Universiti Teknologi MARA
Cawangan Perlis
Jurnal Intelek
Volume 20 Issue 2 (August) 2025

Determinants of Artificial Intelligence and Its Effects on Learning Motivation among Students in Higher Education Institutions

Nik Sarina Nik Md Salleh[1*], Noorazzila Shamsuddin[2], Norshamsiah Ibrahim[3], Roseliza Hamid[4], Sakinah Mat Zin[5], Nazatul Shahreen Zainal Abidin[6]

[1,2,3,4,5]Faculty of Business and Management, Universiti Teknologi MARA, Cawangan Kelantan, 18500 Machang, Kelantan, Malaysia

[6]Academy of Language Studies, Universiti Teknologi MARA, Cawangan Kelantan, 18500 Machang, Kelantan, Malaysia

*Authors' Email Address: *[1]sarina707@uitm.edu.my, [2]nzila614@uitm.edu.my, [3]norshamsiah@uitm.edu.my, [4]rose286@uitm.edu.my, [5]sakin405@uitm.edu.my, [6]nazatul@uitm.edu.my*

Received Date: 31 May 2025
Accepted Date: 12 june 2025
Revised Date: 24 June 2025
Published Date: 31 July 2025

*Corresponding Author

ABSTRACT

Artificial intelligence (AI) is widely acknowledged for its capacity to revolutionise higher education by enabling more dynamic, personalised, and efficient learning environments. This study examines the influence of opportunities to utilise AI, the perceived significance of AI, and students' attitudes towards AI on their motivation to learn. Data were collected from 208 students at Universiti Teknologi MARA (UiTM) Kelantan Branch using a quantitative cross-sectional survey design, based on a targeted sample size of 331. The findings reveal significant positive relationships between students' attitudes, the perceived importance of AI, and their motivation to engage with it in their learning process. The opportunity to utilise AI also emerged as a notable factor in enhancing student motivation. Interpreted through the lens of Expectancy Theory, the results suggest that students are more motivated when they believe their efforts will lead to improved learning outcomes (expectancy), that these outcomes are attainable (instrumentality), and that they are personally meaningful (valence). The effective integration of AI in education requires careful consideration of factors such as faculty preparedness, equitable access, and ethical implications. Institutions must ensure that AI adoption extends beyond mere technological implementation and instead supports students' values, promotes inclusivity, and cultivates an engaging learning environment. This study highlights the importance of a strategic, theory-informed approach to AI integration to enhance student engagement and academic success in higher education.

Keywords: *Attitudes, artificial intelligence, Expectancy Theory, motivation to learn, opportunity to use, perceived importance*

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:

E-ISSN 2231-7716
DOI: http://10.24191/ji.v20i2.6934

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 become more widely used currently, it is crucial to comprehend what encourages or discourages their incorporation in educational settings 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 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.

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 interests 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.

Expectancy Theory and Student Motivation in AI-Based Learning

Expectancy Theory, developed by Vroom (1964), provides a valuable framework for understanding students' motivation to utilise artificial intelligence (AI) within Malaysian higher education institutions. The theory posits that motivation is influenced by three core elements: expectancy (the belief that effort will lead to improved performance), instrumentality (the belief that performance will result in desired outcomes), and valence (the value placed on those outcomes) (Vroom, 1964; Lunenburg, 2011). This theory has been widely applied in educational research to examine how learners' beliefs influence their motivation and performance.

