Research Paper

The impact of ai-suggested content and resources on student curiosity and explorative learning

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ABSTRACT

As educational landscapes evolve, the potential of AI to fuel curiosity and explorative learning among students has sparked growing interest. This study explores how AI-suggested content, student motivation, and Complexity of AI-suggested content drive curiosity and proactive learning behaviours in students. Through exploratory and confirmatory analysis using SPSS and AMOS, it is revealed that AI-suggested content and resources (ACR) and student motivation level (SML) significantly elevate curiosity and engagement. In contrast, certain combinations, such as high content resources and Complexity of AI-suggested content, may unexpectedly hinder exploration. Notably, demographic factors like age, gender, and education showed no significant impact, underscoring the universal potential of AI in personalised learning. These findings highlight the value of tailoring AI resources and fostering motivation to cultivate curiosity, offering a roadmap for educators and developers aiming to unlock the full potential of AI in education.

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1. INTRODUCTION

The advent of artificial intelligence (AI) in educational contexts has the potential to significantly reshape how students interact with learning materials and resources. Specifically, the impact of AI-suggested content on student curiosity and explorative learning is increasingly being recognized as a critical area of study [1]. By leveraging data analytics and machine learning algorithms, AI systems can curate personalized content tailored to each student's interests, which enhances engagement and motivation [2], [3].

Research indicates that personalized learning pathways created by AI can foster a sense of ownership among students, encouraging them to explore topics in greater depth [4]. This approach aligns with constructivist theories that emphasize the active role of learners in their educational journeys, suggesting that when students are provided with resources that resonate with their curiosities, they are more likely to engage in self-directed exploration [5]. Moreover, AI can provide timely feedback, helping students navigate complex concepts [6] and enhance their understanding [7]. While the benefits of AI-suggested content are evident, concerns about over-reliance on technology and its ethical implications have emerged. For instance, students have expressed mixed feelings about AI, indicating both reliance on it for support and concerns regarding academic integrity [8].

Therefore, it is essential to examine how AI recommendations influence not only the depth of learning but also the ethical considerations surrounding student engagement. As AI technologies evolve, empirical research will play a crucial role in understanding their impact on educational outcomes. Investigating how AI influences student curiosity and promotes explorative learning will provide valuable insights into optimizing these tools for educational success [9]. This study aims to critically explore these dynamics, focusing on the potential of AI to inspire a more engaging and explorative learning environment.

Research Objectives

- Examine the effects of AI-suggested content on Student Curiosity: Investigate how personalized AI-generated content influences students' levels of curiosity and interest in various subjects, and identify specific content characteristics that stimulate exploratory behaviours.
- Assess the impact of AI on Explorative Learning Strategies: Analyse the extent to which AI interventions facilitate self-directed and explorative learning strategies among students and evaluate the differences in learning outcomes between AI-assisted and traditional learning environments.
- Evaluate student perceptions of AI Tools: Explore students' attitudes and perceptions toward AI-suggested content in their learning processes, focusing on their views regarding the benefits and ethical implications of using AI in education.

2. RELATED WORK

The integration of artificial intelligence (AI) in education has generated significant scholarly interest, particularly concerning its role in fostering student curiosity and explorative learning. A growing body of research emphasizes the importance of personalized learning experiences enabled by AI, which cater for individual student interests and learning styles, enhancing engagement and motivation [7]. AI systems use advanced algorithms to analyse student data and deliver customized content recommendations that align with their unique interests. This personalized approach not only improves student engagement but also encourages self-directed exploration [10].

When students receive content tailored to their preferences, they are more likely to delve into subjects deeply, fostering a culture of inquiry and critical thinking. This aligns with constructivist learning theories, which assert that students learn best when they actively engage with material that resonates with their existing knowledge and interests [11], [8]. Moreover, the implementation of AI-driven educational tools has been linked to significant improvements in students' intrinsic motivation and academic performance.

