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Unveiling AI Perceptions: How Student Attitudes Towards AI Shape AI Awareness, Usage, and Conceptions

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Abstract

This study examines the relationship between students' attitudes toward artificial intelligence (AI) and both AI competence and conceptions. 176 UK university students completed a survey where they were asked to rate statements in relation to their attitudes towards AI, their AI competence and their conceptions about AI using 5-point Likert-type scales. In relation to AI competence, results indicate that affective attitudes predicted awareness and usage, leading to information avoidance and disengagement. Cognitive attitudes positively predicted AI awareness and usage. Behavioural attitudes, however, did not predict awareness or usage, suggesting that individuals may engage with AI technology without deeper understanding. For AI conceptions, behavioural attitudes were more closely linked to conceptions of AI in educational contexts. Positive behavioural attitudes predicted students' conceptions of AI's role in intelligent tutoring systems, retentions, drop-out reduction, recommendation systems, and personalised learning. In contrast, affective attitudes predicted conceptions of AI's use in classroom monitoring and performance prediction, while cognitive attitudes had little influence. These are areas educators can focus on when designing teaching & assessment strategies in relation to AI.

Introduction

The integration of artificial intelligence (AI) in education has become an increasingly important topic of research, driven by the fast advancements in AI technologies and their potential to revolutionise the teaching and learning process (Zawacki-Richter et al., 2019). Recent literature has extensively covered various aspects of AI in education, emphasising both its potential benefits and challenges. For example, Malik, Pratiwi, Andajani, Numertayasa, Suharti, and Darwis (2023) conducted a comprehensive study involving 245 undergraduate students from 25 Higher Education (HE) institutions to explore their perceptions of AI in education. The study utilised a mixed-methods approach, combining quantitative surveys and qualitative interviews to gain in-depth insights. Their findings indicated an overall positive view of AI, particularly in improving learning efficiency, providing personalised feedback, and supporting academic writing tasks. However, concerns were raised about the reliability of AI in understanding complex human emotions and the potential for over-reliance on technology, suggesting that while AI can be beneficial in educational settings, there is a need for careful integration to address its limitations (Malik et al., 2023). Similarly, Ayanwale and Ndlovu (2024) investigated factors affecting students' acceptance of AI, revealing that trust in AI chatbots significantly influenced their perceived usefulness and ease of use. This finding aligns with the innovation diffusion theory (Do, 2008, p. 11), suggesting that trustworthy AI tools can facilitate smoother adoption in educational contexts. Their research underscores the necessity of building trust in AI technologies to ensure their successful integration and acceptance among students.

Furthermore, Al-Zahrani (2024) examined the potential drawbacks of AI in education, emphasising the need for a balanced approach to its incorporation in teaching and learning. Their study pointed out that while AI can enhance educational outcomes, there are significant ethical concerns that need to be addressed. Key issues highlighted include data privacy, algorithmic biases, and the potential reduction in human interaction. For example, students expressed worries about the vast amounts of personal data collected by AI systems and how this data could be misused. They also stated instances where algorithmic biases could lead to unfair treatment or assessments of students. Moreover, there was a concern that AI might reduce meaningful human interaction, which is crucial for a holistic educational experience. This suggests that ethical considerations and human oversight are essential to address the potential drawbacks of AI in education and underscores the importance of developing strong ethical frameworks to guide the implementation of AI in education, ensuring that the technology supports rather than undermines the core values of education. However, research has also found that while students recognise the drawbacks of AI in education, they also appreciate AI’s ability to provide personalised feedback and support (Mathes, Magantran, & Rahman, 2023). Thus, balancing AI’s capabilities and addressing its ethical implications is crucial for its successful implementation into education.

Moreover, studies have explored how AI can replicate the teaching outcomes achieved by human teachers. Hsin (2024) demonstrated that AI tools like ChatGPT can positively impact students’ learning experiences by offering timely assistance and enhancing their engagement with the material. Their study involved an experimental design with a control group and an AI-intervention group, measuring outcomes in terms of engagement, comprehension, and satisfaction. The results indicated that AI could provide comparable educational benefits to human instruction when appropriately incorporated into teaching. Hsin (2024) also explored the impact of AI on student engagement and academic performance in an HE context. AI software significantly boosted student participation and interaction in online learning environments. The AI tools were able to track student progress and provide tailored recommendations, which helped in maintaining high levels of engagement and academic achievement. This finding further supports the proposal that AI can be crucial in facilitating effective learning environments, comparable to these managed by human educators. AI-driven interventions, such as predictive analytics and personalised learning pathways, have also been found to contribute to reducing dropout rates and improving student success metrics (Ayanwale & Ndlovu, 2024). Ayanwale and Ndlovu (2024) found that by identifying at-risk students early and providing support, AI systems were able to create an encouraging learning environment similar to the interventions provided by human advisors and counsellors. Collectively, these studies demonstrate that AI can be as effective as human teaching. They highlight AI’s potential to better educational outcomes by providing personalised feedback, timely assistance, and tailored learning experiences. The consistent findings across these studies underscore the reliability of AI in replicating key aspects of human instruction.

