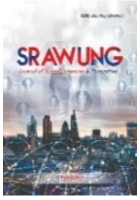


ISSN 2827-8151 (Online)
SRAWUNG: Journal of Social Sciences and Humanities
https://journal.jfpublisher.com/index.php/jssh
Vol. 3, Issue. 4 (2024)
doi.org/10.56943/jssh.v3i4.615

The Correlational Study of Artificial Intelligence in Education on Students' Outcomes

A Study of Higher Education in Private University, Phnom Penh, Cambodia

Dr. By Loeung[1*], Dr. Paradise Ros[2]
[1]loeungbee@gmail.com, [2]paradiseros9999@gmail.com
[1]Senior Lecturer, BELTEI International University, Cambodia; [2]PhD in EAL, Faculty of Education, Arts and Humanities, BELTEI International University, Cambodia

*Corresponding Author: Dr. By Loeung
Email: loeungbee@gmail.com

ABSTRACT

Artificial Intelligence (AI) tool is very popular and essential for both teaching and learning activities in 21st century. While Artificial Intelligence (AI) has grown more widespread in education, its influence on student results is still debated. Some Cambodian universities have highlighted stresses about AI's ability to stifle innovation and learning. This study aimed to assess students' attitudes about AI and their perceptions of AI's role in education, as well as the relationship between these characteristics and student outcomes. Consequently, the aim of this research is to evaluate attitudes regarding Artificial Intelligence (AI) in education and views on the specific impact of AI on student achievements. Quantitative research was employed in the study, and this involved analyzing both descriptive and inferential data. Simple and multivariate regressions were utilized to assess the assess attitudes towards AI in education and specific perceptions in AI's Role in education which impact on students' outcomes. The study has designed accurate questionnaires to survey 222 individuals from higher education in private university in Cambodia. A regression study demonstrates that perceptions of AI's Role in education have considerable impacts on students' outcomes. The study's findings indicate that perceptions about artificial intelligence's role in education have major impacts on students' achievements. This emphasizes the significance of instilling positive attitudes in pupils in order to get the benefits of AI in the classroom.

Keywords: *Artificial Intelligence, Attitude, Higher Education, Perception*

INTRODUCTION

Karaman & Göksu (2024) assert that the development of AI, especially chatbots, has drastically changed educational resources and given rise to a number of creative uses. These consist of facial recognition software, automated evaluation tools, and tailored learning platforms. AI has a wide range of applications in education, demonstrating its ability to transform conventional teaching techniques and improve the learning environment as a whole (Mabuan, 2024).

The subject of computer science known as Artificial Intelligence (AI) is concerned with recreating intelligent activities in computers in order to emulate and perhaps enhance human behavior (Naqvi, 2020). AI has a tremendous impact on science, engineering, and technology, but it is also making a difference in education because to advances in machine learning systems and algorithms. While AI is not always at the forefront of our minds, it has a significant influence on many facets of our life since we engage with AI apps on a regular basis. These tools help us with things like browsing the internet, handling emails, booking medical appointments, finding directions, and obtaining entertainment recommendations.

Existing research on the benefits and problems of teaching presentation skills to students and educators is limited, resulting in a large research vacuum. This gap provides an opportunity to improve our understanding of how presenting skills influence both learning outcomes and teacher efficacy (Jou et al., 2016; Luo et al., 2017; Nguyen et al., 2018; Seo et al., 2021). The most crucial of Moore's three types of interactions, according to the research, is the learner-instructor contact. Instructors may improve student engagement and learning by offering many lines of contact, support, encouragement, and timely feedback (Martin & Bolliger, 2018).

The study aims to examine how AI tools are currently utilized at the chosen university, pinpoint pertinent student results, assess the link between AI integration and these results, explore potential factors that impact this connection, uncover obstacles to AI adoption, and offer suggestions for enhancing AI utilization to enhance student learning and outcomes in higher education.

LITERATURE REVIEW

Multiple artificial intelligence systems are expected to have an influence on learner-instructor interaction in online learning. Goel & Polepeddi (2016) developed an AI-powered teaching assistant to support professors in communicating with students by automatically replying to student introductions, delivering weekly updates, and answering frequently requested questions.

Perin & Lauterbach (2018) have proposed a novel technique of grading utilizing AI that allows students and teachers to communicate grades more rapidly. Luckin et al (2022) indicated that AI solutions have been proved to benefit students and teachers by providing constant feedback on students' learning and progress toward educational goals. According to Ross et al (2018), online adaptive quizzes were designed to assist students by giving individualized learning materials, hence increasing student motivation and participation. According to Heidicker et al (2017), virtual avatars allow users who are geographically separated to collaborate in an immersive virtual environment by increasing the sense of presence.