Research shows that AI can create adaptive learning environments where students can navigate complex topics at their own pace, receiving real-time feedback that promotes deeper understanding [12], [13]. This real-time feedback is critical, as it allows students to engage with materials more interactively and meaningfully, thereby enhancing their exploratory behaviours [6]. Despite the promising aspects of AI in education, concerns regarding ethical implications and over-reliance on technology persist. Students have voiced apprehensions about academic integrity and the potential for AI to diminish their critical thinking skills [8]. These concerns underscore the necessity for a balanced approach to implementing AI technologies in educational settings, ensuring that while students benefit from AI suggestions, they also cultivate essential analytical and problem-solving skills. The potential of AI to enhance student curiosity and explorative learning presents an exciting avenue for future research. Understanding the intricate dynamics between AI-suggested content and student engagement will not only contribute to improving educational outcomes but also shape pedagogical practices in the digital age [9]. As such, empirical investigations into the effectiveness of these AI interventions are essential for guiding educators and policymakers in the responsible adoption of AI technologies.

2.1 Effect of AI-Suggested Content and Resources on Student Curiosity and Exploration Learning

The integration of AI-suggested content and resources has shown significant promise in enhancing student curiosity and promoting exploration-based learning. Recent studies suggest that AI-driven tools such as ChatGPT and other generative AI models can positively impact students' educational experiences by fostering engagement and encouraging independent inquiry. These technologies offer personalized recommendations, support exploratory learning paths, and provide real-time feedback, all of which are essential in cultivating curiosity and deepening understanding [14], [15].

AI's capability to tailor learning experiences based on individual student needs aligns well with contemporary educational models emphasizing student-centred learning. AI systems can assess each student's learning preferences, pace, and previous knowledge to suggest relevant content, which can drive students to explore topics beyond the basic curriculum. This personalization increases perceived value and enhances students' intrinsic motivation to learn, as found in studies on the perceived usefulness and ease of use of AI in educational settings, [15].

Moreover, the Technology Acceptance Model (TAM) has been instrumental in examining students' attitudes toward AI-based learning tools. TAM studies highlight that students are more likely to engage with AI-suggested content when they perceive it as both easy to use and valuable, which ultimately strengthens their curiosity and willingness to explore new content areas. This model helps clarify how perceived ease of use and utility drive students' acceptance and usage of AI tools, creating a supportive environment for exploratory learning [16]. Given these findings, AI literacy emerges as a crucial factor in maximizing the benefits of AI in education.

Students with higher levels of AI literacy are better equipped to utilize AI tools effectively, perceive their usefulness, and thus engage more fully in exploration learning. This reinforces the importance of incorporating AI literacy into educational curricula to foster an environment where AI-suggested content can thrive [15]. In summary, AI-suggested content and resources have the potential to significantly enhance student curiosity and exploration in learning. By providing personalized, relevant, and accessible information, these tools encourage students to pursue self-directed learning. Future research could further explore how different AI technologies might cater to diverse learning styles and subject areas.
This is therefore hypothesized that

2.2 Hypothesis 1

AI-suggested content and resources have a positive effect on Student Curiosity and Exploration Learning.

2.3 Moderating Role of Complexity of AI-Suggested Content and Student Motivation Level

The role of AI-suggested content in educational settings has garnered significant attention in recent research, particularly concerning how content complexity and student motivation impact student curiosity and exploratory learning. The moderating role of these factors the complexity of AI-suggested content and student motivation level affects students' engagement and learning outcomes by influencing how they interact with AI-generated recommendations.

Complexity of AI-Suggested Content

Research shows that the complexity of AI-suggested content can either enhance or hinder student curiosity and exploration. Content that is appropriately challenging fosters curiosity and encourages students to engage in deeper learning activities, whereas overly complex content can lead to frustration and disengagement [16]. Complexity, in this context, refers not only to the cognitive load required to process the material but also to the alignment with students' prior knowledge and skill level [16].

If AI algorithms can balance content difficulty to meet each student's learning capacity, they are more likely to inspire curiosity and sustained engagement [15]. AI-driven systems often utilize adaptive algorithms that adjust content complexity based on continuous assessment of students' progress and responses. Studies emphasize that when content complexity aligns well with students' existing knowledge, it significantly boosts motivation and engagement, leading to a more positive exploration learning experience [4]. However, AI must accurately gauge and adjust content complexity to optimize the learning curve and prevent cognitive overload or boredom.

Student Motivation Level

Student motivation plays a crucial role in determining how effectively they utilize AI-suggested content. Motivation influences a student's willingness to engage with challenging content and persist in exploring new knowledge areas. Intrinsically motivated students, for example, are more likely to benefit from AI-suggested content, even when it is moderately complex, because they tend to seek knowledge for personal satisfaction and curiosity [4]. This intrinsic motivation fuels exploration and encourages students to go beyond merely accepting AI suggestions, instead actively questioning and experimenting with the content provided [17].

