Role of Artificial Intelligence to Enhance Learning Competencies at Secondary School Students

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Abstract - One of the most important parts of every community is its educational system. It has significant links to and effects on all other economic spheres. The main aim of the study is Role of artificial intelligence to enhance learning competencies at secondary school students. Six hundred and five high school students were polled using a modified survey instrument to delve into students' understanding of AI education's most foundational concepts. This research adds to the body of knowledge by emphasizing the significance of students' prior knowledge and skills in the classroom, particularly as they relate to AI instruction.

Keywords - Community, Education, Economic, Artificial, Intelligence, Knowledge

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INTRODUCTION

One of the most important parts of every community is its educational system. It has significant links to and effects on all other economic spheres. As a result of its importance, education is a must-have for all social groups notwithstanding barriers. For instance, many scholars are interested in the difficulty that the education sector has had during COVID-19. Access to education, barriers to entering physical classrooms, and economic concerns are only a few examples of the perennial social dilemmas. There are, and will be, a lot of ways to fix things, but our research is centered on one technological approach: artificial intelligence (AI). The educational system is not immune to the societal shifts brought on by AI. Many nations, like Singapore, Malaysia, and South Korea, have been driven by technological advancements to increase their use of technology in the classroom. Education's bright future is inextricably linked to the development of new technology. More sophisticated machinery will help the educational industry meet the new difficulties and take advantage of new possibilities. Economists, political scientists, military consultants, security analysts, and educators are all taking an interest in the AI industry. The effects of three artificial intelligence (AI) applications on classroom instruction are examined here: smart learning (SL), social robots (SR), and tutoring systems (TS).

Artificial Intelligence

Artificial intelligence (AI) refers to computer systems that can mimic human intellect. The difference between human and animal intelligence is that one has awareness and emotions while the other has not. "Making a machine behave in ways that would be called intelligent if a human were so behaving" is how John MsCarthy, the guy credited with coining the phrase "artificial intelligence" in 1955, described it. In 1950, Alan Turing popularized the idea that computers may eventually mimic human thought. He anticipated that in the not-too-distant future, computers will do computations that people just couldn't be bothered with. The underlying concern is how binary computations will have human meanings, given that computing devices operate on binary numbers. Commonly, when people talk about artificial intelligence, they mean robots that can mimic human intelligence by carrying out tasks like learning and problem solving. An artificial agent is a machine that can learn from experience and make choices that increase the likelihood of success in achieving certain objectives. Since the activities they are doing have become their normal labor and routine technology, they are often omitted from AI, but have been given the moniker artificial intelligence impact as time and development in the domains of AI have progressed. Artificial intelligence (AI) enables highly developed robots to effectively comprehend human speech. Helping robots in complex strategic games, autonomous vehicles, and similar technologies all fall under the umbrella term "artificial intelligence." Knowledge representation, planning, learning, processing, and object usage are at the heart of artificial intelligence research. Statistics-based modelling and computational intelligence are only two examples of the many methods used to advance the field of artificial intelligence. Artificial intelligence (AI) has farreaching implications for a wide range of disciplines, not only computer science.

Artificial Intelligence and Education

In recent years, the education sector has attracted increased attention from AI developers because to the widespread impact of AI applications in this area. The increasing importance of using ICT in the classroom is one of the most noticeable shifts in the educational landscape. The use of AI in the classroom is on the rise, and the field is happy to have it. The Horizon research predicted a 43% growth in AI applications between 2018 and 2022. The same group's analysis forecast an even steeper rise in the use of AI systems than was previously seen. There's no denying AI's potential impact on the future of the education sector. Although many educators have welcomed AI's arrival, many still lack a basic understanding of the technology. Artificial intelligence (AI) is here to stay, and there are tools out there to help teachers use it effectively. The role of AI in classrooms is yet unclear. Artificial intelligence (AI) is a subfield of machine learning that involves programs that can recognize patterns, make predictions, learn to create new patterns, and make autonomous decisions. This means it can adapt to its surroundings and behave appropriately, something that wasn't possible in the original design of the software. This is achieved through AI's rational agents, which are in charge of producing action with a certain end in mind. The phrase "rational agent," which has been used in game theory, economics, decision theory, etc., has been used to describe an actor who knows what they want and acts accordingly to maximize their chances of success.

