INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN PROGRESSIVE EDUCATION & DEVELOPMENT

OPEN ACCESS JOURNAL
Vol 14, Issue 4, (2025) E-ISSN: 2226-6348

Revolutionizing Learning Outcomes: The Integration of Educational Management, Ai-Driven Methodologies, and Digital Tools

Yixiang Wang, Nurfaradilla Binti Mohamad Nasri
Faculty of Education, Universiti Kebangsaan Malaysia (UKM), Bangi, Malaysia
Email: p142758@siswa.ukm.edu.my
Corresponding Authors Email: nurfaradilla@ukm.edu.my

DOI Link: http://dx.doi.org/10.6007/IJARPED/v14-i4/26442

Published Online: 09 December 2025

Abstract
The rapid advancement of Artificial Intelligence (AI) has transformed educational practices, creating opportunities for more personalized and effective learning experiences. This study investigates the impact of AI-driven methodologies and digital tools on learning outcomes in higher education, with a particular focus on educational institutions in Beijing. The research integrates key constructs such as perceived ease of use, perceived usefulness, and adaptive feedback, with user acceptance serving as a mediating factor influencing students' academic performance. A quantitative design was adopted, collecting survey data from 640 respondents, including 234 teachers and 367 students. The results reveal that students perceived all three factors—ease of use, usefulness, and adaptive feedback—as significantly enhancing learning outcomes through user acceptance. However, teachers indicated that perceived usefulness did not exert a significant influence on their acceptance of AI tools. These findings underscore the importance of usability and adaptive features in shaping positive attitudes toward AI in education. The study contributes to educational management by offering insights into the integration of AI technologies, while also outlining limitations and directions for future research.
Keywords: Perceived Ease of Use, Perceived Usefulness, Adaptive Feedback, User Acceptance, Students' Learning Outcomes

Introduction

The integration of artificial intelligence (AI) is reshaping educational institutions by enabling targeted learning interventions and driving transformative changes in teaching and administrative practices. AI-powered tools, particularly virtual assistants, facilitate the development of personalized learning pathways that enhance instructional accessibility and strengthen overall educational capacity (Li, 2023). Countries such as China exemplify this trend, with government policies actively promoting AI adoption to modernize education and align institutional strategies with national objectives.
A central contribution of AI lies in its ability to tailor educational experiences, providing students with adaptive and individualized support that improves engagement, motivation,

and learning outcomes (Valaboju, 2024). Evidence from the Ministry of Education of the People's Republic of China indicates that Chinese schools have integrated AI in diverse ways, from streamlining administrative functions to supporting data-driven decision-making and personalized instruction (Dönmez, 2024). These initiatives highlight China's strategic approach to leveraging AI for enhancing institutional efficiency while offering interactive and student-centered learning experiences across various academic contexts.

Despite these advancements, challenges remain in implementing AI effectively. Misalignment between technological innovation, management policies, and the adaptability of teachers and students can hinder the full potential of AI integration. Haefner et al. (2021) note that uncertainty and inconsistent adoption practices persist across educational institutions. Successful implementation requires not only supportive policies but also sufficient investment in infrastructure, educator training, and resource allocation. Stakeholder attitudes—including those of administrators, teachers, and policymakers—significantly influence the adoption and impact of AI, while discrepancies across institutional policies can create gaps in practical application (Füller et al., 2022). Addressing these challenges is critical to realizing the transformative potential of AI in enhancing teaching, learning, and institutional effectiveness.

The study is guided by the following objectives:

- **RO1:** To evaluate the impact of Perceived Ease of Use (PEOU) on students' learning outcomes in AI-integrated educational settings.
- **RO2:** To analyze the effect of Perceived Usefulness (PU) on students' learning outcomes in AI-integrated educational settings.
- **RO3:** To investigate the influence of Adaptive Feedback (AF) on students' learning outcomes in AI-integrated educational settings.
- **RO4:** To examine the mediating role of user acceptance in the relationship between PEOU, PU, AF, and students' learning outcomes.

Corresponding research questions include:

- **RQ1:** How does PEOU affect students' learning outcomes in AI-integrated education?
- **RQ2:** How does PU affect students' learning outcomes in AI-integrated education?
- **RQ3:** What is the impact of AF on students' learning outcomes in AI-integrated education?
- **RQ4:** What is the mediating role of user acceptance in the relationship between PEOU, PU, AF, and students' learning outcomes?

This research investigates the role of AI-driven tools, digital interventions, and educational management practices in shaping learning outcomes. It focuses on Chinese educational institutions, where AI adoption is accelerating, while offering insights for broader international comparisons. The study employs quantitative methods to capture student and teacher perspectives, providing empirical evidence on the effectiveness of AI in enhancing instructional quality, engagement, and performance.

The significance of the study is both theoretical and practical. Theoretically, it contributes to understanding how AI adoption aligns with constructs such as adaptive feedback, perceived usefulness, and ease of use in educational settings. Practically, the findings offer guidance to teachers, administrators, and policymakers on implementing AI-driven interventions that improve learning outcomes, strengthen institutional efficiency, and foster student satisfaction. Additionally, the research highlights the importance of strategic alignment, policy effectiveness, and behavioral factors in supporting sustainable AI integration.