In conclusion, the integration of AI in education has shown immense potential in improving the teaching and learning processes. The reviewed studies have demonstrated that students generally have a positive perception of AI, particularly in its ability to improve learning and efficiency and provide personalised feedback. These studies also highlight the importance of trust in AI technologies, as trust significantly influences their acceptance and perceived usefulness among students. However, it is critical to acknowledge the ethical and practical drawbacks associated with AI, such as privacy, algorithmic biases, and the reduction in meaningful human interaction. Despite these concerns, the potential of AI to replicate the effectiveness of human teaching is significant. Our study therefore aims to further expand on the understanding of students' perspectives on AI in education particularly focusing on AI competence, attitudes towards AI, and conceptions about AI.

Hypotheses:

1. There is a significant, positive relationship between attitudes towards AI and competency using AI
2. There is a significant, positive relationship between attitudes towards AI and conceptions about AI

Method

Participants

172 students started the survey. One person was removed because they were below the age of 18, 2 were removed as they did not agree to take part in the study, and 2 were removed due to providing duplicate responses. Therefore, the total number of students for is 167. All participants were Higher Education students in the UK (eligibility criteria of the study). In relation to the subject of study, the majority of participants (N = 141, 84.4%) studies Psychology, followed by Psychology (Sport, Health & Exercise) (N = 17, 10.2%). All other subjects were only mentioned once (N = 1, 0.6%); Advanced Clinical Practice, Clinical Mental Health Science, Computer Science, Digital Media, Early Childhood Education, Mathematics, Media and Communications, Project Management, Psychotherapy. 63 (37.7%) were Level 4, 92 (55.1%) were level 5, 6 (3.6%) were Level 6, 5 (3.0%) were Postgraduate/Level 7, and 1 (0.6%) was other. For mode of study, 161 (96.4%) studied full-time and 6 (3.6%) studied part-time.

In relation to gender, 129 (77.2%) were female, 37 (22.2%) were male and 1 (0.6%) preferred not to say. For ethnicity 63 (37.7%) were Asian, 40 (24.0%) were white, 30 (18.0%) were black, 11 (6.6%) were Arab, 8 (4.8%) were Mixed, 7 (4.2%) were other, 6 (3.6%) preferred not to say and 2 (1.2%) were Chinese. Finally, in relation to age, 164 (98.2%) were in the age category 18-30 years old, and 3 (1.8%) were in the age category 31-40 years old. Data collection took place between 12th December 2023 and 6th May 2024. Participants were recruited through social media (e.g., LinkedIn, X, Instagram, WhatsApp) and through the Psychology's recruitment platform SONA.

Materials

Data were collected via an online survey using Jisc (www. JICS.org). The survey contained 5 sections that included questions about students' conceptions about AI in education, their competence in using AI, and their attitudes toward AI.

Section 1: Demographics

At the beginning of the survey, participants were asked a few demographic questions (e.g, their programme of study, type of study (full-time or part-time), level of study, age, gender, ethnicity).

Section 2: Students' Conceptions of AI in Education

This section consisted of the "Conceptions of Artificial Intelligence in education" scale developed by Cheng et al., (2023). This scale consists of 48 items where participants were asked to rate how much they agree with each statement about AI in education conceptions using a 5-point Likert-type scale ranging from (1) Strongly Disagree to (5) Strongly Agree. Example items include "Artificial intelligence in tutoring is useful for offering timely feedback on learning." and "An artificial intelligence grader provides more useful feedback than a human grader.". 24 items were reverse coded and then 8 variables were calculated by summing the scores of 6 items: 1) intelligent tutoring system, 2) students' grading and evaluation, 3) students' retention and drop-out, 4) sentiment analysis in education, 5) recommendation systems, 6) classroom monitoring and visual analysis, 7) personalised learning, and 8) students' performance prediction.

Reliability was measured using Cronbach's α for each of the 8 variables $\alpha 1$ = .63, $\alpha 2$ = .63, $\alpha 3$ = .38, $\alpha 4$ = .68, $\alpha 5$ = .41, $\alpha 6$ = .53, $\alpha 7$ = .34, and $\alpha 8$ = .62. The scores for items 3 and 7 were low but no items were removed because this is an exploratory study, therefore we did not want to deviate from the original scale. The lower reliability scores in our study may be due to our considerably smaller sample size (Cheng et al. (2003) had a sample size of 445). In Cheng et al., (2023) the reliability measures were not mentioned.