METHODOLOGY

Six hundred and five high school students were polled using a modified survey instrument to delve into students' understanding of AI education's most foundational concepts. The poll was modified from one created by Huang, who surveyed Chinese students in grades K-12 who had taken artificial intelligence classes. Due to contextual and cultural variations, the survey is aimed towards their K-12 equivalent in India in order to determine the competences needed to be AI literate in schools. While the poll was conducted following a successful session of experimental teaching, it should be noted that AI education has not been introduced to grades K-12 in Africa and India. The skills needed to understand relatively new areas of study, such artificial intelligence courses, were included in the hardcopy survey. Because it offers greater flexibility, this scale has been embraced because it is more likely to reflect people's objective reality. It was also emphasized that the "faculty of reason" of the participants may be effectively tapped by using a 7-point scale since it provides a more detailed explanation of the theme. Where there are no standardized metrics for measuring concepts like resources and capacities, as Mikalef and Krogstie (2020) point out, this is a common practice in large-scale empirical research contexts.

Data analysis

The average variance extracted (AVE), the composite reliability (CR), and the results of a Cronbach's alpha reliability test are shown in Tables 4.2, 4.3, 4.4, and 4.5, respectively, all of which were calculated using WarpPLS in this work. All of the factor loadings are over 0.5, indicating reliability, and the values vary from 0.63 to 0.80. All of the dependability components add up to a number that is more than or equal to 0.7. The range of values obtained is from 0.74 to 0.87. additionally, an AVE between 0.50 and 0.61, where 0.50 is the lowest and 0.61 the highest. All the numbers are over the cutoff value of 0.5. The absence of collinearity in the data is further shown by the fact that the Variance Inflation Factor (VIF) does not indicate extreme multicollinearity in the measurement. Table 4.4 displays the correlations between the latent variables and the square root of the AVEs, and Table 4.2 displays that all of the model fit and quality indicators pass the predetermined cutoffs.

RESULTS

Demographic Profile

The modified survey was used to collect information from the pupils. There were 614 students who began the survey and 605 who finished it. The fact that the survey was presented after the lesson allowed for a more thorough response from students. As can be seen in Table 4.1, the final data set includes answers from students of varying ages and academic levels. There are somewhat more women than men involved (50.2 vs. 49.8%). There is a roughly equal number of male and female participants in the research.

Table 1 Sample characteristics.

Factors	Sample (N = 605)	Proportion (%)
Gender		
Female	307	50.2
Male	298	49.8
Age		
10–15	244	40
16–20	352	58
20 and above	9	1
Grade		
Grade 9	8	1
Grade 10	161	27
Grade 11	125	21
Grade 12	311	51
Group		
Science	429	71
Art	126	21
Commercial	50	8
School type		
Public	299	49
Private	306	51
School Location		
Urban	489	81
Rural	116	19
Types Mobile device owned		
Phone	334	55
Laptop	19	3
Phone and Laptop	120	20
None	132	22

Table 2 Model fit and quality indices.

No	Model fit and quality indices	Criterion	Result	Interpretation
1	Average path coefficient (APC)	P value ≤ α (5%)	P < 0.001	Acceptable
2	Average R-squared (ARS)	P value ≤ α (5%)	P < 0.001	Acceptable
3	Average adjusted Rsquared (AARS)	P value ≤ α (5%)	P < 0.001	Acceptable
4	Average block VIF (AVIF)	Acceptable if ≤ 5, ideally ≤ 3.3	1.157	Acceptable
5	Average full collinearity VIF (AFVIF)	Acceptable if ≤ 5, ideally ≤ 3.3	1.340	Acceptable
6	Tenenhaus GoF (FoF)	Small ≥ 0.1, Medium ≥ 0.25, Large ≥ 0.36	0.264	Large
7	Sympson's paradox ratio (SPR)	Acceptable if ≥ 0.7, ideally = 1	1.000	Acceptable
8	R-squared contribution ratio (RSCR)	Acceptable if ≥ 0.9, ideally = 1	1.000	Acceptable
9	Statistical suppression ratio (SSR)	Acceptable if ≥ 0.7Acceptable if ≥ 0.7	1.000	Acceptable
10	NLBCDR	Acceptable if ≥ 0.7	1.000	Acceptable