Beyond immediate performance gains, the study provides insights into building adaptable, technology-ready ecosystems that support long-term digital transformation. By exploring psychological and behavioral factors such as user acceptance and adaptive feedback, it presents a comprehensive framework for scalable, student-centered, and inclusive educational innovation. Ultimately, this research emphasizes the potential of AI to create future-ready educational systems that are responsive, personalized, and outcome-oriented.

Literature Review and Hypothesis Development

AI can significantly enhance education by streamlining administrative duties and personalising instruction. However, it also brings up issues with equality and data privacy. AI's advantages may be maximised while resolving these issues with careful and moral application. This study aims to understand the benefits of incorporating AI into educational administration, as well as AI-driven approaches and digital technologies that can be applied in various ways. This chapter formulates hypotheses based on the variables like *perceived ease of use, perceived usefulness and adaptive feedback* and their impact on *students' learning outcomes* to examine the relationship between these elements and makes an argument with the earlier research to fill in the gaps.

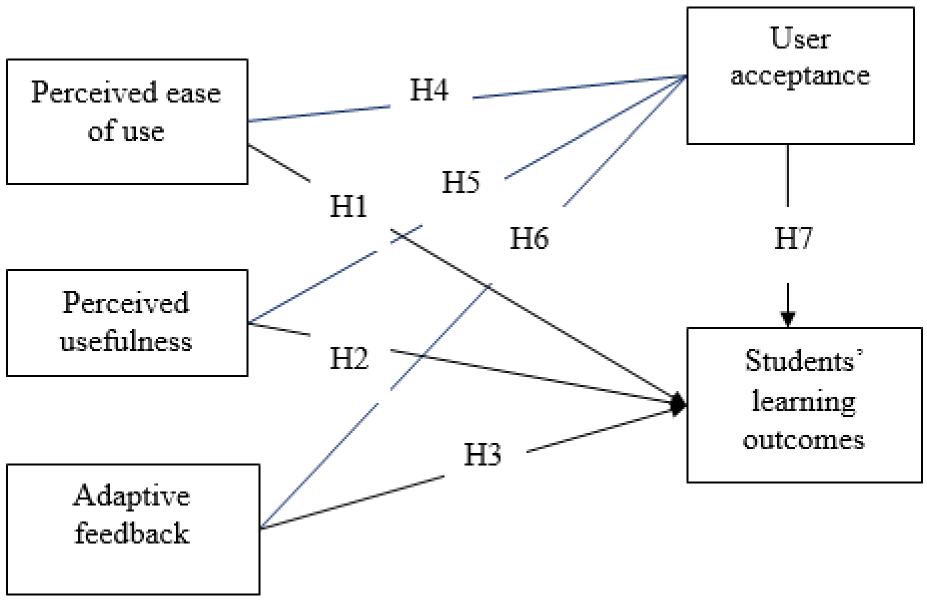

Figure 1: Research Framework

Perceived ease of use and Students' Learning Outcomes

The use of online learning resources has drawn a lot of interest in educational institutions, specifically in secondary schools. This study investigated students' perceived ease of use and their learning outcomes in Beijing secondary schools. Linus et al. (2025) claimed that the use of technology in the classroom is an essential part of modern teaching and learning, particularly in the twenty-first century. Educational institutions are increasingly utilising digital technologies to enhance the quality of the learning experience as *information and communication technology (ICT)* becomes more accessible. These resources, which include *learning management systems (LMS)* like *Google Classroom* and virtual meeting platforms like *Zoom*, have fundamentally altered how educators provide knowledge and how students interact with it.

One well-liked approach for examining how kids utilise technology is the Technology Acceptance Model (TAM). In this context, Abuhassna et al. (2023) asserted that TAM states that *perceived usefulness (PU)* and *perceived ease of use (PEOU)* are the two primary criteria that influence users' propensity to embrace a certain technology. However, the findings of hypothesis testing by Nuryakin et al. (2023) indicate that while perceived ease of use has no significant impact on student satisfaction, it does have a substantial, favourable impact on attitudes towards using online learning. Cao & Chen (2024) highlighted that in China, high school education is now increasingly common. China has recently increased the standard of this educational stage by providing high school pupils with high-quality and varied educational opportunities. High student-teacher ratios and consistency in instructional methods are two issues brought on by the high schools' explosive expansion and the students' learning outcomes. Therefore, the current study developed the hypothesis as to how:
H1: Perceived ease of use has a positive and significant impact on students' learning outcomes.