Section 3: Students' Competency in using AI

This section consisted of "User competence in using AI" scale developed by Wang, Rau and Yuan (2023). This scale consists of 12 items where participants were asked to rate how much they agree with each statement about their AI competencies using a 5-point Likert-type scale ranging from (1) Strongly Disagree to (5) Strongly Agree. Example items include "I can skillfully use AI applications or products to help me with my daily work." and "I always comply with ethical principles when using AI applications or products.". Three items were reverse coded and then 4 variables were calculated by summing the scores of 3 items: 1) awareness, 2) usage, 3) evaluation, and 4) ethics.

Reliability was measured using Cronbach's α for each of the 4 variables $\alpha 1$ = .22, $\alpha 2$ = .64, $\alpha 3$ = .61, $\alpha 4$ = .34. In Wang et al., (2023) the Cronbach's alpha values for the 4 variables were $\alpha 1$ = .73, $\alpha 2$ = .75, $\alpha 3$ = .78, and $\alpha 4$ = .73. The scores for items 1 and 4 were low but no items were removed because this is an exploratory study, therefore we did not want to deviate from the original scale. The lower reliability scores in our study may be due to our considerably smaller sample size (Wang et al. (2003) had a sample size of 601). The difference between the values from our study and the original study may be justified by the different sample sizes used in the studies.

Section 4: Students' Attitudes toward AI

This section consisted of the "Students' attitudes towards AI" scale by Suh and Ahn (2022). This scale consists of 26 items where participants were asked to rate how much they agree with each statement about their attitudes about AI using a 5-point Likert-type scale ranging from (1) Strongly Disagree to (5) Strongly Agree. Example items include "I think every student should learn about AI in university." and "I think AI makes people's lives more convenient".". No items were reverse coded and then 3 variables were calculated by summing the scores of the items: 1) behavioural attitudes (12 items), 2) affective attitudes (10 items), and cognitive attitudes (4 items).

Reliability was measured using Cronbach's α for each of the 3 variables: $\alpha 1$ = .85, $\alpha 2$ = .86, $\alpha 3$ = .73. In Suh and Ahn (2022), Cronbach's α values for the 3 variables were $\alpha 1$ = .96, $\alpha 2$ = .92, and $\alpha 3$ = .91. Similar as the scale above, the difference in the values in Cronbach's reliability test between our study and the original study may be given because of the different sample size used. Our reliability values are high and in line with those of Suh and Ahn (2022), despite their higher sample size of 305.

Data Analysis Strategy

The data were analysed using IBM SPSS Statistics version 28 (IBM Corp, 2021). An alpha level of .05 was used for all statistical tests. No comparisons were made between different student programmes as all students were on the same level playing field in terms of the teaching and learning they received on using AI in Education.

Procedure and Ethical Considerations

The University Ethics Committee gave approval to conduct the study (Ref: 45740-LR-Dec/2023- 48792-2). Participants were presented with a participant information sheet and after reading this, they gave their consent and started the study. Participants were informed that they could withdraw their participation at any point, should they wish, without penalty. They were informed their data would remain confidential and anonymous. At the end of the survey, participants were given a debrief form with links to services, thanked for their participation, and received one participation credit (on the Psychology participant recruitment platform SONA) in recompense for their time.

Results

To address hypothesis 1, four multiple linear regressions were used to assess the ability of attitudes towards AI (behavioural attitudes, affective attitudes, and cognitive attitudes) to predict each of our competency using AI dependent variables (awareness, usage, evaluation and ethics) To ensure linear regression analysis was appropriate, the assumptions of linearity, normality and auto-correlation were checked, and no violations were observed. Specifically, the Durbin-Watson statistic was for 1.95 awareness, 1.86 for usage, 1.76 for evaluation, and 2.03 for ethics. As all values are between 1.5 and 2.5 (Field, 2013), the data are not auto-correlated. The VIF values were between 1.86 and 2.43 (i.e., below the threshold of 10), and the tolerance values between .41 and .54, thus the data does not show any multicollinearity in the predictor variables (Field, 2013).

For awareness of AI, results indicate that the model is statistically significant ($F(3,156) = 6.93$, $p < .001$) and explained 10.1% of the variance in the data (adjusted $R^2 = .101$). From the predictor variables (see Table 1), the following predictors were significant: affective attitudes towards AI negatively predicted awareness of AI and cognitive attitudes towards AI positively predicted awareness of AI. Behavioural attitudes towards AI was not significant.