Due to Aslan et al (2019), AI face analytics were created to boost teachers' presence as coaches in technology-mediated learning settings. When researching these AI systems, it is critical to consider how students and teachers perceive their influence. There is growing curiosity in how students adapt to this new technology and what drives them in this setting as the usage of artificial intelligence in education increases. In this sense, analyzing what drives people may be done effectively with the help of the Expectancy-Value Theory (Gansser & Reich, 2021; Hmoud et al., 2024).

Regarding to Expectancy-Value Theory, both expectancies and task values influence achievement choices, performance, effort, and perseverance (Eccles & Wigfield, 2020). According to this idea, certain task-related beliefs such as perceived aptitude, perceived task difficulty, and an individual's objectives, self-concepts, and emotional recalls all impact expectations and values. According to the Accomplishment-Expectancy Theory, students' motivation, academic accomplishment, and activity choices are impacted by their success expectations and the task's relevance (Rosenzweig et al., 2019). The Idea of Utility Value entails determining how well an activity matches with a person's long-term aspirations. It assesses the task's relevance and usefulness in accomplishing long-term goals (Barron & Hulleman, 2015).

Finally, cost encompasses the possible disadvantages of job engagement, such as the needed effort, the risk of failure, or the opportunity cost incurred as a result of time diverted from other actions (Barron & Hulleman, 2015). When it comes to artificial intelligence, understanding these subcategories is critical for identifying the fundamental variables driving AI system acceptance. Integrating these subcategories gives a comprehensive perspective of the different elements that influence an individual decision to commence and continuous engagement in a specific job, as shown in Table 1.

Table 1. Attitudes towards AI in Education

Expectancy (E)	**Task Value (TV)**	**Utility Value (UV)**	**Intrinsic/Interest Value (IV)**	**Cost (C)**
E1: I believe I can effectively learn to use AI applications in education.	TV1: The capacity to properly apply AI in teaching is vital for me.	UV1: AI applications will help me become a more proficient educator.	IV1**:** I enjoy using AI applications in education.	C1: Putting the effort and time into learning AI applications is profitable for me.
E2: I feel confident in my general knowledge of AI compared to others.	TV2: Learning and implementing AI innovations is a priority for me.	UV2: AI enhances my overall efficiency and effectiveness in education.	IV2**:** I find experiences related to AI interesting and engaging.	C2: Learning an AI application is a relatively easy task for me.
E3: I'm ahead of most of my classmates in using AI apps efficiently.	TV3: Staying updated on AI developments in education is important to me.	UV3: AI assists me in streamlining my daily tasks as an educator.	IV3**:** Following AI developments in education is a stimulating activity for me.	C3: I am eager to devote time away from other pursuits to master AI applications.
E4: I believe I have the potential to excel in using AI applications in education.	TV4: I value strengthening my skills in using AI applications in education.	UV4: AI benefits me in various educational subjects and courses.	IV4**:** Learning to use AI applications is a rewarding experience.	C4: I am not hesitant to invest a significant amount of time and effort to enhance my AI skills.

Source: Barron & Hulleman (2015)

The use of artificial intelligence has the potential to greatly improve education by automating administrative tasks, customizing instruction, and offering valuable insights into student learning. Through predictive analytics, AI can identify possible risks and take timely action. By analyzing student data, educators are able to make more well-informed decisions regarding curriculum and support services. AI is also capable of personalizing learning experiences to match individual students' needs and learning styles, as well as identifying and addressing learning gaps. Additionally, AI can forecast potential career paths for students and adjust interventions to improve learning outcomes (Chen et al., 2020), as mentioned in Table 2.

Table 2. Specific Perceptions of AI's Role in Education

Administrative Tasks (AT)	**Instruction (I)**	**Learning (L)**
AT1: I believe AI can efficiently handle administrative tasks like grading exams and providing feedback.	I1: I believe AI can predict student performance and identify potential risks.	L1: I believe AI can uncover learning shortcomings and address them early.
AT2: I think AI can effectively identify the learning styles and preferences of students.	I2: I think AI can create customized course content based on student needs.	L2: I think AI can predict potential career paths for students.
AT3: I believe AI can assist educators in making data-driven decisions.	I3: I believe AI can support collaborative learning beyond the classroom.	L3: I believe AI can detect learning states and provide adaptive interventions.
AT4: I think AI can provide timely and personalized feedback to students.	I4: I think AI can tailor teaching methods to individual students.	L4: I think AI can personalize university course selections for students.

Source: Chen et al (2020)

According to Lin et al (2017), the terms learning outcome, academic accomplishment, and academic performance all refer to the consequences of students' learning experiences and advancement. There are numerous definitions for learning outcomes, which are defined as statements that indicate the fundamental learning that students have completed and can be reliably reported at the end of a program (Zhu et al., 2019). Cahyono et al (2019) defined a learning outcome as a statement of what a student is expected to know, understand, and/or be capable of accomplishing at the end of a time of study. Table 3 shows how Hoque, (2017); Wei et al., 2021) evaluated learning outcomes based on cognitive, emotional, and psychomotor domains.

