Knowledge, Attitude, Usage of Artificial Intelligence; and Adaptability among Graduate Student

Eudeliza Pana-Anong[1], Zenaida G. Gersana[2], Nenita I. Prado[3]

Liceo de Cagayan University Cagayan de Oro City, Philippines

DOI: https://doi.org/10.47772/IJRISS.2026.100300297

Received: 16 March 2026; Accepted: 22 March 2026; Published: 06 April 2026

ABSTRACT

This study examined the influence of knowledge, attitude, and usage of artificial intelligence (AI) on students' adaptability. It specifically assessed AI-related knowledge in homework assistance, student engagement, and assessment accuracy; students' attitudes in terms of awareness, understanding, and familiarity; and AI usage across functionality, availability, and complexity. Predictive correlational research designs were employed with participants selected from a higher education institution. Data were gathered using validated and reliable survey instruments and analyzed using descriptive statistics, Pearson product-moment correlation, and multiple regression analysis to determine the significant relationships and predictors of adaptability. Results revealed moderate levels of AI knowledge, usage, and adaptability, alongside a high level of positive attitude toward AI. Significant positive relationships were found between adaptability and all AI dimensions, indicating that stronger engagement, familiarity, access, and effective utilization of AI tools are associated with better adaptability. Regression analysis identified familiarity, availability, complexity management, and student engagement as significant predictors of adaptability, while awareness alone did not necessarily translate into improved results without practical competence. The study concludes that meaningful interaction, guided usage, and hands-on experience with AI significantly enhance students' adaptability. It is recommended that higher education institutions implement structured AI literacy programs, provide continuous training and institutional support, and integrate AI tools strategically into instruction to maximize their educational benefits.

Keywords: knowledge, attitude, usage of artificial intelligence, students' adaptability, predictors of adaptability

INTRODUCTION

A study on Artificial Intelligence (AI) was conducted because it was observed personally how Artificial Intelligence is rapidly changing the landscape of education. Students became curious about AI and its use, and whether it truly helps students perform better academically.

This topic interests many people because AI is no longer just a trend—it has become an essential part of learning, research, and productivity. However, it was also noticed that not all students use it effectively or understand its full potential. Some may rely on it heavily, while others are hesitant due to lack of knowledge or negative perceptions. This study wanted to explore these differences and see how knowledge, attitude, and usage are connected to academic success.

This study, hopes to contribute insights that can help both students and educators maximize the benefits of AI responsibly and effectively. It is believed that understanding how AI impacts adaptability can guide schools and universities in integrating technology in ways that truly enhance learning and research.

In the fast-paced digital era, Artificial Intelligence (AI) has become one of the most powerful innovations shaping the future of education. Graduate students living in this age of technological advancement, have witnessed how AI has become an indispensable companion in learning, research, and communication. From AI-driven platforms like ChatGPT that assist in idea generation and academic writing, to tools like Grammarly that enhance writing quality, QuillBot that supports paraphrasing, and Turnitin that checks originality—AI technologies have transformed how students approach academic tasks.

This personal experience has sparked curiosity about how graduate students truly understand and use these tools. While many rely on AI for convenience and efficiency, not all have the same level of knowledge or positive attitude toward its use. Some embrace it as a learning partner, while others remain cautious, questioning its reliability, ethical implications, and effects on critical thinking. These varying perspectives motivated the researcher to explore how knowledge, attitude, and usage of Artificial Intelligence relate to students' adaptability.

The study "Knowledge, Attitude, Usage, and Adaptability of Artificial Intelligence Among Graduate Students" aims to investigate how familiar graduate students are with different AI tools, how they perceive their usefulness and trustworthiness, and how frequently and effectively they integrate them into their academic work. Moreover, it seeks to determine whether these factors contribute to improved academic outcomes or simply create a dependency that may affect independent learning.

THEORETICAL AND CONCEPTUAL FRAMEWORK

The theoretical framework for this study is built upon four key theories: Technology Acceptance Model (TAM); Theory of Planned Behavior (TPB); Unified Theory of Acceptance and Use of Technology (UTAUT) and Information Processing Theory (IPT). Each of these theories contributes a unique perspective on the relationship of knowledge, attitude, usage of artificial intelligence towards respondents' adaptability.

Technology Acceptance Model (TAM), developed by Davis (1989), remains one of the most influential theories in understanding user adoption of technology. It focuses on two main constructs—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—that predict attitudes toward using a technology, which then leads to the intention to use and actual usage. In the context of the study "Knowledge, Attitude, Usage, and Adaptability among Graduate Students", TAM can provide a robust framework for analyzing how these variables interact in the adoption of Artificial Intelligence (AI) and other educational technologies. Knowledge about a technology is crucial for its adoption. Graduate students who have sufficient knowledge of AI are more likely to find it useful and easy to use, which aligns with the TAM framework. For example, a study by Padilla-Meléndez et al. (2017) emphasized the role of prior knowledge in enhancing the perceived usefulness of e-learning systems. Similarly, Chuttur (2020) noted that students with higher knowledge of AI tools demonstrated more favorable attitudes and were more likely to use them.

Attitude towards technology is central in TAM, as it bridges the gap between perception and actual usage. A study by Teo et al. (2019) found that attitudes toward AI and e-learning systems were significantly influenced by PU and PEOU. In particular, they found that students who believed AI could improve their academic work held positive attitudes toward its use, which directly impacted their adaptability.

Theory of Planned Behavior (TPB), proposed by Ajzen (1991), is one of the most widely used frameworks to understand how individuals' attitudes, subjective norms, and perceived behavioral control influence their intentions and behaviors. TPB provides a relevant lens to explore how graduate students' knowledge, attitudes, and external influences shape their usage of technology, including Artificial Intelligence (AI), and how this impacts their adaptability.

With TPB, knowledge can be linked to perceived behavioral control (PBC), which refers to an individual's belief in their ability to perform a behavior. Several studies have shown that individuals who possess greater knowledge about a technology feel more capable of using it. For example, Zhang et al. (2018) found that students who were knowledgeable about educational technologies had higher perceived control over their usage, leading to greater adoption. Similarly, Al-Maroof and Salloum (2020) noted that knowledge directly influenced PBC in the context of AI tools, making students more likely to integrate them into their academic routines.