Table 1. Model Coefficients for Awareness of AI

Model	*β*	*t*	*p*	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		12.53	<.001	8.16	11.21
Behavioural attitudes towards AI	-.06	-0.54	.591	-0.06	0.04
Affective attitudes towards AI**	-.34	-3.06	.003	-0.14	-0.03
Cognitive attitudes towards AI**	.51	4.36	<.001	0.17	0.45

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

For usage of AI, results indicate that the model is statistically significant ($F(3,154) = 7.52$, $p < .001$) and explained 11.1% of the variance in the data (adjusted $R^2 = .111$). From the predictor variables (see Table 2), the following predictors were significant: affective attitudes towards AI negatively predicted usage of AI and cognitive attitudes towards AI positively predicted usage of AI. Behavioural attitudes towards AI was not significant.

Table 2. Model Coefficients for Usage of AI

Model	*β*	*t*	*p*	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		8.34	<.001	6.04	9.79
Behavioural attitudes towards AI	.19	1.78	.077	-0.01	0.12
Affective attitudes towards AI**	-.37	-3.33	.001	-0.19	-0.05
Cognitive attitudes towards AI**	.39	3.31	.001	0.12	0.46

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

For evaluation of AI, results indicate that the model is statistically significant ($F(3,154) = 3.33$, $p = .021$) and explained 4.3% of the variance in the data (adjusted R^2 = .043). From the predictor variables (see Table 3), none of the predictors were significant.

Table 3. Model Coefficients for Evaluation of AI

Model	β	t	p	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		9.80	<.001	6.56	9.87
Behavioural attitudes towards AI	.08	0.77	.445	-0.03	0.07
Affective attitudes towards AI	-.03	-.29	.775	-0.07	0.05
Cognitive attitudes towards AI	.21	1.73	.086	-0.02	0.29

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

For ethical use of AI, results indicate that the model is not statistically significant (F(3,156) = 0.80, p = .496) and explained 0.40% of the variance in the data (adjusted R^2 = .004). To address hypothesis 2, eight multiple linear regressions were used to assess the ability of attitudes towards AI (behavioural attitudes, affective attitudes, and cognitive attitudes) to predict each of our conceptions of AI dependent variables (intelligent tutoring system, students' grading and evaluation, students' retention and drop-out, sentiment analysis in education, recommendation systems, classroom monitoring and visual analysis, personalised learning and students' performance prediction). To ensure linear regression analysis was appropriate, the assumptions of linearity, normality and auto-correlation were checked, and no violations were observed. Specifically, the Durbin-Watson statistic was 2.37 for intelligent tutoring system, 2.03 for students' grading and evaluation, 2.09 for students' retention and drop-out, 2.30 for sentiment analysis in education, 2.08 for recommendation systems, 1.99 for classroom monitoring and visual analysis, 2.04 for personalised learning and 2.18 for students' performance prediction. As all values are between 1.5 and 2.5 (Field, 2013), the data are not auto-correlated. The VIF values were between 1.88 and 2.65 (i.e., below the threshold of 10), and the tolerance values between .38 and .53, thus the data does not show any multicollinearity in the predictor variables (Field, 2013).

For intelligent tutoring systems, results indicate that the model is statistically significant (F(3,151) = 12.14, p < .001) and explained 17.8% of the variance in the data (adjusted R^2 = .178). From the predictor variables (see Table 4), the following predictors were significant: behavioural attitudes towards AI positively predicted intelligent tutoring systems. Affective attitudes towards AI and cognitive attitudes towards AI were not significant. For student grading and evaluation with AI, results indicate that the model is not statistically significant (F(3,153) = 2.50, p = .061) and explained 2.8% of the variance in the data (adjusted R^2 = .028). For the use of AI to determine students' retention and drop-out results indicate that the model is statistically significant (F(3,155) = 6.92, p < .001) and explained 10.1% of the variance in the data (adjusted R^2 = .101).

Table 4. Model Coefficients for Intelligent Tutoring Systems

Model	β	t	p	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		7.43	<.001	6.96	12.00
Behavioural attitudes towards AI*	.33	3.28	.001	0.22	0.22
Affective attitudes towards AI	.13	1.25	.214	0.15	0.15
Cognitive attitudes towards AI	.02	.18	.858	0.25	0.25

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

From the predictor variables (see Table 5), the following predictors were significant: behavioural attitudes towards AI positively predicted students' retention and drop-out. Affective attitudes towards AI and cognitive attitudes towards AI were not significant. For the use of AI in sentiment analysis in education, the model is statistically significant ($F(3,151) = 3.13$, $p = .028$) and explained 4.00% of the variance in the data (adjusted $R^2 = .040$).

Table 5. Model Coefficients for Using AI for Students' Retention and Drop-Out

Model	β	t	p	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		10.00	<.001	9.71	14.49
Behavioural attitudes towards AI*	.27	2.50	.013	0.02	0.18
Affective attitudes towards AI	-.04	-.34	.732	-0.10	0.07
Cognitive attitudes towards AI	.13	1.14	.258	-0.10	0.35

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

From the predictor variables (see Table 6), none of the predictor variables were significant. For the use of AI in recommendation systems, results indicate that the model is statistically significant ($F(3,153) = 4.04$, $p = .008$) and explained 5.50% of the variance in the data (adjusted $R^2 = .050$).

