Fostering Learning Motivation: The Effects of AI (Artificial Intelligence) Adoption among Students in Higher Education Institutions

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DOI: https://dx.doi.org/10.47772/IJRISS.2025.90300209

Received: 23 February 2025; Accepted: 10 March 2025; Published: 08 April 2025

ABSTRACT

Research have widely highlighted the benefits of artificial intelligence (AI) in enhancing dynamic education systems. This study explores whether opportunities to use AI, perceived importance of AI, and attitudes towards AI are critical variables in motivating students to learn. A quantitative survey approach was used, using a questionnaire with a sample of 331 UiTM Kelantan Branch students. Of these, 208 students participated in the online survey. The results show that the opportunity to use AI and its perceived importance are relevant to students' motivation to study at the higher education level. In addition, the findings reveal a significant and strong relationship between students' attitudes and motivation to incorporate AI into their learning process. However, the need for proper intervention in the use of AI must be considered to ensure that quality education, which prioritises student development, is achieved beyond the mere integration of technology.

Keywords: Artificial intelligence (AI), motivation to learn, opportunity to use, perceived importance, attitudes

INTRODUCTION

Artificial intelligence (AI) is a combination of technologies that allows computers to perform a wide range of advanced operations, such as the ability to see, understand, and translate spoken and written language, analyse data, make suggestions, and so on. Currently, there are four primary AI types: reactive, limited memory, theory of mind, and self-aware. These four categories are not created equal. Some are significantly more advanced than others, and some of these types are currently scientifically impossible. Nonetheless, understanding the differences between the various types of AI can help make sense of AI breakthroughs as research pushes the boundaries (Marr, 2021). In education specifically, AI has the ability to improve teaching and learning methods, solve some of the greatest challenges, and hasten the achievement of SDG 4, which aims to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. Rapid technical advancements, however, invariably present a number of risks and difficulties. Artificial intelligence boosts engagement, personalised learning, and delivers valuable insights, yet it also brings up concerns about data privacy, ethical considerations, and possible effects on human connections in education (eSchool News, 2024).

This journal examines the critical factors influencing the use and effectiveness of AI in higher education, with a focus on how these traits directly impact students' motivation to learn. To note, during the COVID-19 pandemic, a survey found that 76% of undergraduate students lack motivation for online learning (Soria et. al., 2020). This could be due to several factors, such as being forced to shift from a traditional classroom to a remote classroom. But then again, as AI technologies became more widely used currently, it is crucial to comprehend what encourages or discourages their incorporation in educational settings in order to maximise their positive benefits on student engagement and academic performance. One of the most significant characteristics of AI in education is its capacity to tailor the learning experience for each individual student. According to Rizvi (2023), this customisation can have a tremendous impact on student motivation and engagement. This personalised method creates a more motivating and student-focused learning environment while also maintaining students' active participation, reducing frustration, and fostering a sense of achievement. To boot, this study intends to assist higher education institutions in developing successful AI adoption strategies that align with their objectives by examining the impact of AI on student motivation. In the end, it aims to provide insights that improve student involvement and advance a fair, moral approach to AI in education, opening the door for meaningful AI-driven learning opportunities.

LITERATURE REVIEW

Motivation to learn

Motivation plays a central role in the learning process (Ryan & Vansteenkiste, 2023). In educational contexts, it involves internal processes that drive the energy, direction, and persistence of behaviours (Reeve, 2024). Learning motivation plays a crucial role in the quality of education. Studies indicate that incorporating AI technology into learning can enhance student motivation due to the AI systems' interactive, adaptive, and engaging teaching methods. Elements like instant feedback and personalised challenges suited to each student's skill level can further heighten their interest in learning. Research identifies motivation as a critical influence on students' learning strategies, engagement, perseverance, cognitive functioning, and learning preferences (Ryan et al., 2022). However, students' motivation can vary widely due to individual and environmental factors (Ryan & Vansteenkiste, 2023).

AI presents a promising approach to enhancing student motivation by delivering personalised and interactive learning experiences (Lu et al., 2024). Studies show that AI-enabled features effectively boost motivation, resulting in higher levels of student satisfaction, enthusiasm, and proactive engagement (Ebadi & Amini, 2024; Huang et al., 2024). Moreover, AI may indirectly increase students' awareness of critical thinking by improving their overall self-confidence and motivation to learn (Jia & Tu, 2024).