Table 3. Students' Outcomes

Cognitive Domain (CD)	Affective Domain (AD)	Psychomotor Domain (PD)
CD1: I can recollect things I learned from the presenters.	AD1: I've got my emotions under control.	PD1: I am able to complete my schoolwork individually.
CD2: I can comprehend the material I received from the lectures.	AD2: I can endure being upset.	PD2: I am competent to conduct experiments autonomously.
CD3: I am able to deconstruct information and demonstrate correlations.	AD3: I can easily get into a good mood.	PD3: I am capable of taking the initiative and working well in a team setting.
CD4: I am not scared to invest a significant amount of time and effort into enhancing my AI skills.	AD4: I can easily feign emotions.	PD4: I am able to concentrate when doing research.
CD5: I am able to use knowledge in new situations.	AD5: I am able to calm down rapidly.	PD5: I am able to show care and respect for instructional equipment.

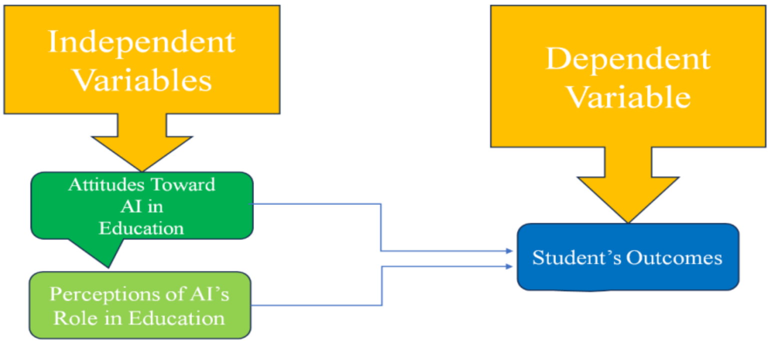
Source: Wei et al (2021); Zhu et al (2019)

Hypothesis Development

H_1: Attitudes toward AI in education have statistically significant impacts on students' outcomes.

H_2: Perceptions of AI's Role in education have statistically significant impacts on students' outcomes.

Figure 1. Framework



Source: Proposed Framework by Researchers (2024)

RESEARCH METHODOLOGY

The study utilized a survey research approach in which all data was gathered and evaluated quantitatively, allowing for both descriptive and inferential analysis. Convenience sampling was used to ensure that only personnel found at their workplaces were included in the research (By, 2024). The survey will be conducted at Cambodian higher education institutions and universities, with participants comprising professors, administrators, and lecturers who are active in teaching and learning utilizing AI for specific tasks in higher education. The actual population is unknown.

Survey on the Reasons for Using Artificial Intelligence was based on The Expectancy-Value Theory framework which was utilized in the development of an artificial intelligence app motivation survey in order to determine the driving forces behind the adoption of AI applications. Expectancy and task value are the two main components of motivation, according to the expectation-value hypothesis. The four sub-dimensions of the task value dimension are cost, interest, utility, and achievement. These components are ranked according to cost, interest, usefulness, and accomplishment (Yurt & Kasarci, 2024). The independent variables are attitudes and perceptions of AI in education while dependent variable is students’ outcomes. It was challenging to investigate the entire population. For this reason, the researcher used a convenient random selection method. Convenience sampling is a method of selecting participants from the target population based on their convenience of access. As a result, the survey’s target respondent count was 222 employees. A pilot test was conducted to ensure the study’s trustworthiness. All variables have Cronbach’s alpha values greater than 0.7, which is considered acceptable (Bonett & Wright, 2015).

To ensure the accuracy and trustworthiness of the information acquired from respondents, a pre-test was conducted before to the actual data collection. Twenty responders with prior expertise with AI in higher education took part in a pilot test. The pilot test included two evaluations: factor analysis and reliability analysis, and it was given in both Khmer and English. The key goals of this study’s factor analysis section were to determine the dimensions of each research construct variable, choose questionnaire questions with high factor loading, and compare these items to theory-suggested ones. The factor analysis employed a variety of criteria, including Eigenvalue, Cumulative Percentage, KMO, Bartlett’s test, and Factor Loading (FL). According to the SPSS results, each component had a score more than 0.6, suggesting that it was reasonable to include in the questionnaire. The evaluation of the relative relevance of the components within each research topic was simplified by categorizing values from high to low. Tables 3 and 4 show that a total of five components were estimated for training efficacy and three constructs for individual work performance (By, 2024).