Attitude is a central element of TPB, referring to the individual's positive or negative evaluation of performing a specific behavior. Graduate students' attitudes toward AI and educational technologies can significantly affect their decision to use these tools. For instance, a study by Nassr et al. (2020) demonstrated that students with a positive attitude toward AI tools were more likely to use them in their academic activities. Similarly, attitudes based on perceived usefulness and relevance were found to have a significant impact on technology acceptance in a study by Hussein et al. (2020).

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), is one of the most comprehensive models for explaining user acceptance and usage of technology. The model integrates several key theories and proposes four core determinants of intention and usage behavior: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). In the context of the study "Knowledge, Attitude, Usage, and Adaptability of Graduate Students", the UTAUT model provides a robust framework for analyzing how various factors influence graduate students' acceptance and usage of Artificial Intelligence (AI) and other technologies, and how these, in turn, affect their adaptability.

In UTAUT, performance expectancy (PE) can be strongly related to students' knowledge of the technology. The more knowledgeable graduate students are about AI, the more they are likely to perceive its usefulness in improving their adaptability. According to a study by Al-Gahtani et al. (2017), students with greater knowledge of AI had higher performance expectations, leading to increased usage. Similarly, Huang and Kao (2020) emphasized the role of knowledge in shaping positive perceptions of AI's usefulness, leading to greater adoption in academic settings.

The Information Processing Theory (IPT), rooted in cognitive psychology, emphasizes how individuals encode, store, retrieve, and utilize information to solve problems and make decisions. In the context of the study IPT provides a framework for understanding how graduate students acquire and use knowledge, form attitudes, and leverage technology to enhance adaptability. The theory is particularly relevant in examining how students process information using Artificial Intelligence (AI) and other educational technologies, and how these processes affect their learning outcomes.

In Information Processing Theory, knowledge acquisition is central, as it involves encoding new information, integrating it into existing cognitive structures, and retrieving it when necessary. Graduate students who effectively use AI tools for information retrieval and analysis are likely to have better-structured knowledge systems. For instance, Azevedo et al. (2018) found that AI tools facilitated knowledge organization and deep learning, allowing students to process information more efficiently. Similarly, Mayer and Moreno (2020) emphasized the importance of technology in enhancing the cognitive processes involved in knowledge retention, with AI tools aiding in better encoding of complex information.

While IPT does not directly address attitudes, it can be inferred that the way graduate students process information influences their attitudes toward AI usage in learning. Attitudes toward technology are often shaped by cognitive evaluations of its usefulness and ease of use. In a study by Liu et al. (2018), graduate students with positive attitudes toward AI tools were more likely to use them, as they perceived these tools to streamline cognitive processes like information organization and problem-solving. Similarly, Santos et al. (2020) found that students who recognized the cognitive benefits of AI-based learning systems developed more favorable attitudes toward these tools, leading to greater acceptance and usage.

Statement of the Problem

This study aims to determine the relationship of the knowledge, attitude, usage and adaptability among graduate students. Specifically, it seeks to answer the following question:

What is the participants' level of knowledge of Artificial Intelligence in terms of:

1.1 Homework assistance;

1.2 Assessment Accuracy; and

1.3 Student Engagement?

What is the participants' level of attitude towards AI in terms of:

2.1 Understanding;

2.2 Awareness; and

2.3 Familiarity?

What is the participants' level of usage of AI in terms of:

3.1 Functionality;

3.2 Availability; and

3.3 Complexity?

What is the level of adaptability of students?

Is there a significant relationship between participants' adaptability and:

5.1 Knowledge of AI,

5.2 Attitude towards AI, and

5.3 usage of artificial intelligence?

Which variables singly, or in combination, best predicts adaptability?

Hypotheses

Based on the preceding research problems, the following null hypotheses were tested at the 0.05 level of significance:

HO1: There is no significant relationship between adaptability, knowledge, attitude, and usage of artificial intelligence

HO2: There is no variable that singly or in combination influence adaptability of the participants.

METHODOLOGY

This chapter presents the methodology to be used by the researcher in conducting the study. It includes the research setting and design, participants of the study, sampling procedures, the research instruments to be used, data gathering procedure, method of data analysis, validity and reliability of instruments, and the statistical techniques used in analyzing the data. By providing a comprehensive and well-structured methodology, we aim to demonstrate the rigor and robustness of the research, enabling readers to assess the quality and credibility of the findings.

Research Design

In examining how knowledge, attitude, usage of artificial intelligence; and adaptability among graduate students, this study utilized predictive correlational research design. Descriptive research design is a type of research methodology that aims to describe characteristics or phenomena as they exist in a specific situation. It does not focus on the reasons behind those characteristics but instead provides a detailed account of the "what" rather than the "why" or "how." The primary purpose is to accurately depict the current state of a subject or population through data collection methods such as surveys, observations, and case studies.

A correlational research design examines the relationship between two or more variables to determine whether they are associated (or correlated) with each other. The primary aim is to identify and measure the strength and direction of the relationship without manipulating the variables. Unlike experimental research, correlational studies do not imply causation; they only indicate whether variables move together in some systematic way. Correlational research helps in understanding patterns, trends, and potential relationships that may warrant further investigation through experimental or more detailed studies.

Predictive Research Design aims to forecast the influence of one variable on another by identifying patterns and relationships that can anticipate future outcomes. In this type of research, the investigator seeks to determine the extent to which an independent variable can predict changes or variations in a dependent variable. Unlike purely correlational studies, predictive research focuses on using existing data to generate reliable predictions about future behavior, performance, or outcomes. This design is particularly useful for understanding the strength and direction of relationships between variables and for developing models that can guide decision-making and interventions in practical settings..

In this study, descriptive research design was used to provide a clear, detailed understanding of the variables involved, including the knowledge, attitude, and usage of artificial intelligence (AI) among graduate students, as well as their adaptability. And correlational research design would explore the relationships between knowledge, attitude, usage of AI, and adaptability. It would help identify if and how these variables are associated with each other, but without establishing cause and effect. Then, predictive research design would seek to establish whether knowledge, attitude, and usage of AI actually cause changes in adaptability. This involves testing for cause-and-effect relationships, where changes in one variable (e.g., AI usage) are shown to lead to changes in another variable (adaptability).