Research indicates that students' motivation directly influences their learning strategies, engagement, goal persistence, cognitive processes, and approaches to learning (Chiu, 2021, 2022). Students' willingness to engage and learn with AI technologies is likely to be influenced by how effectively these technologies are applied in practice. With the continued evolution of AI, its applications in higher education institutions are expected to grow, highlighting the need to understand its effects on students' learning motivation (Hsu & Ching, 2023; Huang et al., 2024). Gaining insights into these impacts will offer valuable guidance for designing and implementing AI technologies in educational environments.

Opportunity to use

The opportunity to use AI in education provides promising avenues to increase student motivation by personalising learning and offering immediate feedback. Personalised learning experiences, supported by AI, help maintain engagement and motivation as the curriculum adapts to individual student's needs (Zou et al., 2021). AI systems can monitor progress and provide tailored suggestions, allowing students to take a more active role in their learning, which boosts their intrinsic motivation (Hung, Hwang & Huang, 2012).

Additionally, the opportunity to use AI-based educational tools reduces administrative tasks for educators, enabling them to focus on meaningful student interactions that further support motivation (Lin et al., 2021). However, careful implementation is necessary to ensure that students continue to develop critical thinking and problem-solving skills rather than becoming overly reliant on automated assistance (Chiu et al., 2023). When used thoughtfully, AI in education offers significant potential for creating dynamic and motivating learning environments that foster both engagement and autonomy. Moybeka et al. (2023) asserted that if AI is integrated carefully as a supplementary tool in conjunction with human engagement, its motivational benefits can be maximised while mitigating any possible drawbacks. The opportunity to use AI should be seen by students as a unique chance to learn new skills and find ways to devote more of their time to satisfying activities that offer greater benefits and learning motivation.

Perceived importance

When users perceive AI as important to their lives, they are more likely to increase their motivation and understanding in utilising the AI systems. In addition, if the users have prior experience with AI, they can feel more connection or trust towards AI and are likely to value it highly and invest their effort in learning AI more effectively (Ehsan et al., 2021). In recent years, AI has been gaining enormous interest in many fields, including education. This is because AI has the ability to increase student motivation and improve their overall learning experience. AI transforms educational maps by providing monitoring systems for synchronising discussion groups, enabling teachers to guide learners' engagement, personalising, and creating a better professional learning environment (Chiu et al., 2023).

A study by Martin, Stamper, and Flowers (2020) found a significant relationship between perceived importance and various factors influencing student readiness for online learning. Fostering a strong sense of self-efficacy among the students can directly influence their persistence, performance, and motivation in academic settings. In another study of AI-enabled learning systems by Kashive, Powale and Kashive (2020) discovered that perceived usefulness and perceived importance of the AI-based learning system as a valuable educational tool helps to increase users' perceptions of the system's importance and their intention to continue using it. Research findings by Fahmy (2024) also point towards the role of AI in providing timely and personalised feedback, which can increase students' perceptions of the importance of their motivation and engagement in learning

Attitudes

The utilisation of AI in educational environments has reformed the way students learn, interact, and engage with their studies. AI technologies offer unique opportunities for personalised learning experiences and enhanced education support, which makes this technology an increasingly relevant part of students' academic lives. For example, Fosner (2024) found that there was a high level of engagement between AI applications and students' engagement that reflects positive attitudes towards the use of AI tools in the learning environment. In addition, Murakami and Inagaki (2024) discovered a clear connection between students' attitudes and motivation to learn AI in data science, and they suggest that promoting positive attitudes and intrinsic motivation can increase students' interest in these critical fields. Besides, attitudes are not static, and they can be influenced by socio-cultural factors and educational experiences that later can help in shaping more positive attitudes toward AI (Kim & Lee, 2024).

However, many researchers have pointed out the need for a deeper understanding of ethical and educational challenges in implementing AI tools, especially in educational environments. It is important to address students' attitudes toward AI and develop a curriculum that integrates ethics with technical skills so that it can help to prepare students for future careers in AI and also continue to engage thoughtfully with AI through various aspects of society (Zhang et al., 2023). According to Wang and Wang (2022), AI-related anxiety caused by the fear or unease relating to AI's capabilities and its implications can lead to negative attitudes and can limit one's interaction with the AI systems, hindering their ability to learn and adapt to new technologies.