Perceived usefulness and Students' Learning Outcomes
Students, upon recognising AI tools and technologies as beneficial and effective for their educational needs, mostly express a greater likelihood to engage with these resources actively and consistently. As remarked by Jeilani & Abubakar (2025), students generally exhibit a favourable perception toward AI tools for autonomous learning, recognising their potential while acknowledging challenges. This positive perception can increase motivation, improve comprehension, and facilitate personalised learning experiences, all of which contribute to better academic performance. In this regard, Aldraiweesh & Alturki (2025) have remarked that social support from peers and instructors also functions as a major determinant and can enhance students' perceptions of the usefulness of AI-based educational tools by providing encouragement, assistance, and guidance that facilitate their effective use. This support not only helps a student better understand the practical benefits of AI technologies but also alleviates concerns related to their complexity or unfamiliarity. In a similar vein, Kashive, Powale & Kashive (2020) have expressed that perceived usefulness is a critical determinant of usage behavior and intention, significantly influencing learners' attitudes, satisfaction levels, and their willingness to engage in learning with the integration of AI-driven methodologies and digital tools. Hence, it can be hypothesized that:
H2: Perceived usefulness has a positive and significant impact on students' learning outcomes.

Adaptive Feedback and Students' Learning Outcomes
The current study is further concentrated on the connection between the adaptive feedback and students' learning outcomes in secondary schools based in Beijing. Authors like Liu et al. (2022) evaluated a learning system using adaptive-feedback behavioural computing technology to comprehend learners' emotional cues while they are learning. According to the results, the adaptive-feedback psychological computing technology system has greatly enhanced students' self-directed learning, reduced their learning concerns, and boosted their learning efficacy. Regardless of the mode, Adaptive Learning (AL) increased students' success,

according to Contrino et al. (2024). Furthermore, the study found that students do better in real-life AL classes than in online ones. Conversely, Gan, An, & Liu's (2021) results show that student feedback behaviour did not significantly affect course exam results directly, and instructor feedback did not significantly affect course exam results indirectly, even though both student feedback behaviour and teacher feedback had a large impact on course satisfaction.

According to some research, Intelligent Tutoring Systems (ITS) that use natural language processing provided adaptive feedback and clarifications, which improved students' conceptual comprehension and problem-solving abilities (Xu, 2024). Mathias Mejeh, Sarbach & Hascher (2024) affirmed that the capacity to produce conversation-promoting, adaptive feedback raises the likelihood that meaningful learning takes place during talks. Considering that students usually struggle to choose and adjust their tactics to suit the specific requirements of their schoolwork, adaptive feedback is essential to success. Hence, this study assessed the correlation between adaptive feedback and students' learning outcomes and hypothesised that:
H3: Adaptive feedback has a positive and significant impact on students' learning outcomes.

Perceived Ease of use and User Acceptance
Perceived ease of use is widely regarded as a key determinant of both students' and teachers' adoption of intelligent educational technologies. Perceived ease of use suggests that individuals are more inclined to use a technology if they believe it will not require significant effort to learn or use. In the context of education, if AI-driven platforms, such as intelligent tutoring systems, automated grading tools, or adaptive learning applications, are designed to be user-friendly and intuitive, students and instructors are more likely to integrate them into their regular academic activities. In the context of ChatGPT, Alshammari & Babu (2025) have expressed that students' perceptions of perceived ease of use significantly influence their acceptance of the tool for academic purposes, shaping both their attitudes toward its use and their intention to integrate it into their learning activities. Likewise, as per the views of Chen et al. (2025), when educational tools, such as intelligent learning platforms and electronic whiteboards, are easy to operate, efficient in workflow, and require minimal additional learning effort, both students and teachers are more likely to display positive attitudes toward their use. Moreover, ease of use reduces technological anxiety and frustration, encouraging consistent usage and building confidence. As users become more comfortable with these tools, their acceptance increases, leading to higher engagement, better learning outcomes, and more efficient teaching-learning practices.
H4: Perceived ease of use has a significant impact on user acceptance.

Perceived Usefulness and User Acceptance
The use of artificial intelligence (AI)-related educational applications in the classroom has grown significantly in recent years. A person's assessment of a usefulness conviction and the degree of that belief may influence perceived usefulness. Hence, this study is imperative to evaluate the connection between perceived usefulness and user acceptance. Despite the high proportion of female new teachers overall, the findings of Zhang et al. (2023) highlight the need to address gender-specific issues in teacher education. Most of the previous studies are based on university students, which makes this study essential for assessing how perceived

usefulness impacts secondary school students' acceptance and how the teachers in such schools may accept the enhanced technological tools.

According to Puspitasari & Nugraha (2023), the desire to use a component is an essential indicator that might mediate perceived usefulness on practical system use when examining the *Learning Management System*. According to TAM, Marikyan & Papagiannidis (2024) stated that users' behavioural intentions, which are based on their perceptions of the technology's utility and simplicity of use, indicate whether technology will be accepted. Numerous studies have also examined mobile learning, including tablet PCs, portable computers, mobile technologies and apps, or simply m-learning. Hence, this study hypothesized that:
H5: Perceived usefulness has a significant impact on User acceptance.