Pilot Testing

To guarantee the precision and dependability of the information obtained from respondents, a pre-test was carried out before to the real data collection (Shrestha, 2021). Twenty respondents with prior experience in a pilot test. The pilot test had two evaluations: factor analysis and reliability analysis, and it was administered in both Khmer and English. The primary objectives of this study's factor analysis portion were to identify the dimensions of each research construct variable, choose questionnaire questions with high factor loading, and compare these items to theory-suggested ones. Numerous criteria were used in the factor analysis, including Eigenvalue, Cumulative Percentage, KMO and Bartlett's test, and Factor Loading (FL). According to the SPSS findings, every component had a score higher than 0.6, indicating that it was appropriate to include it in the questionnaire. The evaluation of the relative significance of the components inside each study concept was made easier by classifying values from high to low. A total of 20 constructs were calculated for attitudes towards AI in education, 12 constructs for Specific perceptions in AI's roles in education, and 15 constructs for student's outcomes detailed in Table 4, 5, and 6.

Table 4. Result of Factor Analysis of Attitude towards AI in Education

Code	Item Description	Factor Analysis			
		FL	KMO	E	Cu%
Expectancy (E)					
E1	I believe I can effectively learn to use AI applications in education.	0.814	0.578	2.163	54.080
E2	I feel confident in my general knowledge of AI compared to others.	0.883			
E3	I'm ahead of most of my classmates in using AI apps efficiently.	0.819			
E4	I believe I have the potential to excel in using AI applications in education.	0.823			
Task Value (TV)					
TV1	The capacity to properly apply AI in teaching is vital for me.	0.676	0.781	2.779	69.473
TV2	Learning and implementing AI innovations is a priority for me.	0.656			
TV3	Staying updated on AI developments in education is important to me.	0.664			

TV4	I value strengthening my skills in using AI applications in education.	0.785			
Utility Value (UV)					
UV1	AI applications will help me become a more proficient educator.	0.585	0.805	2.704	67.598
UV2	AI enhances my overall efficiency and effectiveness in education.	0.691			
UV3	AI assists me in streamlining my daily tasks as an educator.	0.689			
UV4	AI benefits me in various educational subjects and courses.	0.739			
Intrinsic/Interest Value (IV)					
IV1	I enjoy using AI applications in education.	0.760	0.822	2.886	72.157
IV2	I find experiences related to AI interesting and engaging.	0.756			
IV3	Following AI developments in education is a stimulating activity for me.	0.748			
IV4	Learning to use AI applications is a rewarding experience.	0.622			
Cost (C)					
C1	Putting the effort and time into learning AI applications is profitable for me.	0.679	0.768	2.844	71.111
C2	Learning AI applications is a relatively easy task for me.	0.656			
C3	I am eager to devote time away from other pursuits to master AI applications.	0.761			
C4	I am not afraid to devote a large amount of time and effort to improving my AI skills.	0.748			

Source: Processed Data by Researchers (2024)

Table 5. Results of Factor Analysis of Specific Perceptions of AI's Roles in Education

Code	Item Description	Factor Analysis			
		FL	KMO	E	Cu%
Administrative Tasks (AT)					
AT1	I believe AI can efficiently handle administrative tasks like grading exams and providing feedback.	0.566	0.787	2.696	67.410
AT2	I think AI can effectively identify the learning styles and preferences of students.	0.624			
AT3	I believe AI can assist educators in making data-driven decisions.	0.763			
AT4	I think AI can provide timely and personalized feedback to students.	0.744			
Instruction (I)					
I1	I believe AI can predict student performance and identify potential risks.	0.731	0.827	2.946	73.644
I2	I think AI can create customized course content based on student needs.	0.759			
I3	I believe AI can support collaborative learning beyond the classroom.	0.699			
I4	I think AI can tailor teaching methods to individual students.	0.757			
Learning (L)					
L1	I believe AI can uncover learning shortcomings and address them early.	0.688	0.781	2.716	67.895
L2	I think AI can predict potential career paths for students.	0.670			
L3	I believe AI can detect learning states and provide adaptive interventions.	0.685			
L4	I think AI can personalize university course selections for students.	0.673			

Source: Processed Data by Researchers (2024)

Table 6. Results of Factor Analysis of Student Learning Outcomes

Code	Item Description	Factor Analysis			
		FL	KMO	E	Cu%
Cognitive Domain (CD)					
CD1	I can recollect things I learned from the presenters.	0.544	0.838	3.089	61.777
CD2	I can comprehend the material I received from the lectures.	0.649			
CD3	I am able to deconstruct information and demonstrate correlations.	0.612			
CD4	I am not scared to invest a significant amount of time and effort into enhancing my AI skills	0.695			
CD5	I am able to use knowledge in new situations.	0.591			
Affective Domain (AD)					
AD1	I've got my emotions under control.	0.586	0.873	3.486	69.728
AD2	I can endure being upset.	0.757			
AD3	I can easily get into a good mood.	0.666			
AD4	I can easily feign emotions.	0.805			
AD5	I am able to calm down rapidly.	0.672			
Psychomotor Domain (PD)					
PD1	I am able to complete my schoolwork individually.	0.716	0.847	3.166	63.310
PD2	I am competent to conduct experiments autonomously.	0.694			
PD3	I am capable of taking the initiative and working well in a team setting.	0.654			
PD4	I am able to concentrate when doing research.	0.631			
PD5	I am able to show care and respect for instructional equipment.	0.471			