Another study by Chan and Hu (2023) discovered significant concerns among students with the utilisation of AI tools, and many students expressed their worries about the impact of using AI tools on critical thinking, creativity, job prospects, and social values. Therefore, by understanding the dynamics of attitudes, motivation, and integration of AI in educational settings, it can help to unlock the full potential of these transformative technologies.

METHODOLOGIES

This study adopts a quantitative approach using a cross-sectional survey design and utilises modified questionnaires adapted from prior research. The modifications ensure that the questionnaire aligns with AI-driven educational contexts while maintaining validity and reliability from established theories. The instruments include measures for opportunity to use (Tracey et al., 1995), perceived importance (Velada & Caetano, 2007), attitudes (Noe & Schmitt, 1986), and motivation to learn (Yi & Davis, 2003). Items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), chosen based on Chomeya's (2010) assertion that this scale allows respondents to express neutrality without negatively affecting data analysis. Dawes (2008) also supports the use of 5-, 7-, and 10-point scales as equally effective for analytical methods like structural equation modelling and confirmatory factor analysis.

The survey was administered online to improve flexibility and provide diverse options for self-assessment. This study targets students at a public higher education institution (IPTA) in Malaysia, specifically a UiTM campus, where learning activities conducted over one semester in 2024. From the target population of 2,468 students, a minimum sample of 331 was required per Krejcie and Morgan's (1970) sample size recommendation. A total of 208 responses were collected, achieving 62.8% of the required sample size. This response rate aligns with Richardson's (2005) assertion that a 60% or higher response rate is both desirable and attainable for student feedback. Additionally, Roscoe (1975) noted that an acceptable sample size range for most studies lies between 30 and 500.

The skewness values for all variables range from -0.928 to -0.418, within the acceptable range as outlined by Sharma and Ojha (2020). Kurtosis values also fall within the acceptable range for normal distribution (-7 to +7), ranging from 1.274 to 5.389. As both skewness and kurtosis meet these thresholds (Sharma et al., 2020), the data can be considered normally distributed. To ensure internal consistency, Cronbach's alpha was used to assess the reliability of each construct, given that this study covers constructs previously unexplored across various faculties and academic levels. Internal consistency reflects the degree to which items within each construct are interrelated. According to Nunnally and Bernstein (1994), Cronbach's alpha coefficient of above 0.7 is desirable, with items below this threshold are removed to improve reliability. All constructs in this study met acceptable reliability criteria. For the dependent variable of motivation to learn (five items), the Cronbach's alpha value is 0.942, indicating excellent reliability within the range of 0.8 to 0.9 and showing positive item correlation. Opportunity to use, also with five items, produced a Cronbach's alpha of 0.855, considered acceptable (0.7 < 0.8). The independent variable of perceived importance achieved Cronbach's alpha of 0.894, which is also acceptable. For attitudes, the Cronbach's alpha value was 0.878, again indicating excellent reliability (0.8 < 0.9). Overall, all constructs demonstrate reliability scores were above 0.70, confirming their reliability based on established standards.

RESULTS AND DISCUSSION

Demographic Profile Analysis

The following are the frequencies and percentages of the respondents' demographic characteristics at University Technology Mara (UiTM) Kelantan Branch, Machang Campus. Section A of the questionnaires was used to gather the respondents' demographic details, which included their gender, age, level of study, semester, CGPA, sponsorship, and faculty.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue III March 2025

Table 1: Distribution of Respondents on Demographic Profile

Demographic factors		Frequency	Percent (%)
Gender	Male	49	23.6
	Female	159	76.4
Age	Less than 20 years old	174	83.7
	21 years old and above	34	16.3
Education level	Diploma	143	68.8
	Bachelor's Degree	65	31.2
No. of Employees	1-10 employees	48	19.4
	11-30 employees	98	40
	31-50 employees	33	13.3
	51 employees and above	69	27.8
Semester	1	57	27.4
	2	48	23.1
	3	31	14.9
	4	34	16.3
	5	35	16.8
	6	2	1
	7 and above	1	0.5
Sponsorship	2.01 – 2.99	25	12
	3.00 – 3.49	91	43.8
	3.50 – 4.00	42	25
	Not Applicable	50	19.2
Faculty	CGPA		
		12	5.8
		88	42.3
		108	51.9
		3	1.4
	Scholarship	205	98.6
	Self-funded		
	Loan		
	Accountancy		
	Business Management		

Table 1 shows an overview of respondents' demographic profiles. The findings show that out of 208 participants, the majority were female (76.4%, n = 159), while male participants accounted for 23.6% (n = 49). This gender distribution indicates a greater representation of female students in the study sample. The age distribution reveals that a substantial majority of participants were under 20 years old (83.7%, n = 174). In contrast, students 21 years old and older represented only 16.3% (n = 34). This skew suggests that the sample primarily consists of younger students, likely those in the early stages of higher education.