Adaptive Feedback and User Acceptance
Adaptive feedback is a building block in determining user acceptance in digital learning. Mejeh et al. (2024) discuss adaptive feedback that Nieto et al. (2024) consider enhancing self-regulated learning due to the opportunity of receiving immediate and individualized advice. When feedback is aligned to the needs of those being given feedback, it is more likely that learners respond positively, and this will lead to greater engagement and motivation. This is in line with the Technology Acceptance Model (TAM) in which perceived usefulness and perceived ease of use are significant predictors of acceptance.

Aad et al. (2025) build on this and employ a multidimensional TAM framework to AI-driven adaptive learning. The article reveals that adaptive features build trust and satisfaction levels among the users. Unless users have been given feedback that is clear, relevant, and responsive to the individual progress, they will not take the systems more anymore. This increases perceived usefulness and reduces the technology rejection. Adaptive feedback elicits the perceptions of usability by minimizing the mental barriers. The two factors enhance adoption and the subsequent retention use of adaptive learning platforms. Such influence can also be explained by Constructivism theory. The theory focuses on learner activity, self-regulation and individual construction of knowledge. Adaptive feedback is in line with this school of thought since it makes learning interactive and learner focused. Feedback will enable the students to evaluate the route taken, correct, or alter tactics and acquire greater knowledge.
H6: Adaptive feedback has a significant impact on User acceptance.

User Acceptance and Students' Learning Outcomes
The acceptance by students is one of the major components in the determination of learning outcomes. According to the research conducted by Shaikh et al. (2025), the students of institutions of higher learning embrace the e-learning platforms when they view them as helpful and user-friendly. Students will be more motivated and engaged when they accept digital platforms. This acceptance results in improving participation, regular usage and better performance in learning. Therefore, TAM shows the direct effect of positivity of perception of technology into excellent learning outcomes.

Constructivist theory also gives an insight into the relationship Rafiq et al. (2024) noted that online learning environments and digital tools work well because they facilitate engagement

and make learning from students rather than teachers. Constructivist theory emphasizes the use of active learning, reflection and collaboration. Once students embrace these technologies, they get their opportunity to do higher-level learning experiences. Adaptive features and interactive tools enable them to build knowledge in significant manners. The combination of TAM and constructivist theory indicates that acceptance is not only based on how people use technology but also their effectiveness in learning.
H7: User acceptance has a significant impact on students' learning outcomes.

Methodology

Sample and Data Collection Procedure
The target population of this study consists of secondary school teachers from reputed schools in Beijing, China. In line with prior research (Wang et al., 2021), secondary school students were also considered as a complementary population to provide a more comprehensive perspective on the integration of AI-driven tools in education. Data sources such as CEIC Data (2023) and the Beijing Municipal Education Commission (Zhang & Liu, 2022) were consulted to identify representative schools. Table 1 presents an overview of the estimated population of students and teachers across selected institutions.

Table 1
Table on the estimated population of Teachers and Students

School Name	**Estimated No. of Students**	**Estimated No. of Teachers**
RDFZ Chaoyang Branch School	1,200	100
Tsinghua University High School	1,800	150
Beijing No. 4 High School	1,500	120
Beijing 101 Middle School	1,700	140
Beijing Normal University Affiliated School	1,600	130
Total	**7,800**	**640**

Given the impracticality of including the entire population, the Krejcie and Morgan sampling table was used to determine a representative sample size. Accordingly, 234 teachers and 367 students were selected. A simple random sampling technique was employed to minimize bias and ensure that every participant had an equal chance of inclusion. Data were collected through a structured questionnaire survey, which allowed for standardized responses and facilitated quantitative analysis. Ethical guidelines were strictly followed to ensure voluntary participation, informed consent, and confidentiality of responses.

Measurement Scales
Measurement scales were developed to capture the constructs of the study: *perceived ease of use, perceived usefulness, adaptive feedback, user acceptance, and students' learning outcomes*. Research instruments were adapted from validated sources to ensure reliability and validity. For example, items measuring perceived usefulness were drawn from Ebadi and Raygan (2023), while adaptive feedback measures were adapted from Manolache and Epuran (2023). All items were rated on a five-point Likert scale, ranging from *1 = Strongly Disagree* to *5 = Strongly Agree*. In addition, demographic questions were included to capture background characteristics of both teachers and students.

Data Analysis

The study employed a quantitative data analysis approach to examine the relationships among variables and test the research hypotheses. This method ensures objectivity, reduces bias, and supports evidence-based conclusions (Delideli, 2024). Data were analyzed using IBM SPSS to generate descriptive and inferential statistics.

To assess the hypothesized relationships, multiple regression analysis was conducted, allowing the evaluation of the effects of independent variables on the dependent variable through the mediating construct of user acceptance. Reliability of the measurement instruments was tested using Cronbach's Alpha, with an acceptable threshold ranging between 0.7 and 0.9 (Chinnasami & Manickam, 2023). Additionally, validity tests such as the *Kaiser-Meyer-Olkin (KMO) measure* and *Bartlett's test of sphericity* were performed to confirm construct validity.

Beyond hypothesis testing, demographic analyses were also carried out to generate deeper insights into the perspectives of both teachers and students. The results of these analyses provided a robust foundation for evaluating the integration of AI-driven methodologies in secondary education and their influence on learning outcomes.