Research Setting

The research was conducted at Liceo de Cagayan University School of Business, Management, and Accountancy (LdCU-SBMA) is one such institution that has garnered recognition for its commitment to providing quality education in the Philippines. As a renowned research setting, LdCU-SBMA offers a rich environment for exploring various aspects of business education, management practices, and accounting principles.

LdCU-SBMA offers a comprehensive range of academic programs, catering to undergraduate and graduate students seeking a career in business, management, and accounting. The diverse curriculum encompasses courses that cover fundamental business disciplines, including finance, marketing, human resources, operations management, entrepreneurship, and the graduate programs.

Research Participants

The study employed proportionate stratified random sampling, a standard statistical technique that divides a population into distinct subgroups, or strata, based on some shared characteristics (Fleetwood, 2023), where each stratum's sample size corresponded to its population size of the stratum considering the procedure, $n = (n/N) * ns$, where n = sample; N = population size, and ns = stratum size. The formula was designed and reviewed by Hayes et al. (2020) and modified by the researcher to simplify the interpretation of each symbol. Researchers can obtain a sample population that most accurately represents the entire population under study using stratified random sampling (Hayes, 2023).

First stage was to identify the stratum of each program. There were 7 strata. Doctor in Management major in Human Resource Management, Doctor in Management major in Health Care Administration, Doctor in Management major in Leadership and Organization, Master in Business Administration, Master in Management major in Human Resource Management, Master in Management major in Business Management, Master in Management major in Health Care Administration in LDCU-SBMA which has a total of 288 population. The second stage, determined the desired sample size of 169 was divided by the population size of 288, and the quotient value was multiplied by the stratum size (based on the number of populations in each stratum). Whole number was recognized as the sample size obtained from the product value to come up with 169 as its total sample size.

Research Instruments

A survey questionnaire composed of four (4) parts was utilized in this study. The first part is a researcher-made questionnaire composed of sixty (110 items) statements that determined knowledge, attitude, and usage of artificial intelligence; and adaptability of graduate students that uses Likert Scale- Like and described as follows:

The primary data collection method in this research is through a survey questionnaire. . The questionnaire is structured into four parts, each serving a specific purpose. The first part of the questionnaire gathers course information about the participants.

Data for the study were collected through self-made printed questionnaire. This was to check the level of responses on the knowledge, attitude, and usage towards artificial intelligence. A total of 110 items were used with a 5-point Likert Scale which was originated by Likert (1932), with five response options ranging from "Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree" with a score of 5 to "Strongly Agree", and "Strongly Disagree" with a score of 1.

Data Gathering Procedure

The study tools were administered in order to make sure that the protocol was followed. A letter requesting authorization to administer the instruments to graduate program students was submitted to the dean of Liceo de Cagayan University's School of Business, Management, and Accountancy. The participants were provided with a consent letter and informed consent form along with the research instrument, asking them to voluntarily participate in the study and complete the survey tools. A few days after the permission, the distribution of study tools, instructions, and retrieval were scheduled.

An organized and ethically sound online survey administered through Google Forms was used in this study's data collection. The procedure needed the following steps: Approval and Permissions: The relevant approvals were granted by the Dean of the School of Business, Management, and Accountancy (SBMA) at Liceo de Cagayan University. In order to conduct the study, written approval from each of the program chairs was also required. Informed Consent: Each graduate student participant received a copy of the Informed Consent Form. The form, which was added to the Google Form survey questionnaire, had details on the objectives and methodology of the study, a promise of the privacy of the data, and a focus on voluntary participation. Participants had the option to review the form and give their approval.

Participants had the option to examine the form and electronically sign it using the google form. Questionnaire Administration: Using a 5-point Likert scale, the survey was distributed to participants via the Google Forms. The questionnaire came with detailed instructions on how to complete it. There was plenty of time for participants to answer the questionnaire whenever it was convenient for them. Data Review: To make sure that every question was answered completely and accurately, responses that were absent or inconsistent were addressed. The gathered data were immediately and carefully examined. The data were analyzed and interpreted using the appropriate statistical tools.

Validity and Reliability

Content validation and reliability testing were performed on all survey questions utilized in this study. The questionnaire was reviewed by three experts in political science, who assessed whether the items were appropriate, clear, and aligned with the study's objectives. For the reliability of the instrument, a pilot test was conducted prior to the main data collection.

After being piloted, the relevant questionnaires used in this study were subjected to a reliability test using SPSS 20. The questionnaires were administered to 30 students who were not part of the main sample for the pilot study. This process aimed to ensure that the questionnaires were dependable and capable of producing consistent results. Prior to distributing the research questionnaires to the participants, their reliability was assessed using the Cronbach's Alpha Test. The reliability coefficients for all subscales yielded excellent results: Homework Assistance ($\alpha = 0.940$), Assessment Accuracy ($\alpha = 0.824$), Student Engagement ($\alpha = 0.948$), Understanding ($\alpha = 0.900$), Awareness ($\alpha = 0.951$), Familiarity ($\alpha = 0.935$), Functionality ($\alpha = 0.939$), Availability ($\alpha = 0.942$), Complexity ($\alpha = 0.910$), and Adaptability ($\alpha = 0.950$).

All values were well above the acceptable threshold of 0.70, as recommended by Nunnally and Bernstein (1994), indicating a high level of internal consistency and confirming that the questionnaire is a reliable instrument for measuring AI-related knowledge, attitudes, usage, and adaptability among the respondents.

Data Analysis

Data for the study were collected through a survey instrument in Google form and were analyzed using Statistical Package for the Social Science (SPSS). The mean and standard deviation were used to measure the levels of knowledge, usage, adaptability, and attitudes toward Artificial Intelligence.

To ascertain the significant relationship between adaptability among graduate students on artificial intelligence and knowledge, attitude, and usage of artificial intelligence, Pearson Product Moment Correlation was used. To identify the variables that influenced adaptability, Multiple Regression Analysis was used.

RESULTS AND DISCUSSION

This section presents, analyzes, and interprets the collected data. The results, depicted in tabular format with corresponding mean values and descriptive interpretations, are organized to address the specific problems identified in the study.