Regarding academic level, diploma students made up most of the sample (68.8%, n = 143), while bachelor's degree students comprised 31.2% (n = 65). This distribution reflects a higher representation of students at the diploma level, which may influence their perspectives on AI and its role in education. The data on semester levels shows a relatively even distribution among different semesters. The semester distribution shows a concentration in the early academic stages, with 27.4% (n = 57) in the first semester and 23.1% (n = 48) in the second semester. Representation gradually declines across semesters three (14.9%, n = 31), four (16.3%, n = 34), five (16.8%, n = 35), six (1%, n = 2), and with only 0.5% (n = 7) of students in semester seven and above. This spread suggests a balanced representation of students at various stages of their diploma or bachelor's programs. The CGPA distribution among participants shows that the largest proportion of students have a CGPA between 3.00 and 3.49 (43.8%, n = 91). This is followed by students with a CGPA of 3.50 to 4.00 (25.0%, n = 42) and those with a CGPA between 2.01 and 2.99 (12.0%, n = 25). Notably, 19.2% of participants (n = 50) did not provide applicable CGPA data, possibly due to being new students or studying in non-GPA-based programs. This spread highlights a range of academic performance levels, with a notable concentration in the mid-to-high CGPA range.

The funding sources for students show a diverse financial background, with the majority being loan-funded (51.9%, n = 108). Self-funded students made up 42.3% (n = 88), while a smaller proportion receive scholarships (5.8%, n = 12). This distribution indicates that most students rely on financial assistance, which may impact their perceptions and motivations regarding AI usage in education, as financial concerns can influence attitudes toward learning technologies. Nearly all participants are enrolled in the Business Management faculty (98.6%, n = 205), with only a small minority from Accountancy (1.4%, n = 3). This indicates a strong representation of Business Management students, potentially limiting the generalisability of findings across other academic disciplines. This concentration may reflect specific interests or needs related to AI in business studies, which could shape the students' views on AI in education.

The demographic profile reveals a predominantly high-performing, loan-funded group of Business Management students, most of whom were in their early stages of higher education. The diversity in CGPA and sponsorship provides a nuanced understanding of the sample's academic and financial backgrounds, which could influence their engagement with AI and their motivation to learn.

The relationships between opportunity to use, perceived importance, attitude and motivation to learn by using AI

This section presents the findings on the variables influencing AI adoption in higher education and its impact on students' motivation to learn, based on Pearson correlation and multiple regression analyses. As AI tools become more prevalent in educational contexts, understanding which factors drive their effectiveness and how these factors relate to student motivation is essential in enhancing engagement and academic success.

Table 2: Correlation Analysis

Relationship	r-value	p-value	Results
Opportunity to use and Motivation to learn	0.599	<0.001	Strong positive relationship
Perceived importance and Motivation to learn	0.544	<0.001	Strong positive relationship
Attitude and Motivation to learn	0.598	<0.001	Strong positive relationship

Note (s): *p<0.05; ***p<0.001 (one-tail)

Table 2 revealed the significant positive relationship between key variables of AI, which are opportunity to use, perceived importance, and attitudes towards students' motivation to learn at a higher educational level. Each of these variables contributes significantly to students' motivation in AI-supported educational settings, as indicated by high r-values and statistical significance at p<0.00. The strength of these correlations highlights that each factor contributes meaningfully to create a supportive AI environment in education.

Opportunity to Use AI and Motivation to Learn

This result (r value = 0.599; p value <0.001) suggests a strong positive relationship between students' access or opportunity to use AI tools and their motivation to learn. This finding implies that when students are given more opportunities to engage with AI technology, their motivation to participate in learning activities increases. It may indicate that students find value in hands-on AI experiences, which could enhance their engagement and interest in the subject matter. This is in line with previous studies, which support the opportunity offered by AI in education to motivate students to learn (Zou et al., 2021; Lin et al., 2021).