Results

Demographic Information

Demographic information for quantitative research consists of counts related to different demographic criteria about the respondents. The demographic criteria included for this research involve gender, ethnicity and if their resident location is Beijing or not. In table 2 it is seen that in the context of the student respondents in the research, the demographic profile shows that most of the students were male with a count of 216 (58.9%). For the ethnicity of the students, the collected demographic data shows that the majority of the student participants are from the Hui ethnic background. It is also noticed in table 2 that 52.6% of students were not residents of Beijing.

Table 2
Demographic Profile of the Students

		Count	**Column N %**
Gender	Male	216	58.9%
	Female	151	41.1%
Ethnicity	Han	8	2.2%
	Hui	217	59.1%
	Tujia	82	22.3%
	Others	60	16.3%
Resident	Yes	174	47.4%
	No	193	52.6%

Table 3 below consists of the count and percentage of the same demographic groups for the teachers surveyed in this research. This table shows that there are more female teacher respondents than male. The demographic table below also shows that 61.1% of teachers are of Hui ethnicity. Finally, the demographic information about the teachers also indicates that a total of 137 teachers were residents of Beijing.

Table 3
Demographic Profile of the Teachers

		Count	Column N %
Gender	Male	116	49.6%
	Female	118	50.4%
Ethnicity	Han	8	3.4%
	Hui	143	61.1%
	Tujia	47	20.1%
	Others	36	15.4%
Resident	Yes	137	58.5%
	No	97	41.5%

Reliability Analysis

Reliability analysis in statistics involves the measurement of the internal consistency of the research methods. The Cronbach Alpha test is most commonly used for measuring the reliability of the research methods. In this, the calculated value of Cronbach Alpha being greater than 0.7 indicates high reliability. The table 4 below shows that the calculated Cronbach alpha for the items measuring responses of the students is 0.905 which is greater than the threshold. This indicates that all the items used for measuring the constructs regarding the responses of the students are highly reliable.

Table 4
Reliability Analysis for Students

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.907	.905	5

The following table shows the Cronbach alpha value calculated for the items measuring the responses of the teachers. The calculated value is 0.936 which is more than 0.7. This shows that the items used for measuring the teachers' responses are highly reliable in nature.

Table 5
Reliability Analysis for Teachers

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.934	.936	5

Validity Analysis

Validity analysis is usually conducted for explaining how accurately the items are able to measure the constructs as they were intended to. The following KMO and Bartlett's Test is most commonly used for measuring the validity of the research methods. This test explains if the used research items are suitable for factor analysis or not. In this, the significance value has to be less than 0.05 for the factorable research items. Table 6 below indicates that the significance value for the items measuring the responses of the students is 0.000 which is below the threshold, making the items suitable for factor analysis.

Table 6

Validity Analysis for Students

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.862
Bartlett's Test of Sphericity	Approx. Chi-Square	1467.763
	df	10
	Sig.	.000

Table 7 below shows the KMO and Bartlett's test conducted for the items measuring the teacher responses. The significance value calculated in this is again 0.000 which is less than 0.05. Hence, this shows that the items measuring the responses of the teachers in the study are valid and suitable for further factor analysis as well.

Table 7
Validity Analysis for Teachers

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.845
Bartlett's Test of Sphericity	Approx. Chi-Square	1460.436
	df	10
	Sig.	.000

Regression Analysis

In a quantitative study such as the present study, regression analysis is mainly conducted for explaining the direct linear relationships between each of the developed constructs in the study. The significance value is calculated for this analysis with a 95% interval. This value being less than 0.05 makes the item statistically significant. The table 8 (regression analysis for student responses) below shows the calculated significance value for the three independent variables and the mediating variable in the context of the study's dependent variable. The significance value for the variable perceived ease of use is 0.019 which is less than 0.05. This makes the causal relationship between this independent variable and the dependent variable supported. Furthermore, the significance values for the variables perceived usefulness and adaptive feedback are both 0.000. This explains the supported causal effects of these variables on the dependent variable. Finally, the table further shows that the significance value calculated for user acceptance is 0.012 which is again less than 0.05. This explains that the meditation impact of this variable is supported for the study's regression model.

Table 8
Regression Analysis for Students

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)	-.127	.105		-1.210	.227	-.334	.079
	SPEU	.074	.056	.067	1.306	.019	-.037	.184
	SPU	.402	.057	.364	7.026	.000	.289	.514
	SAF	.482	.049	.456	9.779	.000	.385	.579
	SUA	.086	.034	.073	2.515	.012	.019	.153
a. Dependent Variable: SSLO								

The following table consists of the regression analysis for the responses of the teachers in the survey. The significance value calculated for the perceived ease of use below is 0.000 which is less than the threshold value of 0.05. This shows the relationship between this independent variable and the dependent variable of the study are supported. Furthermore, the significance value calculated for perceived usefulness and adaptive feedback are 0.057 and 0.000 which are again within the desired range. This indicates that the causal relationship between these two independent variables and the dependent variable of the study are also supported. Finally for the mediating variable, the significance value calculated below is 0.000 which is less than 0.05. This shows that the mediating impact of this variable on the dependent variable is also supported for the study's regression model.