In the context of AI integration in higher education, these motivational dimensions offer critical insights. The opportunity to utilise AI corresponds to the expectancy component, as students are more likely to be motivated when provided with practical and meaningful opportunities to engage with AI tools in their academic tasks (Tracey et al., 1995). When students believe that using AI can improve their academic performance, their motivation to engage increases accordingly. The perceived importance of AI aligns with valence, suggesting that when students perceive AI as relevant to their academic success or future employability, they are more inclined to value its use (Velada & Caetano, 2007). Research shows that relevance and future applicability of AI are strong motivators in student learning (Zawacki-Richter et al., 2019). Meanwhile, attitudes towards AI relate to both instrumentality and valence. Students with positive attitudes are more likely to believe that using AI leads to beneficial academic outcomes (instrumentality) and that those outcomes are personally meaningful (valence) (Noe & Schmitt, 1986; Davis, 1989). Positive emotional and cognitive responses to AI tools have been associated with increased engagement and academic performance (Salloum et al., 2023; Lim et al., 2023). Hence, the alignment between the independent variables—opportunity to use AI, perceived importance of AI, and attitudes—and the constructs of Expectancy Theory offers a comprehensive lens to examine AI-related learning motivation. In the Malaysian higher education context, where AI adoption is progressing, institutions must not only provide access to AI tools but also promote their relevance and cultivate favourable student attitudes. A theory-driven approach rooted in Expectancy Theory may effectively enhance motivation, engagement, and learning outcomes.

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 students' 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 connected to 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 help 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 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 were 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), a Cronbach's alpha coefficient of above 0.7 is desirable, with items below this threshold being 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 a 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 above 0.70, confirming their reliability based on established standards.

There are various methodological limitations to this study. Determining causal links between variables is limited by the cross-sectional approach (Hunziker & Blankenagel, 2024). The obtained sample size (208) was below the suggested minimum (331), which could have an impact on statistical power and generalizability. The results might not be generally applicable in other situations because the study was restricted to a single public university in Malaysia. Inaccurate self-evaluation and social desirability are two possible biases introduced by using self-reported data. Despite having good reliability scores, alterations may compromise validity, even if they are derived from well-established instruments. Additionally, administering surveys online runs the danger of leaving out students with poor internet connections or low computer literacy, as highlighted by Stosic et al. (2024), which could lead to distracted responses. Finally, data collected at one point in time could not reflect shifts in motivation or opinions over time.

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.

Table 1: Distribution of Respondents on Demographic Profile

Demographic criteria	Characteristic	Frequency	Percentage (%)
Gender	Male	49	23.6
	Female	159	76.4
	TOTAL	208	100
Age	Less than 20 years old	174	83.7
	21 years old and above	34	16.3
	TOTAL	208	100
Level of study	Diploma	143	68.8
	Bachelor	65	31.2
	TOTAL	208	100
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
	TOTAL	208	100
CGPA	2.01-2.99	25	12.0
	3.00-3.49	91	43.8
	3.50-4.00	42	25.0
	Not Applicable	50	19.2
	TOTAL	208	100
Sponsorship	Scholarship	12	5.8
	Self-funded	88	42.3
	Loan	108	51.9
	TOTAL	208	100
Faculty	Accountancy	3	1.4
	Business Management	205	98.6
TOTAL		**208**	**100**

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 received 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.

Determinants of AI (Artificial Intelligence) and its impacts on motivation to learn

This section presents the findings on the determinants 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	Result
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

Table 2 revealed the significant positive relationship between key determinants of AI, which are the opportunity to use, perceived importance, and attitudes towards students' motivation to learn at a higher educational level. Each of these determinants 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 creating 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.

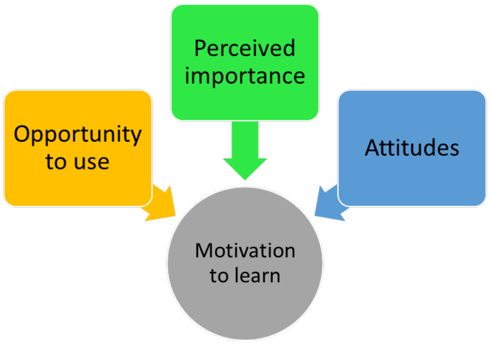

Figure 1: The determinants of AI (Artificial Intelligence) on motivation to learn