On the other hand, students with lower motivation levels may require simpler, more structured AI-suggested content to initially spark their curiosity and gradually increase their motivation. AI-suggested resources tailored to motivation levels could guide students from low to high engagement by gradually building confidence and curiosity through content that is increasingly complex [18], [19]. The interplay between motivation and content complexity can help foster a self-reinforcing loop of curiosity and exploration, making students more open to challenging content over time.

The Interaction of Complexity and Motivation on Curiosity and Exploration Learning

The relationship between content complexity, student motivation, and learning outcomes is complex, with each factor interacting to influence curiosity and exploration. High complexity in AI-suggested content can amplify the curiosity of motivated students by presenting them with stimulating challenges [16]. For less motivated students, however, high complexity may act as a deterrent, reducing engagement and limiting exploration opportunities [4].

Tailoring AI content to student motivation levels while carefully adjusting complexity ensures that content remains both challenging and attainable, fostering an optimal learning environment for curiosity and exploration [20], [17]. In summary, the moderating roles of content complexity and student motivation significantly impact the effectiveness of AI-suggested resources in promoting curiosity and exploration learning. By calibrating content difficulty based on real-time assessments of student motivation, AI-driven learning platforms can better support individual learning needs and encourage sustained, curiosity-driven exploration. Figure 1 below represents the conceptual framework of the study.

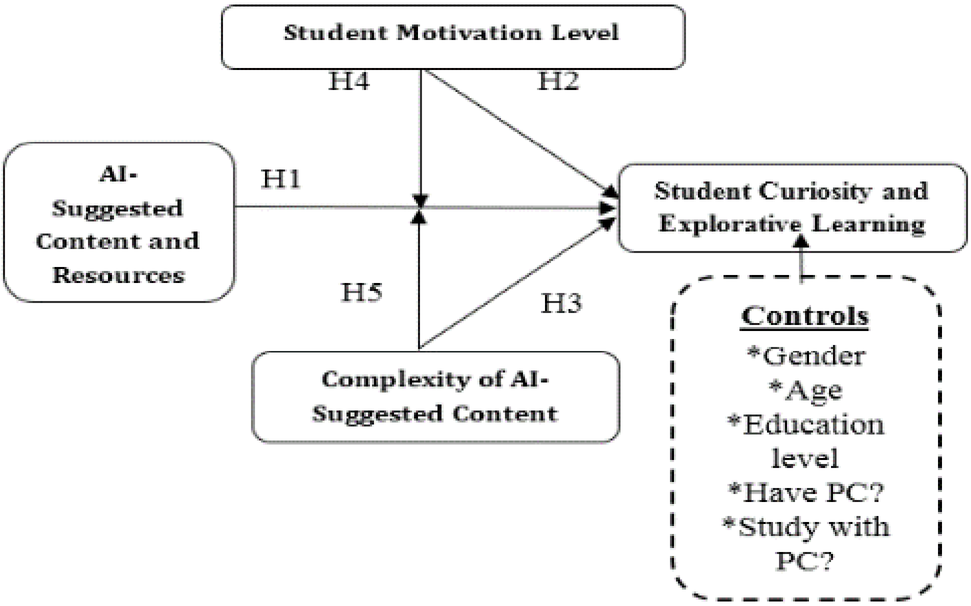

Figure 1. Conceptual Framework

Based on the conceptual framework of the impact of AI-suggested content and Resources, Student Motivation level and Complexity of AI-suggested content on Student Curiosity and Explorative Learning, the following hypotheses have been proposed:

1. H1: AI-suggested content and Resources positively influence Student Curiosity and Exploration Learning.
2. H2: Student Motivation level positively influences Student curiosity and explorative learning.
3. H3: Complexity of AI-suggested Content positively influences Student curiosity and explorative learning.
4. H4: Student Motivation level moderates the relationship between AI-suggested content and Resources and Student curiosity and explorative learning.
5. H5: The complexity of AI-suggested content significantly affects the relationship between AI-suggested content and Resources and Student curiosity and explorative learning.

3. METHODOLOGY

3.1. Research Design

The study aims to examine how AI-suggested content and resources influence students' curiosity and their engagement in explorative learning activities.