Table 1 Summary on the Level of Knowledge and Attitude, Usage, and Adaptability on Artificial Intelligence Among Graduate Students

Variables	Mean	SD	Description	Interpretation
Knowledge	3.30	.950	Moderately Agree	Moderate
Attitude	3.60	.925	Agree	High
Usage	**3.39**	**.938**	Moderately Agree	Moderate
Overall Mean	**3.43**	**.937**	**Moderately Agree**	**Moderate**

Legend:

Scale	Range	Description	Interpretation
5	4.50-5.00	Strongly Agree	Very high
4	3.50-4.49	Agree	High
3	2.50-3.49	Moderately Agree	Moderate
2	1.50-2.49	Disagree	Low
1	1.00-1.49	Strongly Disagree	Very low

The findings indicate that respondents possess a moderate level of AI knowledge (M = 3.30, SD = 0.950), falling within the Moderately Agree range. This suggests that students have a developing understanding of AI applications in academic contexts, particularly in tasks such as homework assistance, engagement, and assessment. While they demonstrate familiarity with AI tools, their depth of comprehension and critical application skills remain limited. The relatively consistent standard deviation reflects shared perceptions across participants, highlighting a common level of understanding. This aligns with Crompton and Burke (2023), who emphasized that although AI awareness among students is rising, variations exist in the ability to apply AI knowledge critically and strategically in educational settings. Consequently, the results underscore the need for structured training and guided experiences to enhance students' conceptual and practical understanding of AI.

In terms of attitude, respondents reported a high overall score (M = 3.60, SD = 0.925), falling within the Agree range and interpreted as High. This indicates that students generally maintain a positive and supportive perception of AI as a learning tool. A strong attitude toward AI suggests that students recognize the value of these technologies in enhancing productivity, simplifying complex tasks, and providing timely academic support. The relatively consistent standard deviation shows that these positive perceptions are fairly uniform among participants. This finding aligns with Dwivedi et al. (2023), who noted that favorable attitudes toward AI are largely influenced by its perceived usefulness and ease of integration into learning activities. The strong positive attitude provides a foundation for further adoption and engagement, indicating that students are receptive to incorporating AI into their academic routines.

Regarding usage, the overall mean (M = 3.39, SD = 0.938) falls within the Moderately Agree range and is interpreted as Moderate. This reflects a moderate level of practical engagement with AI tools, suggesting that while students access and apply AI for academic purposes, there is still room for more consistent and effective utilization. The consistent standard deviation indicates shared experiences in terms of frequency and manner of use. This result is consistent with Bond et al. (2020), who reported that although digital technologies are widely introduced in education, actual depth of usage often remains moderate due to differences in digital readiness, confidence, and pedagogical integration. Taken together, the overall mean of 3.43 (SD = 0.937) reflects a

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue III March 2026

balanced profile in knowledge, attitude, and usage, highlighting that while students have positive perceptions of AI, their knowledge and practical engagement require further development to maximize academic benefits.

Table 2. Relationship Between Adaptability and Knowledge, Attitude, Usage Towards Artificial Intelligence

Variables	R	P-value	Interpretation
Homework Assistance	.613	.000	Significant
Assessment Accuracy	.159	.047	Significant
Student Engagement	.638	.000	Significant
Knowledge	**.651**	**.000**	**Significant**
Understanding	.640	.000	Significant
Awareness	.510	.000	Significant
Familiarity	.708	.000	Significant
Attitude	**.663**	**.000**	**Significant**
Functionality	.706	.000	Significant
Availability	.746	.000	Significant
Complexity	.760	.000	Significant
Usage	**.780**	**.000**	**Significant**

*. Correlation is significant at the 0.05 level (2-tailed).

The Pearson r correlation analysis of the significant positive relationships between adaptability and the different dimensions of artificial intelligence (AI), indicating that stronger AI-related factors are associated with improved academic outcomes. Homework Assistance ($r = .613$, $p = .000$). showed a strong positive correlation towards adaptability suggests that students who utilize AI for homework support tend to achieve higher adaptability. AI-powered tutoring and writing assistants can provide immediate feedback, structured guidance, and personalized explanations, enhancing learning efficiency. This indicated that adaptability is strengthened when students are given timely scaffolding, allowing them to adjust their learning strategies more efficiently. From an adaptive learning perspective, AI functions as a dynamic support system that personalizes instruction, enabling learners to progress at their own pace. This reinforces the idea that adaptability is developed through continuous interaction with responsive learning tools rather than through static instruction alone. Ma et al. (2021) found that AI-supported tutoring systems significantly improve student achievement by offering adaptive and responsive academic assistance.

Assessment Accuracy ($r = .159$, $p = .047$) had a weak positive correlation towards adaptability. This indicates that AI-driven assessment accuracy has a limited yet meaningful association with adaptability. This suggests that adaptability is less influenced by evaluation itself and more by how students act upon feedback. In other words, assessment systems may inform learning, but they do not necessarily transform it unless paired with active engagement strategies. This highlights a limitation in relying solely on AI-driven assessment tools and underscores the need for instructional integration where feedback becomes actionable, aligning with the idea that learning is most effective when feedback leads to behavioral and cognitive change. Automated grading and feedback systems may improve reliability and timeliness of evaluation. Zhai et al. (2021) explain that AI-based assessment tools enhance feedback precision, though their effectiveness depends on integration with instructional practices.

Student Engagement ($r = .638$, $p = .000$) showed a strong positive relationship towards adaptability. This implies that AI-enhanced engagement is closely linked to better adaptability. Interactive AI systems can foster active participation, sustained attention, and motivation. This finding suggests that adaptability is not simply a cognitive outcome but also a behavioral and motivational process. AI tools that promote interactivity, such as simulations or intelligent tutoring systems, encourage sustained attention and deeper involvement, which are essential for developing flexible learning strategies. From a constructivist standpoint, students who are actively engaged are more likely to experiment, reflect, and adjust their approaches to learning. This implies that engagement acts as a mechanism through which adaptability is developed, reinforcing the idea that meaningful learning occurs when students are actively involved rather than passively receiving information. Henrie et al. (2018) highlight that technology-facilitated engagement significantly predicts improved academic achievement in digital learning environments.