From the predictor variables (see Table 7), the following predictors were significant: behavioural attitudes towards AI positively predicted the use of AI in recommendation systems. Affective attitudes towards AI and cognitive attitudes towards AI were not significant. For the use of AI in classroom monitoring and visual analysis, results indicate that the model is statistically significant ($F(3,153) = 5.63$, $p = .001$) and explained 8.20% of the variance in the data (adjusted $R^2 = .082$).

Table 6. Model Coefficients for the Use of AI in Sentiment Analysis

Model	*β*	*t*	*p*	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		7.19	<.001	8.60	15.12
Behavioural attitudes	.12	1.09	.278	-0.05	0.17
Affective attitudes	.10	.87	.387	-0.07	0.17
Cognitive attitudes	.05	.39	.699	-0.25	0.37

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

Table 7. Model Coefficients for the Use of AI in Recommendation Systems

Model	*β*	*t*	*p*	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		11.93	<.001	12.71	17.76
Behavioural attitudes towards AI*	.26	2.34	.021	0.02	0.18
Affective attitudes towards AI	-.22	-1.91	.058	-0.19	0.01
Cognitive attitudes towards AI	.16	1.26	.209	-0.09	0.39

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

Table 8. Model Coefficients for the use AI in Classroom Monitoring and Visual Analysis

Model	*β*	*t*	*p*	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		8.70	<.001	9.08	14.41
Behavioural attitudes towards AI	-.01	-.05	.96	-.09	0.08
Affective attitudes towards AI*	.33	2.78	.006	0.04	0.25
Cognitive attitudes towards AI	-.01	-.09	.928	-0.27	0.25

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

From the predictor variables (see Table 8), the following predictors were significant: affective attitudes towards AI positively predicted the use of AI in classroom monitoring and visual analysis. Cognitive attitudes towards AI and behavioural attitudes towards AI were not significant. For the use of AI in personalised learning, results indicate that the model is statistically significant ($F(3,151) = 6.21$, $p < .001$) and explained 9.20% of the variance in the data (adjusted $R^2 = .092$). From the predictor variables (Table 9), the following predictors were significant: behavioural attitudes towards AI positively predicted the use of AI in personalised learning. Affective attitudes towards AI and cognitive attitudes towards AI were not significant.

Table 9. Model Coefficients for the Use of AI in Personalised Learning.

Model	*β*	*t*	*p*	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		10.39	<.001	10.55	15.50
Behavioural attitudes towards AI*	.35	3.31	.001	0.05	0.22
Affective attitudes towards AI	-.06	-.55	.586	-0.12	0.07
Cognitive attitudes towards AI	.03	.21	.836	-0.20	0.25

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

For the use of AI in predicting students' performance, results indicate that the model is statistically significant ($F(3,152) = 4.16$, $p = .007$) and explained 5.80% of the variance in the data (adjusted $R^2 = .058$). From the predictor variables (Table 10), the following predictors were significant: affective attitudes towards AI positively predicted the use of AI in predicting students' performance. Cognitive attitudes towards AI and behavioural attitudes towards AI were not significant.

Table 10. Model Coefficients for the Use of AI in Predicting Students' Performance.

Model	*β*	*t*	*p*	95.0% CI	
				Lower Bound	Upper Bound
(Constant)		7.35	<.001	8.10	14.05
Behavioural attitudes towards AI	.18	1.71	.090	-0.01	0.18
Affective attitudes towards AI*	.25	2.15	.033	0.01	0.23
Cognitive attitudes towards AI	-.18	-1.47	.144	-0.48	0.07

The * indicates significant predictor at $p < .05$ and ** indicates $p < .001$.

Discussion

In relation to hypothesis 1, testing the relationship between students' attitudes towards AI and students' competency using AI, results showed that affective and cognitive attitudes seemed to play a key role. In more detail, affective attitudes, such as fear or distrust, negatively predicted AI awareness and usage. Cognitive attitudes, reflecting deep information processing and knowledge organisation, positively predicted AI awareness and usage. Behavioural attitudes, however, did not predict awareness or usage. Also, no attitudes significantly predicted the evaluation of AI, and ethical use of AI.

In relation to hypothesis 2, testing the relationship between students' attitudes towards AI and students' conceptions about AI, results showed that behavioural attitudes played a significant role here. Positive behavioural attitudes predicted students' conceptions of AI's role in intelligent tutoring systems, retention, drop-out reduction, recommendation systems, and personalised learning. In contrast, affective attitudes predicted conceptions of AI's use in classroom monitoring and performance prediction, while cognitive attitudes had little influence. Models predicting the role of AI in grading, evaluation, and sentiment analysis in education were not significantly influenced by students' attitudes.