Specifically, students from different levels of education are recruited randomly to fill out a questionnaire independently.

3.2 Sampling Size and Sampling Procedure

To account for potential attrition and to ensure robustness in data analysis, a sample of 279 students was targeted, with equal random assignment to the experimental (AI-suggested content) and control (traditional content) groups.

This sample size is expected to provide adequate statistical power for detecting significant differences between groups and examining the impact of AI-suggested content on student curiosity and explorative learning.

3.3. Measures / Measurement Constructs

A carefully structured questionnaire was created to collect data, emphasizing appropriate language and the proper sequence of questions. Following this, the questionnaire was tested with a small group of participants to gather feedback and make further improvements before distributing it online for data collection.

All items were assessed using a five-point Likert scale, enabling participants to express the intensity of their viewpoint on a scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5), with "Disagree" (2), "Indifferent" (3), and "Agree" (4) as middle options. The questionnaire had five sections. Section a collected demographic information about respondents.

Section B had measurement items of AI-suggested content and Resources. Section C presented items under the Student Motivation Level. Section D represented the Complexity of AI-Suggested Content. Section E presented items on Student Curiosity and Explorative Learning. The demographic data for this study is represented in detail in Table 1.

Table 1. Respondents' Demographics

Profile of respondents	Frequencies (N)	%
Gender:	279	100
Male	232	83.2
Female	47	16.8
Age (Years):	279	100
15 – 19	179	64.2
20 – 29	86	30.8
30 – 40	4	1.4
Above 40	10	3.6
Level of Education:	279	100
Basic (JHS)	187	67.0
Secondary (SHS)	10	3.6
BSc	76	27.2
Masters	6	2.2
Do you have a Computer at Home?		
Yes	231	82.8
No	48	17.2
Do you study with the computer?		
Yes	235	84.2
No	44	15.8

3.4. Exploratory Factor Analysis

An Exploratory Factor Analysis (EFA) was conducted to examine the underlying factor structure of four key constructs in the study: AI-Suggested Content and Resources (ACI), Student Motivation Level (SML), Complexity of AI-Suggested Content (CAC), and Student Curiosity and Explorative Learning (SCEL). These constructs are critical in today's educational landscape, particularly as blended and technology-enhanced learning environments become more prevalent. The EFA was performed using Principal Component Analysis (PCA) with Varimax rotation to maximize the interpretability of the results.

The findings indicated that all communalities exceeded 0.50. As part of the analysis, it was essential to assess the overall significance of the correlation matrix using Bartlett's Test of Sphericity. This test provides valuable insights into the likelihood that the correlation matrix reveals meaningful correlations among its components. The results were significant, χ^2 (n = 279) = 9311.524 ($p < 0.001$), confirming the matrix's suitability for factor analysis [21].

The Kaiser-Meyer-Olkin measure of sampling adequacy (MSA) was 0.957 with p-value <0.001, signifying that the data is highly appropriate for factor analysis.

The analysis aimed to identify how different items group together to form components that reflect the major constructs within the educational framework. The factor loading of each item is presented in Table 2.

Table 2 . Exploratory Factor Analysis (Efa)

Measurement Items	Components			
AI-Suggested Content and Resources	1	2	3	4
ACR1	.826			
ACR2	.848			
ACR3	.831			
ACR4	.812			
ACR5	.818			
ACR6	.826			
ACR7	.807			
Student Motivation Level				
SML1	.829			
SML2	.818			
SML3	.813			
SML4	.836			
SML5	.853			
SML6	.791			
SML7	.776			
Complexity of AI-Suggested Content				
CAC1		.923		
CAC2		.918		
CAC3		.929		
CAC4		.917		
CAC5		.900		
CAC6		.847		
CAC7		.927		
Student Curiosity and Explorative Learning				
SCEL1			.609	
SCEL2			.669	
SCEL3			.670	
SCEL4			.667	
SCEL5			.699	
SCEL6			.706	
SCEL7			.672	
Total Variance Explained				78.538%
Kaiser-Meyer-Olkin Measure of Sampling Adequacy				.957
Bartlett's Test of Sphericity		Approx. Chi-Square		9311.534
			df	378
			Sig.	.000
a. Determinant				7.967E-16

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 4 iterations.