General Structural Model

The coefficients and variation of the routes in the overall structural model are shown in Table 4.5. Overall, cognitive ability is the best predictor of collaborative success, whereas expertise with human collaboration tools has the greatest bearing on AI knowledge. Each hypothesis is confirmed. In this research, we employed the WarpPLS program to put our partial least square (PLS) route modeling theories to the test. Research models with many components and numerous elements may be more easily analyzed using a structural equation modelling (SEM) strategy. Figure 4.1 displays the hypothesis tests using route coefficients and variance descriptions. As can be seen in Figure 4.1, a high level of teamwork competence predicts a low level of skill competence and a high level of self-learning competence and a high level of self-learning competence. HTC SLC = 0.30 and t = 7.53 show a positive correlation between human competence with collaboration tools and self-learning competence, whereas HTC Content = 0.29 and t = 7.28 show a positive correlation between human competence with collaboration tools and the contents of AI. Cognitive ability and AI content were shown to have a strong relationship. In this model, individual intelligence is seen as the most important factor in determining a group's success. Not only that, but the R2 for Skill Competence was 6%, the R2 for Team Competence was 10%, the R2 for AI Contents was 13%, and the R2 for Learning Competence was 21%. All the observed discrepancies between the model and reality are statistically insignificant.

Table 3 Consistent weight distribution and sturdy construction.

Items	TWC	CAI	SKC	CC	SLC	HTC	*f*	CR	AVE
TWC							0.096	0.821	0.61
TW1	0.805								
TW2	0.757								
TW4	0.77								
CAI							0.032	0.746	0.50
CAI1		0.639							
CAI4		0.736							
CAI5		0.732							
SKC							0.059	0.798	0.57
SKC1			0.806						
SKC2			0.772						
SKC4			0.682						
CC							0.094	0.820	0.60
CC1				0.767					
CC2				0.795					
CC3				0.769					
SLC							0.116	0.870	0.57
SLC1					0.732				
SLC2					0.783				
SLC3					0.809				
SLC4					0.695				
SLC5					0.759				
HTC							0.096	0.820	0.53
HTC1						0.706			
HTC2						0.718			
HTC3						0.791			
HTC4						0.701			

Table 4 Connections between AVEs and latent variables

	TWC	CAI	SKC	CC	SLC	HTC
TWC	0.778					
CAI	0.239	0.704				
SKC	0.432	0.294	0.755			
CC	0.31	0.241	0.243	0.777		
SLC	0.369	0.298	0.361	0.366	0.757	
HTC	0.355	0.336	0.344	0.368	0.391	0.73

Table 5 Coefficients of paths in a generic model standardised.

Hypotheses	Path Links	β	T Ratio	P-value	Result
H1	CC → TWC	0.31	7.90	<0.001	Significant
H2	CC → SKC	0.24	6.15	<0.001	Significant
H3	CC → SLC	0.26	6.49	<0.001	Significant
H4	HTC → SLC	0.30	7.53	<0.001	Significant
H5	HTC → CAI	0.29	7.28	<0.001	Significant
H6	CC → CAI	0.14	3.37	<0.001	Significant

Multigroups Model Evaluation By Sex And Education Type

To verify the variations in core abilities needed to acquire AI in an African environment across gender and school type, we conducted a multigroup study using WarpPLS Bootstrapping. In this research, the multigroup path coefficient shows that men and women see the world differently. Male students are more likely to believe that cognitive and teamwork skills impact AI literacy, whereas female students are more likely to believe that cognitive and skill competences are necessary to acquire AI. Both the beta coefficient for human collaboration tools competence and the measures of cognitive competence and self-learning competence show that women do better than males. Women have a higher association with AI content than men do when it comes to human collaboration tool competence. Men have a stronger correlation with AI subject knowledge than women do (β= 0.09/ β= 0.17). All the ways matter regardless of a person's sex, except for the cognitive skill element of AI for women. Women's intelligence does not indicate their ability to understand material presented in AI classes.