Knowledge (r = .651, p = .000). showed a strong correlation on adaptability. This finding indicates that students who possess both conceptual understanding and practical knowledge of AI are better equipped to integrate these tools effectively into their academic tasks. Rather than using AI passively, knowledgeable students are more likely to apply it strategically—selecting appropriate tools, interpreting outputs accurately, and aligning AI assistance with learning objectives. This reflects a higher level of cognitive engagement, where learners move beyond basic usage to critical and purposeful application. From a cognitive perspective, knowledge serves as a foundation for decision-making and problem-solving, enabling students to maximize the benefits of AI in complex academic situations. Furthermore, AI literacy enhances students' ability to evaluate the reliability and relevance of AI-generated information, reducing dependency and promoting independent thinking. As supported by Chiu (2023), students with stronger AI knowledge demonstrate improved academic competence and digital problem-solving skills, reinforcing the idea that knowledge is not only a predictor of performance but also a key driver of effective and responsible technology use in learning environments.

Understanding (r = .640, p = .000). also showed a strong positive relationship towards adaptability. This suggests that students who move beyond surface-level familiarity and develop a meaningful understanding of how AI tools function are better positioned to use these technologies effectively in their learning processes. Conceptual understanding enables learners to critically evaluate AI-generated outputs, recognize limitations, and make informed decisions about when and how to apply these tools. This reflects higher-order thinking skills, where students engage in analysis, evaluation, and strategic application rather than passive acceptance of information. From a cognitive and constructivist perspective, understanding allows learners to integrate new knowledge with prior experiences, leading to more meaningful and transferable learning outcomes. Furthermore, students with a strong grasp of AI concepts are less likely to become overly dependent on technology, as they can independently assess the accuracy and relevance of AI-assisted results. As emphasized by Holmes et al. (2022), meaningful understanding of AI principles not only supports improved adaptability but also promotes responsible and ethical use of technology, reinforcing the role of understanding as a key factor in both academic success and digital competence.

Awareness (r = .510, p = .000) had a moderate positive correlation towards adaptability. This indicates that awareness of AI tools and their potential applications contributes to improved academic outcomes. Awareness enables students to identify opportunities where AI can effectively support learning. Falloon (2020) notes that digital awareness is a critical factor in enhancing students' academic productivity in technology-rich environments.

Familiarity (r = .708, p = .000) showed a strong positive correlation on adaptability this suggests that familiarity with AI tools enhances confidence and efficiency, leading to better performance. Repeated interaction with AI systems builds competence and reduces cognitive strain. Scherer et al. (2019) found that familiarity with digital tools significantly predicts successful academic technology integration.

Attitude (r = .663, p = .000) had a strong positive relationship on adaptability. This finding indicates that students who hold a positive attitude toward AI are more likely to embrace these technologies as valuable learning tools, leading to increased motivation, engagement, and willingness to experiment with new approaches to learning. A favorable attitude fosters openness to innovation, which encourages students to integrate AI into their academic tasks more consistently and effectively. From a behavioral perspective, attitude influences not only the intention to use technology but also the persistence and effort exerted in utilizing it, especially when challenges arise. This aligns with the Technology Acceptance Model, which posits that positive perceptions of usefulness and ease of use significantly drive technology adoption and continued usage. Furthermore, students with positive attitudes toward AI are more likely to view it as a support system rather than a replacement for their own abilities, promoting a balanced and productive use of technology. As supported by Teo (2019), positive attitudes toward educational technologies significantly influence both adaptability and the likelihood of sustained technology adoption, highlighting attitude as a key factor in developing adaptive and effective learning behaviors in AI-enhanced environments.

Functionality (r = .706, p = .000) showed a strong correlation towards adaptability. This implies that perceived AI functionality contributes to improved adaptability. When students believe AI systems are useful and reliable, they are more likely to use them effectively. This suggests that when AI tools are viewed as reliable, efficient, and capable of meeting academic needs, students are more likely to integrate them into their learning processes in a meaningful and sustained manner. Perceived functionality goes beyond simple usability; it reflects the extent to which students believe that AI can genuinely enhance their productivity, accuracy, and overall learning experience. Scherer et al. (2021) confirm that perceived usefulness strongly predicts academic success in technology-enhanced learning contexts.

Availability (r = .746, p = .000) had a very strong positive relationship towards adaptability. This finding implies that adaptability is not solely dependent on students' abilities but is also significantly shaped by the learning environment and the accessibility of technological resources. When AI tools are readily available, students are provided with continuous opportunities to practice, explore, and refine their skills, leading to more effective and independent learning. Availability reduces barriers to engagement, allowing learners to seek immediate support, clarify concepts, and complete tasks more efficiently. From an equity perspective, this highlights the importance of ensuring equal access to digital technologies, as disparities in availability may directly affect students' ability to adapt and succeed academically. As supported by Maniano (2019), access to digital technologies is strongly associated with improved student achievement, emphasizing that consistent availability serves as a foundation for sustained learning and skill development.

Complexity (r = .760, p = .000) showed a strong positive correlation on adaptability. This suggests that complexity, rather than being a hindrance, can serve as a catalyst for cognitive growth when students possess the necessary skills to handle it. Engaging with complex AI tools requires higher-order thinking skills such as analysis, problem-solving, and decision-making, which contribute to the development of digital competence and adaptability. From a cognitive perspective, exposure to complex systems challenges learners to go beyond basic usage and develop deeper understanding and strategic thinking. This implies that students who successfully interact with advanced AI technologies are likely to become more resilient and flexible in addressing academic challenges. As highlighted by Sailer et al. (2021), learners who can effectively navigate complex digital environments tend to achieve stronger academic outcomes, reinforcing the idea that complexity fosters intellectual growth when supported by adequate skills and guidance.

Usage (r = .780, p = .000) had a strongest correlation on adaptability. This finding suggests that adaptability is highly influenced by the frequency and quality of interaction with technology, where repeated use leads to increased familiarity, efficiency, and mastery. Regular usage enables students to integrate AI seamlessly into their learning routines, improving productivity, comprehension, and task completion. From a behavioral perspective, frequent use reinforces learning habits and promotes self-regulated learning, as students become more confident in applying AI tools to various academic tasks. This aligns with experiential learning principles, where knowledge and skills are developed through continuous practice and application. As supported by Crompton and Burke (2023), sustained integration of AI in academic activities significantly improves student achievement, highlighting that adaptability is strengthened not just by access to technology but by active and consistent utilization of it.