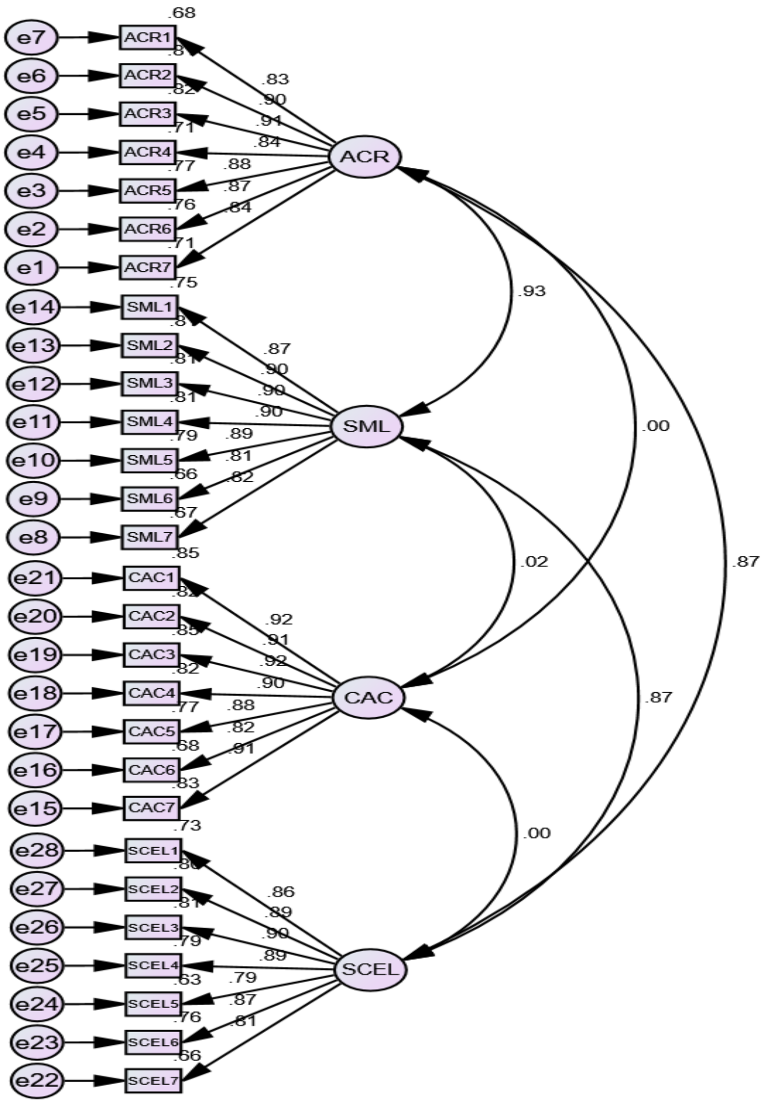

Figure 2. Exploratory Factor Analysis

Figure 2, the Exploratory Factor Analysis (EFA) identifies four latent constructs ACR, SML, CAC, and SCEL each measured by multiple observed variables. The factor loadings for all items exceed the acceptable threshold, indicating strong construct validity.

The convergent validity of the scale items was assessed using Average Variance Extracted (AVE). The AVE values for AI-Suggested Content and Resources (ACI), Student Motivation Level (SML), Complexity of AI-Suggested Content (CAC), and Student Curiosity and Explorative Learning (SCEL) exceeded the recommended threshold of 0.50. Although the AVE for Student Curiosity and Explorative Learning (SCEL) was close to this threshold. On a positive note, Construct Reliability for each item was greater than the 0.7 benchmark, demonstrating that the scales utilized in this study are indeed reliable. (Refer to Table 3).

Table 3. Construct Reliability

Constructs	No. of Items	AVE	Construct Reliability

ACR	7	0.679	0.937
SML	7	0.667	0.933
CAC	7	0.826	0.971
SCEL	7	0.450	0.851

4. RESULTS AND DISCUSSION

4.1 Confirmatory Factor Analysis

In this study, confirmatory analysis was rigorously tested on predefined hypotheses about the impact of AI-suggested content on student curiosity and explorative learning. Confirmatory analysis, as defined by Jöreskog [22], enables researchers to examine specific, theory-driven predictions with structured statistical tests. Using this approach, we aim to validate hypotheses grounded in established theories of educational AI and self-directed learning [23]. This confirmatory approach allows for a structured evaluation of AI's role in promoting curiosity and engagement, enhancing the study's rigour and contributing to a deeper understanding of AI in educational contexts.