According to this method of categorizing educational institutions, students at private schools are more likely to believe that their level of cognitive and teamwork competence has an effect on their AI literacy than students at public schools, while students at public schools are more likely to believe that they need cognitive and self-learning competences in order to learn AI. Except for the cognitive competency components of AI in private schools, all the other routes are relevant. Students at for-profit educational institutions do not demonstrate a correlation between IQ and AI course topic comprehension. This analysis compared male and female students as well as those attending public and private schools to see whether there are any differences in the suggested model. Overall, both sexes, both private and public schools, and all structural model routes are statistically significant. Two-tailed hypothesis testing revealed that the transition from CC to CAI was statistically significant only among males and in public school settings. Females and private schools both had t-test values below the threshold of 1.96, at 1.65 and 1.75 respectively.

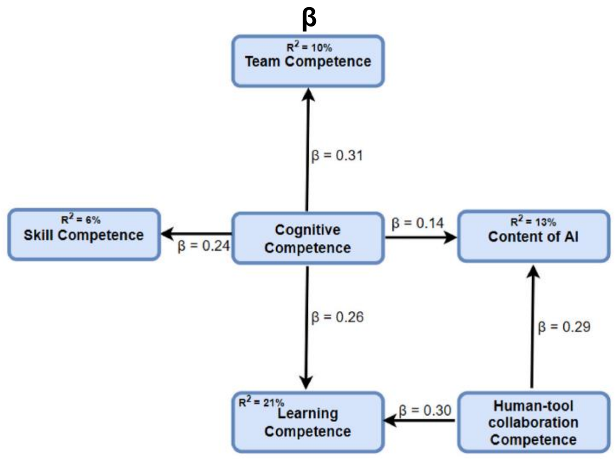

Fig. 1 Tested hypotheses result.

Table 6 Multigroup path coefficients by gender and school type, with associated null and alternative hypotheses

Path	Male	Female	Private	Public	Different
CC → TWC	6.29***	4.98***	6.93***	4.57***	YES
CC → SKC	3.77***	4.75***	5.92***	2.97**	YES
CC → SLC	6.00***	3.53***	4.27***	5.12***	YES
HTC → SLC	4.84***	5.84***	4.96***	5.79***	YES
HTC → CAI	2.84**	6.45***	5.16***	5.12***	YES
CC → CAI	2.99**	1.65	1.75	2.95**	YES

CONCLUSION

This research adds to the body of knowledge by emphasizing the significance of students' prior knowledge and skills in the classroom, particularly as they relate to AI instruction. Since competency goes beyond cognitive characteristics and includes skills and interpersonal traits that are suited to the environment, it is important to investigate the function of learners' competencies in order to successfully design materials that will engage them. This article highlights the value of cooperation and the necessity of human-tool collaboration in AI education. This discovery highlights the value of student collaboration in keeping up with the rapid speed of technological change. There are no discernible disparities between sexes or between different types of schools, as shown by the multigroup study. Gender disparities in AI learning have only been the subject of a small number of research thus far. This research contributes to the existing body of knowledge on the gender and schooling-related disparities in AI learning. There are, of course, certain caveats to this work that should not be overlooked despite the fact that the findings of this research shed some light on the link between several essential competences for comprehending the content of AI and AI literacy. To begin, A limited number of pupils from five separate Indian secondary schools make up our sample. It is possible that the conclusion drawn from the research isn't universally shared by students from other schools or locations. Instead of doing research in a single nation or setting, comparative research is required so that relevant contextual patterns may be derived. This is because contexts vary depending on several factors, including setting and peculiarities. More schools and kids from other parts of the nation and Africa should be included in future research. Furthermore, future research might verify the results of this study by, for instance, implementing activities that encourage students to work together to improve their AI literacy via cooperation. Second, it's possible that we won't get a full picture of the kids' essential AI-learning skills because of the quantitative method. Finally, the length of the class time is cited as a drawback of the research. It would have been ideal if the AI content introduction had been implemented throughout the course of an academic semester or session.

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