Table 9
Regression Analysis for Teachers

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)	-.223	.047		-4.783	.000	-.315	-.131
	TPEU	.839	.034	.769	24.564	.000	.772	.907
	TPU	-.009	.021	-.009	-.432	.057	-.049	.032
	TAF	.198	.031	.201	6.412	.000	.137	.259
	TUA	.049	.017	.051	2.949	.004	.016	.083
a. Dependent Variable: TSLO								

Hypothesis Testing

Hypothesis testing in a quantitative design-based study such as the current study is conducted for judging the developed relationships between the different variables of the study. There were seven hypotheses which were developed for the study, in the context of both students as well as teacher respondents. As can be seen in table 10, all the hypotheses have been supported based on the findings of the regression analysis conducted above. This indicates that firstly there exists a significant direct impact of perceived ease of use, perceived usefulness and adaptive feedback on the learning outcomes of the students as per the survey responses of the students. The findings below also show that the mediating role of user acceptance is also supported between these mentioned relationships between the independent variables and the dependent variable of the study.

Table 10
Hypothesis Testing for Students

Hypothesis	Results
H1: Perceived ease of use has a positive and significant impact on students' learning outcomes	Supported
H2: Perceived usefulness has a positive and significant impact on students' learning outcomes	Supported
H3: Adaptive feedback has a positive and significant impact on students' learning outcomes	Supported
H4: Perceived ease of use has a significant impact on user acceptance	Supported
H5: Perceived usefulness has a significant impact on User acceptance	Supported
H6: Adaptive feedback has a significant impact on User acceptance	Supported
H7: User acceptance has a significant impact on students' learning outcomes	Supported

Table 11 below shows that all the seven hypotheses related to the responses of the teachers are also supported based on the regression analysis conducted in the above sections. This explains that there is a significant impact of perceived ease of use, perceived usefulness and adaptive feedback on the student's learning outcomes based on the survey responses of the teachers. The mediating impact of user acceptance is also supported as can be seen below.

Table 11
Hypothesis Testing for Teachers

Hypothesis	Results
H1: Perceived ease of use has a positive and significant impact on students' learning outcomes	Supported
H2: Perceived usefulness has a positive and significant impact on students' learning outcomes	Supported
H3: Adaptive feedback has a positive and significant impact on students' learning outcomes	Supported
H4: Perceived ease of use has a significant impact on user acceptance	Supported
H5: Perceived usefulness has a significant impact on User acceptance	Supported
H6: Adaptive feedback has a significant impact on User acceptance	Supported
H7: User acceptance has a significant impact on students' learning outcomes	Supported

Discussion and Conclusion

The findings of this study provide robust support for the proposed hypotheses, demonstrating a significant alignment with existing theoretical frameworks and empirical literature. Consistent with Li, Linus et al. (2025), the results confirm that technology has become a central driver in contemporary education, enhancing student learning experiences through AI-driven digital tools. Similarly, the influence of perceived ease of use on student attitudes, as reported by Nuryakin et al. (2023), is corroborated in this study, highlighting that intuitive and accessible platforms foster positive engagement. Alshammari and Babu (2025) also emphasize the role of ease-of-use in ChatGPT adoption, further validating the positive association observed here.

Beyond usability, the study underscores the importance of adaptive feedback and social support in promoting self-regulated learning. Mejeh et al. (2024) and Nieto et al. (2024)

highlight the role of personalized feedback in facilitating learner autonomy, a finding reinforced in the current research. Additionally, Shaikh et al. (2025) demonstrate that the acceptability of e-learning platforms enhances learner motivation, which aligns with the increased engagement observed among participants in this study. Constructivist perspectives are similarly supported, as digital tools facilitate student-centered, interactive learning environments (Rafiq et al., 2024). Moreover, social support mechanisms enhance perceived usefulness (Aldraiweesh & Alturki, 2025), while adaptive learning contributes to improved academic outcomes (Contrino et al., 2024). Collectively, these findings confirm that all hypotheses are both evidence-based and theoretically grounded.

From a theoretical perspective, the study reaffirms the relevance of the Technology Acceptance Model (TAM) and constructivist theory in digital education contexts. Ease of use and perceived usefulness remain critical determinants of technology acceptance, while interactive, student-centered tools significantly improve learning outcomes. Practically, the study demonstrates that AI-driven platforms—including responsive chatbots, adaptive feedback systems, and internet-based resources—enhance engagement, motivation, and self-regulated learning. Peer and instructor support further strengthens students' confidence and facilitates more effective adoption of AI tools. These insights suggest that educational institutions should actively integrate digital platforms that provide adaptive and personalized support while simultaneously offering targeted training programs to enhance AI literacy and proficiency. Policies that foster collaboration among educational institutions, technology developers, and government stakeholders can ensure equitable access, thereby maximizing the potential of AI-driven learning for both learners and institutions.