Table 3. Multiple Regression Analysis for the Variables that Singly or in Combination, Significantly influence Adaptability

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Interpretation
	B	Std. Error	Beta			
(Constant)	0.873	0.166		5.270	0.000	Significant
Student Engagement	0.120	0.056	0.149	2.132	0.035	Significant
Awareness	-0.213	0.073	-0253	2.939	0.004	Significant
Familiarity	0.333	0.089	0.385	3.743	0.000	Significant
Availability	0.245	0.091	0.298	2.700	0.008	Significant
Complexity	0.215	0.085	0.256	2.406	0.017	Significant
R=.810 R^2=.655 F=57.414 P=.000						

The results of Multiple Regression Analysis for the variables that, singly or in combination, significantly influence adaptability As shown in the table, the R value is .810, indicating a strong positive relationship between adaptability and the independent variables included in the model. The R^2 value of .655 suggests that 65.5% of the variance in adaptability is explained by the combined influence of Student Engagement, Awareness, Familiarity, Availability, and Complexity.

The F value of 57.414 with a p-value of .000 indicates that the overall regression model is statistically significant. This confirms that the set of independent variables, when taken together, significantly predicts adaptability. The result implies that AI-related behavioral and perceptual factors collectively play a substantial role in shaping students' adaptability to AI.

Among the variables tested, Student Engagement ($\beta = 0.149$, $p = .035$), Awareness ($\beta = -0.253$, $p = .004$), Familiarity ($\beta = 0.385$, $p = .000$), Availability ($\beta = 0.298$, $p = .008$), and Complexity ($\beta = 0.256$, $p = .017$) were found to have statistically significant effects on adaptability. Familiarity showed the largest beta coefficient ($\beta = 0.385$), indicating that greater familiarity with AI tools contributes most strongly to improved adaptability to AI. Availability and Complexity also demonstrated notable positive influences, suggesting that access to AI tools and the ability to manage their complexity enhance learning outcomes.

Interestingly, Awareness yielded a ($\beta = 0.253$), implying that higher awareness alone without corresponding competence or strategic use may not necessarily translate into adaptability to AI. This may indicate that mere recognition of AI tools is insufficient unless accompanied by practical skills and meaningful engagement. Student Engagement, although having the smallest beta coefficient among the predictors, still significantly contributes to adaptability to AI, emphasizing the importance of active participation in AI-supported learning activities.

The results indicate that a one-point increase in Familiarity corresponds to a 0.333-point increase in adaptability, highlighting the importance of hands-on experience with AI tools. Similarly, a one-point increase in Availability leads to a 0.245-point increase in performance, reinforcing the role of accessible technological resources in academic success. Complexity shows a positive coefficient, suggesting that students who effectively manage AI-related challenges tend to perform better academically. Conversely, the negative coefficient for Awareness indicates that awareness without applied competence may not directly enhance performance.

These findings are reinforced by recent empirical studies highlighting the importance of meaningful interaction with artificial intelligence in educational settings. Kong et al. (2021) emphasized that students who demonstrate higher familiarity and active engagement with AI technologies tend to achieve better academic outcomes, particularly in areas requiring analytical thinking and problem-solving. Similarly, Hwang et al. (2020) reported that student performance in technology-enhanced learning environments is strongly influenced by the quality of digital tool integration and the level of learner engagement. They argued that when AI tools are purposefully embedded into instructional design through adaptive feedback, intelligent tutoring systems, and data-driven recommendations students demonstrate improved learning efficiency, motivation, and achievement. Furthermore, Zhai et al. (2023) highlighted that AI literacy extends beyond awareness or favorable attitudes; it requires practical competence, ethical understanding, and the ability to critically evaluate AI-generated outputs. Their research found that students with stronger applied AI skills achieved significantly higher adaptability compared to those with only theoretical knowledge.

CONCLUSION

Based on the findings of the study, the graduate students maintain a highly positive attitude toward artificial intelligence. Their strong awareness, understanding, and familiarity indicate broad acceptance of AI as a valuable academic tool. This favorable perception creates a supportive foundation for successful AI integration in education, as positive attitudes often encourage openness to technology adoption and innovation in learning environments.

In terms of usage, AI tools are moderately utilized in academic activities. Although students recognize AI's functionality and have access to available tools, their engagement has not yet reached an advanced or fully integrated level. This suggests that institutional support, structured guidance, and improved usability features are essential to promote more consistent and meaningful AI use in academic contexts.

Regarding adaptability, the findings indicate that students demonstrate moderate competence in AI-related subjects. Their ability to complete AI-related tasks on time reflects good time management and responsibility; however, the presence of some performance challenges shows that mastery is still developing. This implies that while students are adapting to AI-supported learning, continued academic support and skill development are necessary to strengthen overall performance.

AI-related knowledge, attitudes, and usage are significantly associated with better adaptability to AI. Particularly, frequent usage, effective management of AI complexity, and consistent availability of tools are significantly related with adaptability to AI. Thus, the null hypothesis claiming that There is no significant relationship between adaptability, knowledge, attitude, and usage of artificial intelligence is rejected.

Finally, familiarity with AI tools is the best predictor of adaptability to AI, followed by availability, complexity management, and student engagement. Hands-on experience, accessibility of AI resources, and active engagement are the most critical factors in enhancing students' academic success in AI-integrated learning environments. Therefore, the the null hypothesis that there is no variable that singly or in combination influence adaptability to AI among graduate students is rejected.

RECOMMENDATION

Based on the findings and conclusions of the study, the following recommendations are put forward:

Policymakers may develop a clear and balanced regulatory framework that promote the responsible and ethical use of artificial intelligence in education. Policies should not only regulate misuse but also encourage structured integration of AI as a learning support tool. Given that familiarity and usage significantly influence adaptability, policies should prioritize digital literacy programs, AI competency standards, and guidelines that emphasize skill-based application rather than mere awareness.

Commission on Higher Education (CHED) is encouraged to formulate national guidelines and model frameworks for AI integration in higher education institutions (HEIs). These guidelines should include capacity-building programs, faculty training initiatives, and curriculum enhancement that embed AI literacy across disciplines. CHED may also consider funding support for AI infrastructure and institutional readiness programs to ensure equitable access and responsible implementation across public and private HEIs.