Figure 1 illustrates the key determinants 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 determinants' 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, properly utilising artificial intelligence (AI) in higher education necessitates a thorough comprehension of the elements that affect both its successful use and its effect on students' motivation to learn. Essential factors, including faculty preparedness, equal access, and ethical issues, must be addressed to guarantee that AI augments rather than impedes the educational experience. As AI advances, it has considerable potential for providing more personalized, adaptive, and efficient educational experiences. Nevertheless, its integration must be executed with careful consideration to advance both institutional objectives and the establishment of an inclusive and inspiring learning atmosphere. Analysed via the framework of Expectancy Theory, the results indicate that students exhibit heightened motivation when they perceive their efforts will result in enhanced learning outcomes (expectancy), that these goals are achievable (instrumentality), and that they hold personal significance (valence). The favorable correlations identified among perceived significance, attitudes, and motivation highlight the necessity of matching AI-enhanced learning methodologies with students' beliefs and expectations. A deliberate and balanced strategy for AI integration, rooted in motivational theory, can enhance engagement, elevate academic performance, and significantly influence the future of education.

ACKNOWLEDGEMENTS

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.

FUNDING

This research did not receive specific grants from any funding agency in the public, commercial or not-for-profit sectors.

AUTHORS' CONTRIBUTION

The manuscript was developed collaboratively, with each author contributing to specific sections. Shamsuddin, N., Hamid, R. and Mat Zin, S. authored the introduction and literature review. Nik Md Salleh, N.S., and Ibrahim, N. were responsible for the methodology, data collection, data analysis, and findings. Zainal Abidin, N.S., made significant contributions to proofreading. All authors reviewed and approved the final manuscript.

CONFLICT OF INTEREST DECLARATION

We certify that the article is the original work of the author and co-authors. The article has not received prior publication and is not under consideration for publication elsewhere. This research/manuscript has not been submitted for publication and has not been published in whole or in part elsewhere. We confirm the fact that all authors have contributed significantly to the work, credibility and validity of the data and their interpretation to be submitted to Jurnal Intelek.

REFERENCES

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education, 20*(1), 43.

Chiu, T. K. F. (2021). Digital support for student engagement in blended learning based on self-determination theory. *Computers in Human Behavior, 124,* 106909. https://doi.org/10.1016/j.chb.2021.106909

Chiu, T. K. F. (2022). Applying the Self-determination Theory (SDT) to explain student engagement in online learning during the COVID-19 pandemic. *Journal of Research on Technology in Education, 54*(sup1), 14–30. https://doi.org/ 10.1080/15391523.2021.1891998

Chiu, T. K., Moorhouse, B. L., Chai, C. S., & Ismailov, M. (2023). Teacher support and student motivation to learn with an Artificial Intelligence (AI) based chatbot. *Interactive Learning Environments*, 1-17.

Chiu, T. K., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 4*, 100118.

Dawes, J. (2008). Do data characteristics change according to the number of scale points used? An experiment using 5-point, 7-point and 10-point scales. *International Journal of Market Research, 50*(1), 61-104. https://doi.org/10.1177/147078530805000106

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Ebadi, S., & Amini, A. (2024). Examining the roles of social presence and human-likeness on Iranian EFL learners' motivation using artificial intelligence technology: A case of CSIEC chatbot. *Interactive Learning Environments*, *32*(2), 655-673.

Ehsan, U., Passi, S., Liao, Q. V., Chan, L., Lee, I., Muller, M., & Riedl, M. O. (2021). The Who in explainable AI: How AI background shapes perceptions of AI explanations. *Arxiv*.

eSchool News. (2024, February 5). What are the Benefits and Risks of Artificial Intelligence in Education? ESchool News. https://www.eschoolnews.com/digital-learning/2024/02/05/what-are-the-benefits-and-risks-of-artificial-intelligence-in-education/

Fahmy, Y. (2024). Student perception on AI-driven assessment: motivation, engagement and feedback capabilities (Bachelor's thesis, University of Twente). https://purl.utwente.nl/essays/100985

Fosner, A. (2024). University students' attitudes and perceptions towards AI tools: implications for sustainable educational practices. *Sustainability, 16*(19), 8668.

