of the significant constructs in this study, wherein the outcomes from the analysis highlight that motivation significantly influences the intention and engagement of the pupils, in turn leading to better educational outcomes. This finding is consistent with the views of Chiu et al. (2024), who have remarked that students’ motivation has a direct impact on their learning approaches, their engagement level, and their persistence in accomplishing goals, and influences their thinking processes and learning approaches. It can be concluded that feedback is a crucial part of the educational process, and its interface with learning, teaching, and curriculum has always remained a significant element for getting successful learning outcomes and improving student academic performance.

The ideas obtained after the data analysis outcome, it can be said that Perceived usefulness of AI based feedback system as well as its ease of use, both are very significant in terms of enhancing the interest of students in the improvement of academic performances. Apart from this, the effectiveness of the feedback is also identified as a significant inductor of academic performance improvement. In addition, the presence or generation of good quality motivation level is associated with the academic performance enhancement as effectively as possible. All the correlations obtained in this case, indicates a satisfactory level of moderate correlations.

Conclusion

The study has investigated the impact of an AI-based dynamic feedback system on student academic performance in higher education. It is focused on variables like perceived ease of use, perceived usefulness, feedback, and motivation. The outcome derived from correlation analysis, descriptive statistics, multiple regression analysis, and reliability tests has confirmed that these variables have a significant positive effect on student academic performance. The reliability analysis indicated strong internal consistency of the survey items, while correlation coefficients showed significant associations between the independent and dependent variables. However, regression analysis established that motivation and perceived usefulness had the strongest effect, followed by ease of use and feedback. Along with this, all the hypotheses were satisfied, highlighting that user-friendly AI tools, their perceived value, timely feedback, and enhanced motivation collectively improve academic outcomes.

Based on the findings, different recommendations can also be made. Firstly, higher education institutions should adopt AI-based feedback systems, which are user-friendly and intuitive, as ease of use can encourage continuous engagement. Secondly, the system developers should focus on enhancing the perceived usefulness by ensuring feedback is practical, personalized, and directly linked to the academic goals of the students. Thirdly, AI systems must provide constructive and timely feedback that supports the students to recognise their weaknesses and improve their performance. Ultimately, institutions should leverage AI tools to foster motivation by incorporating gamification goal-setting features and progress tracking, which stimulate student engagement and persistence. The integration of AI-driven feedback systems represents a significant potential to improve learning and teaching processes in higher education. By combining technology innovation with pedagogical strategies, institutions can enhance student academic performance, prepare learners for success, and promote self-regulated learning in increasingly digitalised learning environments. Meanwhile, the study is limited to select universities and focuses on the variables, including broader institutional and socio-cultural factors. The future research could explore cross-country comparison, longitudinal impact, and integration of advanced AI features like predictive analytics to enhance feedback personalization for long-term student academic success.

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