Perceived Importance of AI and Motivation to Learn

The positive correlation (r value = 0.544, p value < 0.001) between the perceived importance of AI and motivation to learn highlights that students who recognise the relevance and potential of AI in their studies are more motivated to engage in learning. This suggests that emphasising the practical applications and future benefits of AI could positively influence students' motivation, as highlighted by Fahmy (2024) and Martin et al. (2020). Thus, educators might consider integrating discussions on the real-world importance of AI to foster a learning environment that enhances motivation.

Attitude Towards AI and Motivation to Learn

The Pearson correlation analysis shows that students' attitudes toward AI and their motivation to learn have an r value of 0.598 and a p value of <0.001, which indicates that both have significant positive relationships. This result implies that students who have a positive outlook on AI are more likely to feel motivated. This finding suggests that improving students' attitudes toward AI, possibly through positive experiences, and demonstrating AI's educational benefits could be the key to boosting motivation levels. Attitudinal shifts may be encouraged through introductory courses on AI ethics, benefits, and real-life applications. Past studies (Fosner, 2024; Murakami & Inagaki, 2024) support the notion that attitudinal shifts towards AI, facilitated by positive experiences and real-life applications, play a crucial role in enhancing students' motivation to learn.

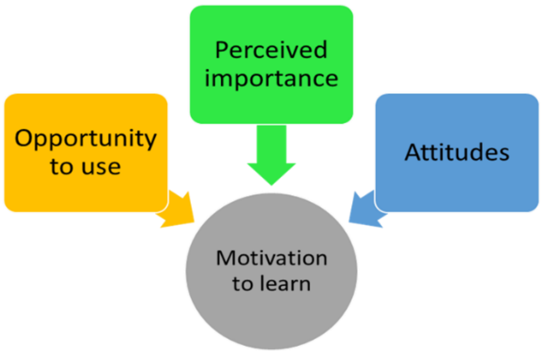

Figure 1: The variables of AI (Artificial Intelligence) on motivation to learn

Figure 1 illustrates the key variables of motivation to learn in the context of Artificial Intelligence (AI) adoption in motivation to learn. This model suggests that fostering a supportive environment where students have ample opportunities to use AI, perceive the importance of AI in their educational journey, and hold positive attitudes toward AI can significantly enhance their motivation to engage in learning activities. The convergence of these factors – opportunity, perceived importance, and attitudes – creates an environment that promotes high motivation levels among students. By addressing each of these aspects, educators can create more engaging and effective AI-integrated learning experiences that not only support academic goals but also prepare students for future AI-driven landscapes. To maximise these variables' effects on motivation, educators could increase accessibility to AI tools, ensuring students can interact and experiment with them. Besides that, educators need to emphasise the relevance of AI in future careers, making its applications clear and meaningful. Educators can cultivate positive perceptions of AI through workshops, discussions, and real-life examples that highlight the ethical and beneficial aspects of AI.

CONCLUSION

In conclusion, leveraging the advantages of artificial intelligence in educational environments requires an understanding of the causes of AI and how it affects students' willingness to learn in higher education institutions. Institutions can more effectively modify their strategies to boost student motivation and engagement by knowing the key factors that affect the successful use of AI technology, such as faculty training, accessibility, and ethical concerns. AI has enormous potential to deliver more individualised and efficient learning experiences as it develops. Educational administrators must approach AI integration thoughtfully in order to guarantee that it not only meets institutional goals but also fosters a friendly and motivating environment for all students. Ultimately, a careful and balanced approach to AI adoption will be necessary to shape the course of education and help students achieve academic success.

ACKNOWLEDGMENTS

We express our deepest gratitude to our dedicated research team for their unwavering support and motivation, as well as to our respected institution. The highest appreciation is also directed to all parties who took part in this priceless journey, whether directly or indirectly. We recognise and appreciate your understanding and the valuable time you have dedicated to our research and writing. Your contributions are truly memorable and deserve special recognition.

To cite this document: Nik Sarina, Noorazzila, Norshamsiah, Roseliza, Sakinah, Nazatul Shahreen & Hasrudy (2025). Fostering Learning Motivation: Variables And Effects of AI (Artificial Intelligence) Adoption Among Students in Higher Education Institutions.

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