Source: Processed Data by Researchers (2024)

Table 7 demonstrates how the questions' reliability was determined using the study's dependability, which was guaranteed by performing a pilot test. Cronbach's alpha values for all variables above 0.7, which is deemed acceptable, and were determined using the SPSS software. Table 7 shows the findings of a study on the number of items in research variables. The table includes eight study variables. The table displays the number of items (# OF ITEMS) and the alpha coefficient (ALPHA) for each variable. The alpha coefficient evaluates a test's internal consistency or reliability. The alpha coefficients for each of the eight research variables in this study are greater than 0.6, suggesting that they are all very consistent (Bonett & Wright, 2015).

Table 7. Result of Reliability

No.	Research Variables	ALPHA (N=222)	# OF ITEMS
1	Expectancy (E)	0.708	4
2	Task Value (TV)	0.853	4
3	Utility Value (UV)	0.839	4
4	Intrinsic/Interest Value (IV)	0.871	4
5	Cost (C)	0.864	4
6	Administrative Tasks (AT)	0.837	4
7	Instruction (I)	0.881	4
8	Learning (L)	0.842	4
9	Cognitive Domain (CD)	0.845	5
10	Affective Domain (AD)	0.890	5
11	Psychomotor Domain (PD)	0.853	5

Source: Processed Data by Researchers

Multiple regression will be utilized to study the relationship between a single dependent variable and several independent variables. The multiple regression equation will examine the influence of Attitudes toward AI in Education and Perceptions of AI's Role in Education on student results (Maulud & Abdulazeez, 2020).

Description:

$Yi = \beta_0+\beta_1 X_{1i}+\beta_2 X_{2i}+\beta_3 X_{3i}+\ldots\ldots\ldots\ldots\ldots\ldots + \varepsilon i$

Where,
Y= Dependent Variable
B_0= Constant
$B_1 \ldots B_{11}$= Slop of Regression
$X_1 \ldots X_{11}$= Independent Variables
E_i = Error Term

Hypotheses for Study
Hypothesis 1: ATE $\Longrightarrow$ SC
Hypothesis 2: SPE $\Longrightarrow$ SC

RESULT AND DISCUSSION

Table 8 shows that the majority of poll participants (62.2%) were female, with 85.5% being under the age of 30. The most frequent level of education was a Bachelor's degree (78.8%), followed by a Diploma (3.7%) and a Master's (4.1%). The majority of participants had 1-2 years of experience (50.6%), followed by 3-4 years (31.1%). University students made up the vast majority of participants (57.7%), followed by teachers (18.7%) and lecturers (14.9%). The most popular wage range was $300-$500 (40.2%), followed by $100-$300 (41.5%).

Table 8. Result of Demographic Analysis

Demographic	Description	Frequency	Percentage
Gender	Male	84	37.8
	Female	138	62.2
Age	Below 30	206	85.5
	30 To 40	13	5.4
	40 To 50S	1	0.4
	Above 50	2	0.8
Education	Diploma	9	3.7
	Bachelor	190	78.8
	Master	10	4.1
	PhD	13	5.4
Experiences	1 year to 2 years	122	50.6
	3 years to 4 years	75	31.1
	5 years to 6 years	14	5.8
	Above 7 Years	11	4.6
Current Positions	Lecturer	36	14.9
	Teacher	45	18.7
	University students	139	57.7
	Administrators	2	0.8
Salary	Below 200$	100	41.5
	300$ To 500$	97	40.2
	600$ To 800$	22	9.1
	Above 900$	3	1.2

Source: Processed Data by Researchers

The table 9 displays the findings of a descriptive statistical study on a sample of 222 people. The data focuses on several study factors, including expectation, task value, utility value, intrinsic value, cost, administrative tasks, teaching, learning, cognitive domain, emotional domain, and psychomotor domain. The mean ratings for each variable show a generally favorable agreement level, with the majority of scores falling into the "agree" and "greatly agree" categories. The standard deviations indicate moderate variety in replies, implying that while general consensus is favorable, individual perspectives differ.

Table 9. Result of Descriptive Statistics

Code	Research Variables (n=222)	Mean (M)	SD	Level of Analysis
E	Expectancy (E)	3.509	0.667	Agreement Level
TV	Task Value (TV)	3.567	0.609	Agreement Level
UV	Utility Value (UV)	3.541	0.607	Agreement Level
IV	Intrinsic/Interest Value (IV)	3.515	0.609	Agreement Level
C	Cost (C)	3.393	0.693	Agreement Level
AT	Administrative Tasks (AT)	3.487	0.604	Agreement Level
I	Instruction (I)	3.507	0.654	Agreement Level
L	Learning (L)	3.474	0.623	Agreement Level
CD	Cognitive Domain (CD)	3.499	0.586	Agreement Level
AD	Affective Domain (AD)	3.473	0.656	Agreement Level
PD	Psychomotor Domain (PD)	3.537	0.587	Agreement Level

*Note: 1.00-1.79 = significantly disagree, 1.80-2.59 = disagree, 2.60-3.39 = neutral, 3.40-4.19 = agree, and 4.20-5.00 = greatly agree.