School Administrators are encouraged to invest in reliable AI-powered educational platforms, licensed academic tools, and faculty development programs. Since availability and familiarity significantly predict adaptability, institutions should provide structured training sessions, workshops, and technical support systems to ensure students and teachers can effectively use AI tools. Establishing AI usage policies at the institutional level can also help maintain academic integrity while maximizing educational benefits.

Teachers may develop strategically on how to integrate AI tools into instructional design, assessment methods, and classroom engagement activbities. Rather than viewing AI as a replacement, teachers should use it to enhance personalized learning, provide timely feedback, and support differentiated instruction. Continuous professional development in AI literacy and ethical technology use will help teachers guide students in using AI responsibly and effectively.

Graduate Students are encouraged to actively develop practical familiarity with AI tools beyond basic awareness. Since hands-on usage and competence strongly influence adaptability, students should engage in self-directed learning, attend AI-related training, and apply AI tools critically in research and coursework. Emphasis should be placed on ethical usage, critical evaluation of AI outputs, and integrating AI as a productivity-enhancing tool rather than a dependency mechanism.

Future Researchers may explore another research designs to examine the impact of AI familiarity and usage on academic achievement. Researchers may also investigate additional variables such as digital literacy, self-efficacy, ethical awareness, and institutional readiness to further explain variations in performance. Comparative studies across disciplines or educational levels may provide deeper insights into how AI integration influences learning outcomes in diverse academic contexts.

REFERENCES

1. Alamri, M., Aldhafeeri, F., & Almukadi, W. (2020). AI in education: Opportunities and challenges in developing countries. International Journal of Educational Technology in Higher Education, 17(1), 19.
2. Al-Emran, M., & Malik, S. I. (2020). The impact of Artificial Intelligence (AI) on Higher Education: A systematic literature review. International Journal of Educational Technology in Higher Education, 17(1), 1-20.
3. Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology acceptance model in M-learning context: A systematic review. Computers & Education, 125, 389-412.
4. Al-Maroof, R. S., & Al-Emran, M. (2018). Students' acceptance of Google Classroom: Anexploratory study using PLS-SEM approach. International Journal of Emerging Technologies in Learning (iJET), 13(6), 112-123.
5. Al-Qaysi, N., Mohamad-Nordin, N., & Al-Emran, M. (2020). A systematic review of social media acceptance from the perspective of educational and information systems theories and models. Journal of Educational Computing Research, 57(8), 2085-2109.
6. Baker, T., & Smith, L. (2019). Developing students' AI skills: Strategies and frameworks for higher education. Journal of Educational Technology Research and Development, 67(5), 1231-1247.
7. Bearman, M., Ajjawi, R., & Dawson, P. (2023). Artificial intelligence in higher education: Implications for teaching, learning, and assessment. Studies in Higher Education. Advance online publication.
8. Bozkurt, A. (2023). Generative artificial intelligence (AI) powered conversational educational agents: The inevitable paradigm shift. Asian Journal of Distance Education, 18(1), 198–204.*
9. Brown, S. E., Johnson, T. D., & Allen, K. M. (2022). Longitudinal analysis of student attitudes towards AI in higher education. Journal of Educational Technology Research and Development, 70(3), 587-604.
10. Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Skill shift: Automation andthe future of the workforce. McKinsey Global Institute.
11. Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence in education: A systematic review. Computers and Education: Artificial Intelligence, 3, 100067. https://doi.org/10.1016/j.caeai.2022.100067
12. Chan, C. K. Y., & Tsi, L. H. (2024). Academic integrity in the age of artificial intelligence: Implications for teaching and learning. Educational Technology & Society, 27(1), 1–15.
13. Chen, L., Wang, Y., & Zhang, X. (2020). Personalized learning through AI: Enhancing adaptability in higher education. Journal of Computer Assisted Learning, 36(4), 450-464.
14. Chen, Y., & Huang, R. (2019). Challenges and strategies for integrating AI into higher education: An empirical study. Journal of Educational Computing Research, 57(4), 1067-1088.
15. Chiu, T. K. F. (2023). The impact of generative AI on education: Opportunities, challenges, and implications for teaching and learning. Educational Technology & Society, 26(4), 1–14.
16. Chiu, T. K. F., & Chai, C. S. (2021). The role of AI in supporting student learning: A systematic review of recent research. Computers & Education, 170, 104225.
17. Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating? Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(1), 1–14. https://doi.org/10.1080/14703297.2023.2190148
18. Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. Computers and Education: Artificial Intelligence, 4, 100125. https://doi.org/10.1016/j.caeai.2023.100125
19. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.
20. Dillenbourg, P., Zufferey, G., & Jermann, P. (2020). Orchestrating AI-enhanced learning environments: What does it take? Journal of Learning Analytics, 7(2), 58-75.
21. Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. Information Systems Frontiers, 21, 719-734.