Hsu, Y. C., & Ching, Y. H. (2023). Generative Artificial Intelligence in Education, Part Two: International Perspectives. *TechTrends*, *67*(6), 885-890. https://doi.org/10.24059/olj.v24i2.2053

Huang, F., Wang, Y., & Zhang, H. (2024). Modelling Generative AI Acceptance, Perceived Teachers' Enthusiasm and Self-Efficacy to English as a Foreign Language Learners' Well-Being in the Digital Era. *European Journal of Education*, e12770.

Hunziker, S., & Blankenagel, M. (2024). Cross-sectional research design. In *Research design in business and management: A practical guide for students and researchers* (pp. 187-199). Wiesbaden: Springer Fachmedien Wiesbaden.

Hung, C. M., Hwang, G. J., & Huang, I. (2012). A project-based digital storytelling approach for improving students' learning motivation, problem-solving competence and learning achievement. *Journal of Educational Technology & Society*, *15*(4), 368-379.

Jia, X. H., & Tu, J. C. (2024). Towards a New Conceptual Model of AI-Enhanced Learning for College Students: The Roles of Artificial Intelligence Capabilities, General Self-Efficacy, Learning Motivation, and Critical Thinking Awareness. *Systems*, *12*(3), 74.

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.

Kim, S. W., & Lee, Y. (2024). Investigation into the influence of socio-cultural factors on attitudes toward artificial intelligence. *Education and Information Technologies, 29*(8), 9907-9935.

Krejcie, R. V. and Morgan, D. W. (1970). Table for determining sample size from a given population. *Educational and Psychological Measurement*, *30*(3), 607-610.

Lim, C. P., Liew, S. K., & Hashim, H. (2023). Attitudes toward AI-assisted learning: A Malaysian perspective. *Malaysian Journal of Learning and Instruction*, *20*(1), 103–121. https://doi.org/10.32890/mjli2023.20.1.5

Lin, P. Y., Chai, C. S., Jong, M. S. Y., Dai, Y., Guo, Y., & Qin, J. (2021). Modelling the structural relationship among primary students' motivation to learn artificial intelligence. *Computers and Education: Artificial Intelligence*, *2*, 100006.

Lu, G., Hussin, N. B., & Sarkar, A. (2024, May). Navigating the future: Harnessing artificial intelligence-generated content (AIGC) for enhanced learning experiences in higher education. In *2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE)* (pp. 1-12). IEEE.

Lunenburg, F. C. (2011). Expectancy theory of motivation: Motivating by altering expectations. *International Journal of Management, Business, and Administration*, *15*(1), 1–6.

Marr, B. (2021, July 2). Understanding the 4 Types of Artificial Intelligence. Bernard Marr. https://bernardmarr.com/understanding-the-4-types-of-artificial-intelligence/

Martin, F., Stamper, B., & Flowers, C. (2020). Examining student perception of their readiness for online learning: Importance and confidence. *Online Learning, 24*(2), 38-58.

Moybeka, A. M., Syariatin, N., Tatipang, D. P., Mushthoza, D. A., Dewi, N. P. J. L., & Tineh, S. (2023). Artificial Intelligence and English classroom: the implications of AI toward EFL students' motivation. *Edumaspul: Jurnal Pendidikan*, *7*(2), 2444-2454.

Murakami, Y., Sho, Y., & Inagaki, T. (2024). Improving motivation in learning AI for undergraduate students by case study. *Journal of Information Processing, 32*, 175-181.

Noe, R. A. and Schmitt, N. (1986). The influence of trainee attitudes on training effectiveness: Test of a model. *Personnel psychology*, *39*(3), 497-523.