Limitations and Future Directions

Despite its contributions, this study has several limitations. First, the exclusive focus on students in Beijing limits the generalizability of the findings to other geographic or demographic contexts. The uneven distribution of educational resources across urban and rural regions in China further constrains the applicability of results, as infrastructural limitations—such as unreliable internet access and limited availability of up-to-date technology—may impact AI adoption. Additionally, the study did not account for the influence of shortages in trained educators and administrators on the effective implementation of AI tools, nor did it examine potential adverse effects of excessive AI reliance on learners' memory development and creativity.

Future research could expand the scope of investigation in several directions. Studies may explore the potential of AI to enhance personalized learning by leveraging real-time student data to diagnose learning gaps and deliver tailored interventions. Further research could also evaluate the effectiveness of AI in improving administrative efficiency and equitable resource allocation within educational institutions. Ethical considerations remain critical; future studies should assess algorithmic biases, data privacy, and policy frameworks to ensure responsible AI integration in education. Collectively, these directions can provide deeper insights into both the pedagogical and operational potential of AI while addressing the limitations identified in this study.

Theoretical and Contextual Contributions

This study makes significant contributions both theoretically and contextually. Theoretically, it advances the Technology Acceptance Model (TAM) and constructivist learning perspectives by integrating adaptive feedback as a central construct alongside perceived usefulness and ease of use, thereby extending their explanatory power in AI-driven educational contexts. By empirically validating the mediating role of user acceptance, the research refines our understanding of how psychological and behavioral factors interact to influence learning outcomes. Contextually, the study contributes to the growing body of research on AI in education by focusing on secondary schools in Beijing, a setting characterized by rapid digital transformation and strategic government investment in smart education. These findings provide context-specific insights into how cultural, institutional, and policy-driven factors shape the adoption and effectiveness of AI-driven methodologies, offering guidance for both Chinese and international educational institutions navigating similar transitions.

References

Abuhassna, H., Yahaya, N., Zakaria, M. A. Z. M., Zaid, N. M., Samah, N. A., Awae, F., Nee, C. K., & Alsharif, A. H. (2023). Trends on Using the Technology Acceptance Model (TAM) for Online Learning: A Bibliometric and Content Analysis. International Journal of Information and Education Technology, 13(1), 131–142. https://doi.org/10.18178/ijiet.2023.13.1.1788

Aldraiweesh, A. A., & Alturki, U. (2025). The Influence of Social Support Theory on AI Acceptance: Examining Educational Support and Perceived Usefulness using SEM analysis. IEEE Access. https://doi.org/10.1109/ACCESS.2025.3534099

Alshammari, S. H., & Babu, E. (2025). The mediating role of satisfaction in the relationship between perceived usefulness, perceived ease of use and students' behavioural intention to use ChatGPT. Scientific Reports, 15(1), 7169. https://doi.org/10.1038/s41598-025-91634-4

Cao, L., & Chen, R. (2024). Secondary Education (High School) in China. 137–210. https://doi.org/10.1007/978-981-97-7415-9_4

Chen, X., Jiang, L., Zhou, Z., & Li, D. (2025). Impact of perceived ease of use and perceived usefulness of humanoid robots on students' intention to use. Acta Psychologica, 258, 117. https://doi.org/10.1016/j.actpsy.2025.105217

Chinnasami, S., & Manickam, R. (2023). Classification of the Architecture Using IBM SPSS Statistics. *REST Publisher*.https://doi.org/10.46632/aae/1/3/5

Contrino, M. F., Reyes-Millán, M., Vázquez-Villegas, P., & Membrillo-Hernández, J. (2024). Using an adaptive learning tool to improve student performance and satisfaction in online and face-to-face education for a more personalized approach. Smart Learning Environments, 11(1). https://doi.org/10.1186/s40561-024-00292-y

Delideli, J. (2024). Statistical Test Proficiency and Data Analysis Literacy through Statistical Package for the Social Sciences (SPSS) Workshop. *Journal of Interdisciplinary Perspectives*, *2*(10), 254-264.https://doi.org/10.69569/jip.2024.0438

Dönmez, E. (2024). The future of education: AI-supported reforms in the USA and China. In Global Agendas and Education Reforms: A Comparative Study (pp. 135-150). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-97-3068-1_7

Füller, J., Hutter, K., Wahl, J., Bilgram, V., & Tekic, Z. (2022). How AI revolutionizes innovation management – Perceptions and implementation preferences of AI-based innovators. *Technological Forecasting and Social Change*, *178*(178), 121598. https://doi.org/10.1016/j.techfore.2022.121598

Gan, Z., An, Z., & Liu, F. (2021). Teacher feedback practices, student feedback motivation, and feedback behavior: How are they associated with learning outcomes? Frontiers in Psychology, 12(1). https://doi.org/10.3389/fpsyg.2021.697045

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda☆. *Technological Forecasting and Social Change*, *162*, 120392.https://doi.org/10.1016/j.techfore.2020.120392