Source: Processed Data by Researchers

Analysis of Correlations

The Table 10 shows the findings of a correlation study that looked at the correlations between student performance and several attitudes regarding AI in education, such as expectation, task value, utility value, intrinsic/interest value, and cost. The correlation coefficients, which range from.59 to.83, show substantial positive correlations between these variables. This implies that students' good views regarding AI, such as believing it would enhance results, appreciating its tasks, and finding it entertaining, are highly linked to actual positive student outcomes.

Table 10. Result of Correlation Analysis of Attitudes towards AI in Education

Variable	1	2	3	4	5	6
Students' outcomes	1					
Expectancy	.59**	1				
Task Value	.64**	.68**	1			
Utility Value	.66**	.74**	.75**	1		
Intrinsic/Interest Value	.74**	.69**	.68**	.83**	1	
Cost	.75**	.75**	.68**	.77**	.82**	1

Source: Processed Data by Researchers

The Table 11 shows the findings of a correlation study that looked at the correlations between student outcomes and perceptions of AI's involvement in education, especially administrative work, instruction, and learning. The correlation coefficients, which range from.78 to.86, show substantial positive correlations between these variables. This implies that students' positive opinions of AI's participation in administrative duties, instruction, and learning are highly linked to better student results.

Table 11. Result of Correlation Analysis Perceptions of the Roles of AI in Education

Variable	1	2	3	4	5	6
Students' outcomes	1					
Administrative Tasks	.78**	1				
Instruction	.81**	.86**	1			
Learning	.82**	.80**	.82**	1		

Source: Processed Data by Researchers

Multiple Regression Analysis

The table shows the findings of a regression study that looked at the association between student outcomes and a variety of factors, including particular opinions of AI's role in education and attitudes toward AI. The modified R-square of.733 suggests that the model accounts for a large percentage of the variation in students' results. The F-statistic of 305.098, with a significance level of.000, validates the entire model's relevance. The Durbin-Watson value of 1.955 indicates that there is no substantial autocorrelation in the residuals, implying that the model's assumptions are satisfied.

Figure 2. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.858[a]	.736	.733	.29625	.736	305.098	2	219	.000	1.955

a. Predictors: (Constant), Specific Perceptions of AI's Role in Education, Attitudes Towards AI in Education

b. Dependent Variable: Students' outcomes

Source: Processed Data by Researchers

Table 12 shows the findings of a regression study that looked at the link between student performance and several factors, including expectation, task value, utility value, intrinsic/interest value, and cost. The coefficients are the standardized beta weights for each predictor, which represent each variable's unique contribution to predicting student outcomes. The significance levels (Sig.) indicate which factors have a statistically significant effect on student outcomes. Collinearity statistics, such as tolerance and VIF, examine predictor multicollinearity, ensuring that redundant variables do not have an undue impact on the model. Overall, the investigation sheds light on the aspects that have a major impact on students' outcomes when using AI in education.

Table 12. Regression Results on Attitudes of AI on Students' Outcomes

Coefficients							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	.922	.155		5.947	0.000		
Expectancy	-.043	0.061	-0.050	-0.709	0.479	0.353	2.836
Task value	0.154	0.068	0.163	2.254	0.25	0.335	2.986
Utility Value	-0.19	0.083	0.020	-0.222	0.824	0.225	4.436
Intrinsic/Interest value	0.293	0.086	0.311	3.402	0.001	0.210	4.756
Cost	0.360	0.069	0.434	5.191	0.000	0.251	3.986
a. Dependent Variable: Students' Outcomes							

Source: Processed Data by Researchers (2024)

Table 13 shows the findings of a regression study that looked at the association between student outcomes and a variety of factors, including administrative chores, teaching, and learning. The coefficients are the standardized beta weights for each predictor, which represent each variable's unique contribution to predicting student outcomes. The significance levels (Sig.) indicate which factors have a statistically significant effect on student outcomes. Collinearity statistics, such as tolerance and VIF, examine predictor multicollinearity, ensuring that redundant variables do not have an undue impact on the model. Overall, the investigation sheds light on the aspects that have a major impact on students' outcomes when using AI in education.