Attitudes Towards AI and AI Competence

Our results showed that affective attitudes towards AI negatively predicted AI awareness. Negative affective attitudes, such as fear or distrust of AI, lead to information avoidance (Sweeny, Melnyk, Miller, & Shepperd, 2010). Individuals who have strong negative emotions towards AI may consciously or unconsciously avoid learning more about it, thereby reducing their awareness. Furthermore, negative affective responses like distrust or fear and make people less likely to engage with educational content or discussions, leading to lower awareness (Slovic, 1993). If affective attitudes are negative, they could also reduce trust in AI-related information sources. Lack of trust can lead to disengagement from discussions or learning opportunities about AI, thus decreasing awareness. The negative prediction of awareness by affective attitudes towards AI could be due to the cognitive and psychological mechanisms that emotional responses trigger (Schepman, & Rodway, 2023). These mechanisms may lead individuals to avoid information, become cognitively overloaded, or engage in motivated reasoning, all of which can decrease their overall awareness of AI. Understanding these dynamics is crucial for developing strategies to improve public awareness and engagement with AI.

Cognitive attitudes towards AI positively predict awareness of AI because they reflect an individual's engagement in deep, systematic processing of information, the development of well-organised knowledge structures, and an active pursuit of understanding. These cognitive processes are essential for acquiring, retaining, and applying knowledge about AI, which naturally leads to greater awareness. The literature supports the idea that cognitive attitudes are strongly linked to how individuals interact with and comprehend complex subjects like AI, thereby increasing their overall awareness.

Behavourial attitudes did not predict AI awareness. This may result from students using the technology without understanding it. Research by Selwyn (2004) on digital literacy suggests that many users engage with technology on a superficial level, focusing on functionality rather than understanding the underlying technology. This behaviour might explain why individuals can use AI technologies without becoming more aware of AI as a concept. When it comes to usage of AI, the results were in line with those for awareness. Affective attitudes negatively predicted usage, cognitive attitudes positively predicted usage and behavioural attitudes did not predict usage. This is likely due to the strong link between awareness and usage. Those with low awareness are unlikely to use AI.

For evaluation of AI, whilst the regression model was significant, none of the attitudes were significant predictors. The type of evaluation the scale was measuring requires more objective and experience-based assessment. This is likely to be more heavily based on evaluative reasoning rather than attitude-based judgements. This is consistent with Petty and Cacioppo's (1986) Elaboration Likelihood Model (ELM). For ethical use of AI, the model was not significant. This may be due to the relatively low awareness and use of AI – if one is not aware of or using AI, then one cannot ethically use it.

Attitudes Towards AI and AI Conceptions

Behavioural attitudes towards AI positively predicted students' conceptions of intelligent tutoring systems. This is in line with findings from Alzahrani (2023) and Ma, Adesope, Nesbit, and Liu (2014) highlighting that behavioural attitudes play a crucial role in the successful implementation of AI and Intelligent Tutoring Systems in educational settings. For student grading and evaluation with AI, results indicate that the model was not statistically significant. This suggests that students' attitudes towards AI do not predict their conceptions of AI's ability to perform grading and evaluation. Students view human and AI graders as competent and trustworthy, but AI graders are perceived as less caring unless their feedback includes more verbal immediacy (Abendschein, Lin, Edwards, Edwards, & Rijhwani, 2024). Additionally, when comparing the effectiveness of human and computer grading Boring (2005) showed that there were significant correlations between human essay grading and computerised essay grading. This indicates AI tools may be rather accurate at grading tasks.

Behavioural attitudes towards AI positively predicted students' conception about the use of AI for students' retention and drop-out whilst affective and cognitive attitudes towards AI did not. Although research has shown that AI can offer opportunities for personalized learning and enhanced student engagement, potentially reducing dropout rates in higher education (das Neves Meroto et al., 2024), it is not entirely clear how this relates to positive behavioural attitudes. Future research could seek to clarify this relationship. For the use of AI in sentiment analysis in education, results indicate that the model is statistically significant, but none of the predictor variables were significant. This could be because the use of sentiment analysis in education (e.g., 'Artificial intelligence can accurately detect my positive or negative opinions about my teaching experience.') is still a very abstract concept and one may not have seen its implementations. Therefore, attitudes may not be relevant with regard to this factor. Sentiment analysis techniques, including machine learning and deep learning, are being applied to analyse student feedback and enhance pedagogical practices (Shaik, Tao, Dann, Xie, Li, & Galligan, 2023). However, the educational applications and usability of sentiment analysis remain limited, with most research focusing on technical aspects rather than educational implications (Grimalt-Álvaro & Usart, 2023). For example, you can use AI to detect whether students are attending, however this does not support you in your teaching practice.