22. García, E., Herrera, F., & Benítez, J. M. (2019). Understanding student attitudes toward AI and its impact on educational tool adoption. Journal of Interactive Learning Research, 30(4), 413-429.
23. Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. Education Sciences, 13(7), 692. https://doi.org/10.3390/educsci13070692
24. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Center for Curriculum Redesign.
25. Holmes, W., Persson, J., Chounta, I.-A., Wasson, B., & Dimitrova, V. (2022). Artificial intelligence and education: A critical view through the lens of human rights, democracy and the rule of law. Council of Europe Publishing.
26. Honicke, T., & Broadbent, J. (2017). The influence of academic self-efficacy on academic performance: A systematic review. Educational Research Review, 17, 63–84. https://doi.org/10.1016/j.edurev.2015.11.002
27. Hossain, M. S., Ahmadi, M., & Rahman, S. M. (2022). Barriers to positive attitudes towards AI in higher education. Computers & Education, 178, 104393.
28. Howard, S. K., Tondeur, J., Ma, J., & Yang, J. (2020). What factors help and hinder the uptake of AI in schools? A systematic literature review. Journal of Computer Assisted Learning, 36(1), 1-12.
29. Hwang, G.-J., & Tu, Y.-F. (2021). Roles and research trends of artificial intelligence in education: A systematic review. Educational Technology & Society, 24(4), 1–18. Mathematics, 9(6), 584. https://doi.org/10.3390/math9060584
30. Jöhnk, J., Rabhi, L., & Zarnekow, R. (2021). Student resistance to AI: Attitudinal factors influencing adoption in higher education. Journal of Artificial Intelligence in Education, 32(1), 113-135.
31. Johnson, W. L., & Lester, J. C. (2018). Face-to-face with a virtual human: The design of AI-driven tutoring systems for higher education. Computers & Education, 126, 84-92.
32. Joksimović, S., Poquet, O., & Dowell, N. (2021). AI-driven analytics in higher education: Impacts on student engagement and learning outcomes. Journal of Learning Analytics, 8(1), 1-17.
33. Karimi, M., White, J., & Mirzaei, M. (2019). Barriers to AI adoption in higher education. Journal of Educational Technology Systems, 48(1), 3-21.
34. Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274
35. Kumar, R., Gupta, S., & Singh, R. (2021). Analyzing demographic factors affecting AI usage in higher education. Journal of Interactive Learning Research, 32(1), 27-42.
36. Lim, C. P., Wang, T., & Graham, C. (2022). Digital transformation in education: Institutional readiness and technology integration. Educational Technology Research and Development, 70(5), 2401–2420. https://doi.org/10.1007/s11423-022-10123-4
37. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2017). Intelligence Unleashed: An Argument for AI in Education. Pearson Education.
38. Martin, F., Polly, D., & Ritzhaupt, A. (2020). Examining attitudes towards AI across different academic disciplines. Educational Technology & Society, 23(4), 45-56.Miao, F., Holmes, W., & Huang, R. (2021). Integrating AI into the Curriculum: Approaches and Strategies in Higher Education. Journal of Educational Technology Research and Development, 69(3), 789-810.
39. Mustafa, K., Rahman, M., & Wang, S. (2021). The impact of perceived ease of use and perceived usefulness on AI tool usage among university students. Journal of Educational Technology & Society, 24(4), 57-69.
40. Nguyen, D. T., Sharma, P., & Wong, P. (2018). AI-driven learning tools: Their effectiveness and implications for student performance. Journal of Educational Technology Research and Development, 66(6), 1441-1454.
41. Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. Computers and Education: Artificial Intelligence, 2, 100020. https://doi.org/10.1016/j. caeai.2021.100020
42. Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. Frontline Learning Research, 5(4), 1–17. https://doi.org/10.14786/flr.v5i4.229

43. Raffaghelli, J. E. (2023). AI in education: Critical perspectives on student engagement and digital competence. Frontiers in Education, 8, 1181397. https://doi.org/10.3389/ feduc.2023.1181397
44. Redecker, C., & Punie, Y. (2017). European framework for the digital competence of educators: DigCompEdu. European Commission, Joint Research Centre.
45. Sampson, D. G., Ifenthaler, D., Spector, J. M., & Isaias, P. (2018). Digital technologies: Sustainable innovations for improving teaching and learning. Springer.
46. Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. Computers & Education, 128, 13-35.
47. Selwyn, N. (2019). Should robots replace teachers? AI and the future of education. Learning, Media and Technology, 44(2), 77-91.
48. Sharma, P., Choudhary, S., & Kaur, R. (2019). Exploring the factors influencing AI tool usage in higher education. International Journal of Educational Technology in Higher Education, 16(1), 45.
49. Shin, D. (2021). The effects of explainability and causability on trust in AI systems. Computers in Human Behavior, 119, 106716. https://doi.org/10.1016/j.chb.2021.106716
50. Southworth, J., Migliaccio, L., & Dawson, S. (2023). Developing AI literacy in higher education: Student perspectives and institutional responsibilities. Computers and Education: Artificial Intelligence, 4, 100123. https://doi.org/10.1016/j.caeai.2023.100123
51. Tempelaar, D. T., Rienties, B., & Nguyen, Q. (2020). Learning analytics and students' academic performance: The role of self-regulated learning and motivation. Computers in Human Behavior, 104, 106173. https://doi.org/10.1016/j.chb.2019.106173
52. Teo, T. (2019). Students' acceptance of educational technology: The role of self-efficacy and perceived usefulness. Educational Technology & Society, 22(3), 1–13.*
53. Thomas, P., Akkaya, M., & Braun, S. (2020). AI usage in STEM versus non-STEM education: A comparative study. Computers in Human Behavior, 109, 106345.
54. Touretzky, D. S., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning AI for K–12: What should every child know about AI? Proceedings of the AAAI Conference on Artificial Intelligence, 33(1), 9795–9799. https://doi.org/10.1609/aaai.v33i01.33019795
55. Venkatesh, V., Thong, J. Y., & Xu, X. (2017). Unified theory of acceptance and use of technology: A synthesis and the road ahead. Journal of the Association for Information Systems, 17(5), 328-376.
56. Viberg, O., Hatakka, M., & Bälter, O. (2020). The impact of AI-based systems on student engagement in higher education: A longitudinal study. Journal of Educational Technology & Society, 23(3), 53-65.
57. Wang, Q., Lai, C., & Zhao, F. (2020). Determinants of AI tool usage among university students: A technology acceptance model approach. Journal of Educational Technology Research and Development, 68(6), 2789-2805.
58. Wang, Q., Wang, L., & Huang, S. (2018). Demographic factors and their influence on the adoption of AI technologies in education. Computers & Education, 126, 194-206.
59. Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. Learning, Media and Technology, 45(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995
60. Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. Learning, Media and Technology, 45(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995
61. Xing, W., & Du, D. (2019). The impact of AI on educational outcomes: A meta-analysis. Journal of Educational Data Mining, 11(3), 24-35.
62. Yılmaz, R., & Keser, H. (2019). Attitudes towards AI and adaptability: A correlational study. Journal of Computer Assisted Learning, 35(3), 352-361.
63. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 16(1), 39.
64. Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. Complexity, 2021, 8812542. https://doi.org/10.1155/2021/8812542

65. Zhang, J., & Chen, L. (2020). Influence of familiarity on student attitudes towards AI in education. International Journal of Educational Technology in Higher Education, 17(1), 19.
66. Zhong, R., Huang, Y., & Liu, S. (2021). AI in the humanities and social sciences: A literature review. Journal of Educational Technology Research and Development, 69(4), 1221-1237.
67. Zhou, W., & Song, H. (2018). Analyzing the impact of academic year on AI tool usage among university students. Journal of Computing in Higher Education, 30(3), 549-568