Table 13. Regression Results on Attitudes of AI on Students' Outcomes

Coefficients							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	0.602	0.120		5.040	0.000		
Administrative Tasks	0.170	0.068	0.179	2.499	0.013	0.230	4.349
Instruction	0.252	0.67	0.288	3.790	0.000	0.205	4.883
Learning	0.409	0.59	0.445	6.903	0.000	0.284	3.521
a. Dependent Variable: Students' outcomes							

Source: Processed Data by Researchers (2024)

The Table 14 shows the findings of a regression study that looked at how attitudes and perceptions influenced students' outcomes. The coefficients provide the standardized beta weights for each predictor, which signify their unique contribution to forecasting student outcomes. The significance levels (Sig.) indicate that both attitudes and perceptions have a statistically significant influence on student outcomes. Collinearity statistics, such as tolerance and VIF, examine predictor multicollinearity, ensuring that redundant variables do not have an undue impact on the model. Overall, the findings indicate that students' attitudes about AI and perceptions of AI's role in education are major determinants of academic performance.

Table 14. Regression Results of Students' Outcomes

Coefficients								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
	(Constant)	0.577	0.126		4.583	0.000		
	Attitudes	0.40	0.072	0.040	0.563	0.574	2.36	4.232
	Perceptions	0.789	0.069	0.822	11.513	0.000	2.36	4.232
a. Dependent Variable: Students' Outcomes								

Source: Processed Data by Researchers (2024)

Table 15 shows the hypothesis testing among 2 main independent variables on students' outcomes. H_1 has negatively impacted on students' outcomes which the p-value is more than 0.05, but H_2 is highly positive on students' outcomes which the p-value is less than 0.05. This table concluded the 32 constructs in the relationships with hypothesis testing for the study which showed that only 1 main hypothesis is supported in the study.

Table 15. Summarized Result of Hypothesis Testing

Constructs	Hypo.	Relationships	p-value	Result
Attitudes Towards AI in Education (ATE)	H_1	ATE $\longrightarrow$ SC	0.574	Rejected
Specific Perceptions of AI's Role in Education (SPE)	H_2	SPE $\longrightarrow$ SC	0.000	Supported

Source: Processed Data by Researchers (2024)

CONCLUSION

The study found that students' views regarding AI and perceptions of its function in education had a substantial influence on their academic performance. Both attitudes and perceptions have a statistically significant impact on student results, suggesting that promoting favorable attitudes and views of AI is critical for improving student performance. Positive views regarding AI, such as believing it can improve learning and teaching, result in improved academic performance. Positive attitudes, on the other hand, regard AI as a useful tool for learning and teaching, not a danger. The combined influence of attitudes and perceptions is greater than each variable alone, emphasizing the necessity of addressing all components when incorporating AI into education. The ramifications for education include curriculum creation, teacher training, and policy development, all of which should assist AI integration while assuring student advantages.

Recommendation

Future study might look at the particular aspects that influence students' attitudes and views of AI, as well as its long-term impact on student outcomes. Furthermore, studying the efficacy of various AI strategies in fostering favorable student outcomes might offer educational practitioners with useful insights.

REFERENCES

Aslan, S., Alyuz, N., Tanriover, C., Mete, S. E., Okur, E., D'Mello, S. K., & Arslan Esme, A. (2019). Investigating the Impact of a Real-time, Multimodal Student Engagement Analytics Technology in Authentic Classrooms. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–12. https://doi.org/10.1145/3290605.3300534

Barron, K. E., & Hulleman, C. S. (2015). Expectancy-Value-Cost Model of Motivation. In *International Encyclopedia of the Social & Behavioral Sciences* (pp. 503–509). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.26099-6

Bonett, D. G., & Wright, T. A. (2015). Cronbach's Alpha Reliability: Interval Estimation, Hypothesis Testing, and Sample Size Planning. *Journal of Organizational Behavior*, *36*(1), 3–15. https://doi.org/10.1002/job.1960

By, L. (2024). The Effect of Training Effectiveness on Individual Work Performance in Business Organizations in Cambodia. *SRAWUNG: Journal of Social Sciences & Humanities*, *3*(3), 1–19. https://doi.org/10.56943/jssh.v3i3.583

Cahyono, A. N., Zaenuri, & Subagja, M. (2019). The Design of Blended Learning Modules for Higher Education. *Journal of Physics: Conference Series*, *1387*(1), 012121. https://doi.org/10.1088/1742-6596/1387/1/012121

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. *IEEE Access*, *8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, *61*, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*, *65*, 101535. https://doi.org/10.1016/j.techsoc.2021.101535

Goel, A. K., & Polepeddi, L. (2016). *Jill Watson: A Virtual Teaching Assistant for Online Education*.

Heidicker, P., Langbehn, E., & Steinicke, F. (2017). Influence of avatar appearance on presence in social VR. *2017 IEEE Symposium on 3D User Interfaces (3DUI)*, 233–234. https://doi.org/10.1109/3DUI.2017.7893357

Hmoud, M., Swaity, H., Hamad, N., Karram, O., & Daher, W. (2024). Higher Education Students' Task Motivation in the Generative Artificial Intelligence Context: The Case of ChatGPT. *Information*, *15*(1), 33. https://doi.org/10.3390/info15010033

Hoque, M. E. (2017). Three Domains of Learning: Cognitive, Affective and Psychomotor. *Evolutionary Psychology*, *2*(2), 45–51.