Jeilani, A., & Abubakar, S. (2025, March). Perceived institutional support and its effects on student perceptions of AI learning in higher education: the role of mediating perceived learning outcomes and moderating technology self-efficacy. In Frontiers in Education (Vol. 10, p. 98). Frontiers Media SA. https://doi.org/10.3389/feduc.2025.1548900

Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. The International Journal of Information and Learning Technology, 38(1), 1-19. https://doi.org/10.1108/IJILT-05-2020-0090

Li, Y. (2023). Where does AI-driven Education, in the Chinese Context and Beyond, go next? *International Journal of Artificial Intelligence in Education*. https://doi.org/10.1007/s40593-023-00341-6

Linus, A. A., Aladesusi, G. A., Monsur, I. A., & Elizabeth, F. J. (2025). Perceived Usefulness, Ease of Use, And Intention to Utilize Online Tools for Learning Among College of Education Students. http://ejournal.upi.edu/index.php/

Liu, H.-L., Wang, T.-H., Lin, H.-C. K., Lai, C.-F., & Huang, Y.-M. (2022). The Influence of Affective Feedback Adaptive Learning System on Learning Engagement and Self-Directed Learning. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.858411

Marikyan, D., & Papagiannidis, S. (2024). Technology Acceptance Model: A Review. Open.ncl.ac.uk. https://open.ncl.ac.uk/theories/1/technology-acceptance-model/

Mathias Mejeh, Sarbach, L., & Hascher, T. (2024). Effects of adaptive feedback through a digital tool – a mixed-methods study on the course of self-regulated learning. Education and Information Technologies. https://doi.org/10.1007/s10639-024-12510-8

Mejeh, M., Sarbach, L., & Hascher, T. (2024). Effects of adaptive feedback through a digital tool–a mixed-methods study on the course of self-regulated learning. *Education and Information Technologies,* 29(14), 1-43.https://link.springer.com/article/10.1007/s10639-024-12510-8

Nuryakin , Pierre, L., & Hussein Gibreel Musa. (2023). The Effect of Perceived Usefulness and Perceived Easy to Use on Student Satisfaction The Mediating Role of Attitude to Use Online Learning. APMBA (Asia Pacific Management and Business Application), 011(03), 323–336. https://doi.org/10.21776/ub.apmba.2023.011.03.5

Puspitasari, A., & Nugraha, H. (2023). The impact of perceived ease of use and perceived usefulness on actual system use through intention to use as an intervening variable in subscription video on demand services (Study on Netflix users in Semarang City). World Journal of Advanced Research and Reviews, 2023(03), 1354–1366. https://doi.org/10.30574/wjarr.2023.18.3.1230

Rafiq, S., Iqbal, S., & Afzal, A. (2024). The impact of digital tools and online learning platforms on higher education learning outcomes. *Al-Mahdi research journal (MRJ),* 5(4), 359-369.http://ojs.mrj.com.pk/index.php/MRJ/article/view/342

Saad, S., Ramli, Z., Sarmila, M. S., Nor, M., & Ali, S. (2025). Exploring the Adoption of AI-Driven Adaptive Learning in Higher Education: A Multidimensional TAM Perspective. *International Journal of Academic Research in Business and Social Sciences,* 15(5), 1011-

1025.https://kwpublications.com/papers_submitted/17068/exploring-the-adoption-of-ai-driven-adaptive-learning-in-higher-education-a-multidimensional-tam-perspective.pdf

Shaikh, I. M., Tanakinjal, G. H., Amin, H., Noordin, K., & Shaikh, J. (2025). Students'e-learning acceptance: empirical evidence from higher learning institutions. *On the Horizon: The International Journal of Learning Futures,* 33(1), 1-13.https://www.emerald.com/oth/article-abstract/33/1/1/1239888

Sukmawati, S. (2023). Development of quality instruments and data collection techniques. *Jurnal Pendidikan Dan Pengajaran Guru Sekolah Dasar (JPPGuseda)*, *6*(1), 119-124.https://journal.unpak.ac.id/index.php/JPPGuseda/article/view/7527

Taherdoost, H. (2021). Data collection methods and tools for research; a step-by-step guide to choose data collection technique for academic and business research projects. *International Journal of Academic Research in Management (IJARM)*, *10*(1), 10-38.https://hal.science/Hal-03741847/

Valaboju, V. K. (2024). The Synergy of Just-in-Time Learning and Artificial Intelligence: Revolutionizing Personalized Education. *International Journal of Computer Engineering and Technology (IJCET)*, *15*(5), 707-715.https://doi.org/10.5281/zenodo.13884988

Wang, Y., Liu, C., & Tu, Y. F. (2021). Factors affecting the adoption of AI-based applications in higher education. Educational technology & society, 24(3), 116-129. http://index.j-ets.net/Published/24_3/ETS_24_3_09.pdf

Xu, Z. (2024). AI in education: Enhancing learning experiences and student outcomes. Applied and Computational Engineering, 51(1), 104–111. https://doi.org/10.54254/2755-2721/51/20241187

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. International Journal of Educational Technology in Higher Education, 20(1). https://doi.org/10.1186/s41239-023-00420-7

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00420-7