Behavioural attitudes towards AI positively predicted the use of AI in recommendation systems and personalised learning. Affective and cognitive attitudes towards AI were not significant. This could be because AI tools can provide educators and students suggestions about teaching and learning that can save time and enhance their experience. For example, educators use AI tools to generate quizzes for the students (Sagin, Ozkaya, Tengiz, Geyik, & Geyik, 2024) and students use AI tools to make flashcards whilst revising or to consolidate their knowledge (Anggoro & Pratiwi, 2023). Also, AI can be used to personalise learning experiences tailored to individual students' needs, preference and pace of learning (Ashwini, Kumar, Nandan, & Suman, 2023) This may be because these competencies relate to one's behaviour, thus behavioural attitudes are the most relevant. Affective attitudes towards AI positively predicted conceptions of the use of AI in classroom monitoring and visual analysis and predicting students' performance. Behavioural and cognitive attitudes did not. Research has shown that AI systems can be used to effectively monitor students' attendance and their attention in classroom (Parambil, Ali, Alnajjar, & Gochoo, 2022). In organizational settings, leader monitoring methods can negatively affect citizenship behaviour directly, but may also positively influence it indirectly through perceptions of fairness (Niehoff & Moorman, 1993). These findings suggest that the relationship between emotion and being monitored is multifaceted, involving factors such as self-awareness, social evaluation, and perceptions of justice, which can modulate emotional and behavioural responses to surveillance (Robles, Sukumaran, Rickertsen, & Nass, 2006).

Conclusion

This study underscores the significant impact of affective, cognitive, and behavioural attitudes on individuals' engagement with AI, particularly in terms of awareness, usage, and conceptions. Negative affective attitudes hinder both AI awareness and usage, reflecting a pattern of information avoidance. Conversely, positive cognitive attitudes enhance both awareness and usage, highlighting the importance of deeper information processing and engagement with AI-related content.

Behavioural attitudes, while less influential on awareness and usage, play a crucial role in shaping students' conceptions of AI within educational contexts, particularly regarding intelligent tutoring systems, personalised learning, and student retention. These findings suggest that improving student awareness and usage of AI requires addressing negative affective attitudes and promoting cognitive engagement. Moreover, fostering positive behavioural attitudes may enhance the adoption of AI in educational settings. Future research should explore how these attitudes can be strategically influenced to improve AI literacy, ethical use, and integration into both personal and professional domains. By addressing these areas, educators, policymakers, and technologists can better align AI development with users' needs and perceptions.

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References

Abendschein, B., Lin, X., Edwards, C., Edwards, A., & Rijhwani, V. (2024) Credibility and altered communication styles of AI graders in the classroom. *Journal of Computer Assisted Learning*. https://doi.org/10.1111/jcal.12979

Alzahrani, L. (2023). Analyzing students' attitudes and behavior toward artificial intelligence technologies in higher education. *International Journal of Recent Technology and Engineering (IJRTE), 11*(6), 65-73.

Al-Zahrani, A. M. (2024). Unveiling the Shadows: Beyond the Hype of AI in Education. *Heliyon, 10*(9), e30696–e30696. https://doi.org/10.1016/j.heliyon.2024.e30696

Anggoro, K. J., & Pratiwi, D. I. (2023). Fostering Self-Assessment in English Learning with a Generative AI Platform: A Case of Quizizz AI. *Studies in Self-Access Learning Journal, 14*(4). http://dx.doi.org/10.37237/140406

Ashwini, N., Kumar, N., Nandan, M., & Suman, V. (2023). Leveraging Artificial Intelligence in Education: Transforming the Learning Landscape. International Research Journal of Computer Science, 10(05), 192-196. https://doi.org/10.26562/irjcs.2023.v1005.16

Ayanwale, M. A., & Ndlovu, M. (2024). Investigating factors of students' behavioral intentions to adopt chatbot technologies in higher education: Perspective from expanded diffusion theory of innovation. *Computers in Human Behavior Reports 14*, 100396. https://doi.org/10.1016/j.chbr.2024.100396

Boring, R. L. (2005, September). The validity of human and computerized writing assessment. *In Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 49, No. 7, pp. 759-763). Sage CA: Los Angeles, CA: Sage Publications. https://doi.org/10.1177/154193120504900704

Cheng, L., Umapathy, K., Rehman, M., Ritzhaupt, A., Antonyan, K., Shidfar, P., Nicholas, J., & Abramowitz, B. (2023). Designing, developing, and validating a measure of undergraduate students' conceptions of artificial intelligence in education. *Journal of Interactive Learning Research, 34*(2), 275-311. https://www.learntechlib.org/primary/p/222246/

das Neves Meroto, M. B., da Silva Franqueira, A., de Queiróz, C. L. C., dos Santos Filho, E. B., da Costa, I. T., da Silva Cunha, P. R., da Silva, R.G., & Lima, V. V. (2024). Combating school dropout with Artificial Intelligence in Brazilian higher education. *Contribuciones a las Ciencias Sociales*, *17*(2), e5182-e5182. https://doi.org/10.55905/revconv.17n.2-147

Do, T. (2008). *Rogers' Five Main Attributes of Innovation on the Adoption Rate of Online Learning* (p. 11). 08-15.