Nunnally, J. C. & Bernstein, I. H. (1994). *Psychometric theory* (3rd Ed.). New York: McGraw-Hill

Reeve, J. (2024). *Understanding motivation and emotion*. John Wiley & Sons.

Richardson, J. T. (2005). Instruments for obtaining student feedback: A review of the literature. *Assessment & evaluation in higher education*, *30*(4), 387-415.

Rizvi, Samreen. (2023). Revolutionizing Student Engagement: Artificial Intelligence's Impact on Specialized Learning Motivation. *International Journal of Advanced Engineering Research and Science.* 10. 10.22161/ijaers.109.4.

Roscoe, J. T. (1975). *Fundamental research statistics for the behavioural sciences [by] John T. Roscoe*. New York, NY: Holt, Rinehart and Winston.

Ryan, R. M., & Vansteenkiste, M. (2023). Self-determination theory. In *The Oxford Handbook of Self-Determination Theory* (pp. 3-30). Oxford University Press.

Ryan, R. M., Duineveld, J. J., Di Domenico, S. I., Ryan, W. S., Steward, B. A., & Bradshaw, E. L. (2022). We know this much is (meta-analytically) true: A meta-review of meta-analytic findings evaluating self-determination theory. *Psychological Bulletin*, *148*(11-12), 813.

Salloum, S. A., Al-Emran, M., & Shaalan, K. (2023). Artificial intelligence and student engagement: A systematic review. *Education and Information Technologies*, *28*, 1–22. https://doi.org/10.1007/s10639-022-11118-5

Sharma, C., & Ojha, C. S. P. (2020). Statistical parameters of hydrometeorological variables: Standard deviation, SNR, skewness and kurtosis. In *Advances in Water Resources Engineering and Management* (pp. 59-70). Springer: Singapore. DOI: 10.1007/978-981-13-8181-2_5

Soria, K. M., Chirikov, I., & Jones-White, D. (2020). The obstacles to remote learning for undergraduate, graduate, and professional students. SERU Consortium, University of California - Berkeley and University of Minnesota. https://cshe.berkeley.edu/serucovid-survey-report

Stosic, M. D., Murphy, B. A., Duong, F., Fultz, A. A., Harvey, S. E., & Bernieri, F. (2024). Careless responding: Why many findings are spurious or spuriously inflated. *Advances in Methods and Practices in Psychological Science, 7*(1), 25152459241231581.

Tracey, J. B., Tannenbaum, S. I. and Kavanagh, M. J. (1995). Applying trained skills on the job: The importance of the work environment. *Journal of Applied Psychology*, *80*(2), 239.

Velada, R., & Caetano, A. (2007). Training transfer: The mediating role of perception of learning. *Journal of European Industrial Training*, *31*(4), 283–296. https://doi.org/10.1108/03090590710746441

Wang, Y. Y., & Wang, Y. S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments, 30*(4), 619-634.

Yi, M. Y. and Davis, F. D. (2003). Developing and validating an observational learning model of computer software training and skill acquisition. *Information Systems Research*, *14*(2), 146-169.Chomeya, R. (2010). *Quality of psychology test between Likert scale 5 and 6 points. Journal of Social Sciences,* *6*(3), 399-403. https://thescipub.com/abstract/10.3844/jssp.2010.399.403

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education*, *16*, Article 39. https://doi.org/10.1186/s41239-019-0171-0

Zhang, H., Lee, I., Ali, S., DiPaola, D., Cheng, Y., & Breazeal, C. (2023). Integrating ethics and career futures with technical learning to promote AI literacy for middle school students: An exploratory study. *International Journal of Artificial Intelligence in Education, 33*(2), 290-324.

Zou, D., Zhang, R., Xie, H., & Wang, F. L. (2021). Digital game-based learning of information literacy: Effects of gameplay modes on university students' learning performance, motivation, self-efficacy and flow experiences. *Australasian Journal of Educational Technology*, *37*(2), 152-170