Jou, M., Lin, Y.-T., & Wu, D.-W. (2016). Effect of a blended learning environment on student critical thinking and knowledge transformation. *Interactive Learning Environments*, *24*(6), 1131–1147. https://doi.org/10.1080/10494820.2014.961485

Karaman, M. R., & Göksu, İ. (2024). Are Lesson Plans Created by ChatGPT More Effective? An Experimental Study. *International Journal of Technology in Education*, *7*(1), 107–127. https://doi.org/10.46328/ijte.607

Lin, M.-H., Chen, H.-C., & Liu, K.-S. (2017). A Study of the Effects of Digital Learning on Learning Motivation and Learning Outcome. *Eurasia Journal of Mathematics, Science and Technology Education*, *13*(7), 3553–3564. https://doi.org/10.12973/eurasia.2017.00744a

Luckin, R., Cukurova, M., Kent, C., & du Boulay, B. (2022). Empowering Educators to be AI-ready. *Computers and Education: Artificial Intelligence*, *3*, 100076. https://doi.org/10.1016/j.caeai.2022.100076

Luo, N., Zhang, M., & Qi, D. (2017). Effects of different interactions on students' sense of community in e-learning environment. *Computers & Education*, *115*, 153–160. https://doi.org/10.1016/j.compedu.2017.08.006

Mabuan, R. A. (2024). ChatGPT and ELT: Exploring Teachers' Voices. *International Journal of Technology in Education*, *7*(1), 128–153. https://doi.org/10.46328/ijte.523

Martin, F., & Bolliger, D. U. (2018). Engagement Matters: Student Perceptions on the Importance of Engagement Strategies in the Online Learning Environment. *Online Learning*, *22*(1). https://doi.org/10.24059/olj.v22i1.1092

Maulud, D., & Abdulazeez, A. M. (2020). A Review on Linear Regression Comprehensive in Machine Learning. *Journal of Applied Science and Technology Trends*, *1*(2), 140–147. https://doi.org/10.38094/jastt1457

Naqvi, A. (2020). *Artificial Intelligence for Audit, Forensic Accounting, and Valuation*. Wiley. https://doi.org/10.1002/9781119601906

Nguyen, T. D., Cannata, M., & Miller, J. (2018). Understanding student behavioral engagement: Importance of student interaction with peers and teachers. *The Journal of Educational Research*, *111*(2), 163–174. https://doi.org/10.1080/00220671.2016.1220359

Perin, D., & Lauterbach, M. (2018). Assessing Text-Based Writing of Low-Skilled College Students. *International Journal of Artificial Intelligence in Education*, *28*(1), 56–78. https://doi.org/10.1007/s40593-016-0122-z

Rosenzweig, E. Q., Wigfield, A., & Eccles, J. S. (2019). Expectancy-Value Theory and Its Relevance for Student Motivation and Learning. In *The Cambridge Handbook of Motivation and Learning* (pp. 617–644). Cambridge University Press. https://doi.org/10.1017/9781316823279.026

Ross, B., Chase, A.-M., Robbie, D., Oates, G., & Absalom, Y. (2018). Adaptive quizzes to increase motivation, engagement and learning outcomes in a first year accounting unit. *International Journal of Educational Technology in Higher Education*, *15*(1), 30. https://doi.org/10.1186/s41239-018-0113-2

Seo, K., Dodson, S., Harandi, N. M., Roberson, N., Fels, S., & Roll, I. (2021). Active learning with online video: The impact of learning context on engagement. *Computers & Education*, *165*, 104132. https://doi.org/10.1016/j.compedu.2021.104132

Shrestha, N. (2021). Factor Analysis as a Tool for Survey Analysis. *American Journal of Applied Mathematics and Statistics*, *9*(1), 4–11. https://doi.org/10.12691/ajams-9-1-2

Wei, X., Saab, N., & Admiraal, W. (2021). Assessment of cognitive, behavioral, and affective learning outcomes in massive open online courses: A systematic literature review. *Computers & Education*, *163*, 104097. https://doi.org/10.1016/j.compedu.2020.104097

Yurt, E., & Kasarci, I. (2024). A Questionnaire of Artificial Intelligence Use Motives: A Contribution to Investigating the Connection between AI and Motivation. *International Journal of Technology in Education*, *7*(2), 308–325. https://doi.org/10.46328/ijte.725

Zhu, J., Chen, J., McNeill, N., Zheng, T., Liu, Q., Chen, B., & Cai, J. (2019). Mapping Engineering Students' Learning Outcomes From International Experiences: Designing an Instrument to Measure Attainment of Knowledge, Skills, and Attitudes. *IEEE Transactions on Education*, *62*(2), 108–118. https://doi.org/10.1109/TE.2018.2868721