Field, A. (2013). Discovering statistics using IBM SPSS statistics.

Grimalt-Álvaro, C., & Usart, M. (2023). Sentiment analysis for formative assessment in higher education: a systematic literature review. Journal of computing in higher education, 1-36. https://doi.org/10.1007/s12528-023-09370-5

Hsin, W. J. (2024). The impact of AI tools on student engagement and academic performance in higher education. *Journal of Educational Technology*, 36(1), 55-72. https://doi.org/10.1016/j.jet.2024.01.003

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. Journal of educational psychology, 106(4), 901. http://dx.doi.org/10.1037/a0037123

Malik, A. R., Pratiwi, Y., Andajani, K., Numertayasa, I. W., Suharti, S., & Darwis, A. (2023). Exploring artificial intelligence in academic essay: higher education student's perspective. *International Journal of Educational Research Open,* 5, https://doi.org/10.1016/j.ijedro.2023.100296

Mathes, W. T. A., Magantran, S., & Rahman, N. S. M. B. A. (2023). Students' Perception Towards the Usage of Artificial Intelligence in Tertiary Education.*Selangor Humaniora Review*, *7*(2), 58–70. https://share.journals.unisel.edu.my/ojs/index.php/share/article/view/267

Niehoff, B.P., & Moorman, R.H. (1993). Justice As a Mediator Of The Relationship Between Methods Of Monitoring And Organizational Citizenship Behavior. *Academy of Management Journal, 36*, 527-556. https://doi.org/10.5465/256591

Parambil, M. M. A., Ali, L., Alnajjar, F., & Gochoo, M. (2022, February). Smart classroom: A deep learning approach towards attention assessment through class behavior detection. In 2022 Advances in Science and Engineering Technology International Conferences (ASET) (pp. 1-6). IEEE. https://doi.org/10.1109/ASET53988.2022.9735018

Petty, R. E., Cacioppo, J. T., (1986). The elaboration likelihood model of persuasion (pp. 1-24). Springer New York.

Robles, E., Sukumaran, A., Rickertsen, K., & Nass, C. (2006). Being watched or being special: how I learned to stop worrying and love being monitored, surveilled, and assessed. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/1124772.1124894

Sağın, F. G., Özkaya, A. B., Tengiz, F., Geyik, Ö. G., & Geyik, C. (2024). Current evaluation and recommendations for the use of artificial intelligence tools in education. *Turkish Journal of Biochemistry, 48*(6), 620-625. https://doi.org/10.1515/tjb-2023-0254

Schepman, A., & Rodway, P. (2023). The General Attitudes towards Artificial Intelligence Scale (GAAIS): Confirmatory validation and associations with personality, corporate distrust, and general trust. *International Journal of Human–Computer Interaction, 39*(13), 2724-2741. https://doi.org/10.1080/10447318.2022.2085400

Selwyn, N. (2004). The information aged: A qualitative study of older adults' use of information and communications technology. Journal of Aging studies, 18(4), 369-384. https://doi.org/10.1016/j.jaging.2004.06.008

Shaik, T., Tao, X., Dann, C., Xie, H., Li, Y., & Galligan, L. (2023). Sentiment analysis and opinion mining on educational data: A survey. Natural Language Processing Journal, 2, https://doi.org/10.1016/j.nlp.2022.100003

Slovic, P. (1993). Perceived risk, trust, and democracy. *Risk Analysis*, 13(6), 675-682. https://doi.org/10.1111/j.1539-6924.1993.tb01329.x

Suh, W., & Ahn, S. (2022). Development and validation of a scale measuring student attitudes toward artificial intelligence. *Sage Open, 12*(2), https://doi.org/10.1177/21582440221100463

Sweeny, K., Melnyk, D., Miller, W., & Shepperd, J. A. (2010). Information avoidance: Who, what, when, and why. *Review of General Psychology*, 14(4), 340-353. https://doi.org/10.1037/a0021288

Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & information technology, 42*(9), 1324-

1337. https://doi.org/10.1080/0144929X.2022.2072768

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*(1). Springer open. https://doi.org/10.1186/s41239-019-0171-0

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