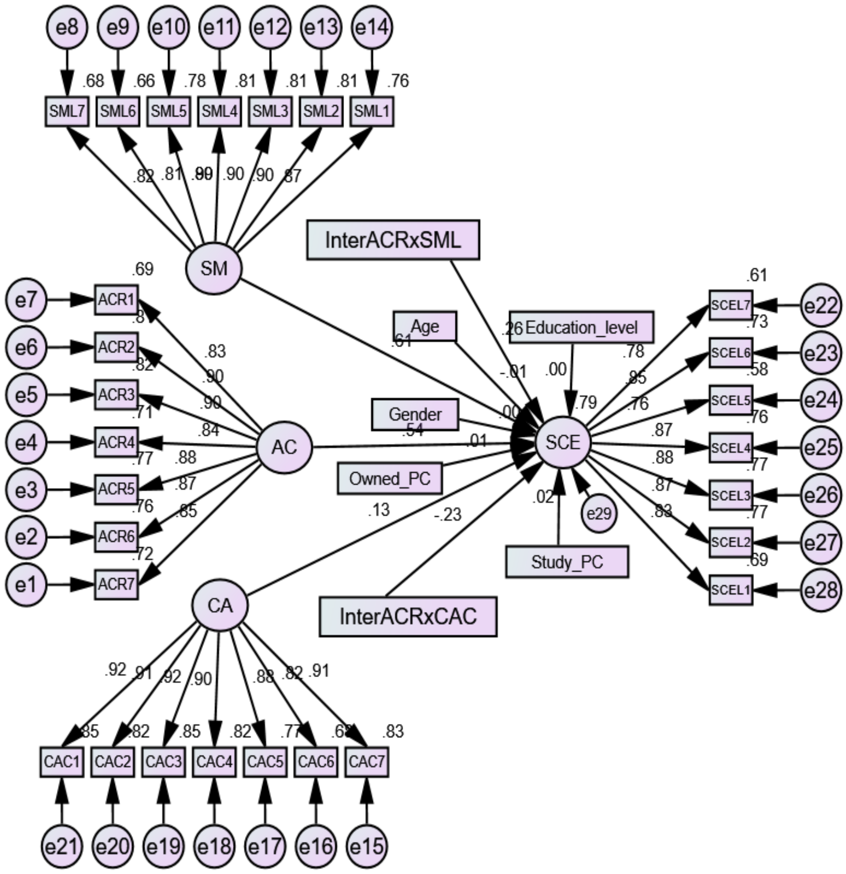

Figure 3. Structural Equation Model

Figure 3 presents the Structural Equation Model (SEM) showing the relationships between various constructs, including AI-suggested content (AC), student motivation level (SM), complexity of AI-suggested content (CA), and student curiosity and explorative learning (SCE). The model illustrates significant path coefficients, with ACR (AI-suggested content) and SML (Student Motivation Level) showing positive influences on SCE (Student Curiosity and Exploration). Interaction effects, such as InterACRxSML and InterACRxCAC, highlight the combined impact of AI-suggested content with motivation and content complexity on exploratory learning outcomes. Demographic factors like age, gender, and education show minimal effects on SCE.

Table 4. Path Coefficients

Paths	Unstd. Estimates	S. E.	C. R.
Gender → SCEL	-.001	.084	-.012
Age → SCEL	-.12	.043	-.279
Educ → SCEL	-.006	.053	-.122
OwnedPC → SCEL	.025	.097	.257
StudyPC → SCEL	.035	.095	.371
ACR → SCEL	.433	.065	6.656
SML → SCEL	.526	.076	*6.878*
CAC → SCEL	.073	.026	2.826
InterACRxSML → SCEL	.137	.028	4.853
InterACRxCAC → SCEL	-.117	.022	-5.326

Table 4 presents the path analysis results showing the influence of demographic factors and key variables on SCEL. While variables like gender, age, education, and computer ownership show negligible or insignificant effects (C.R. values close to zero), ACR, SML, and CAC have strong positive impacts on SCEL, with interaction terms (InterACRxSML and InterACRxCAC) also showing significant effects.

Discussion

A regression analysis was conducted in this study to determine relationships between various demographics, computer access, and interaction of variables on the dependent variable Student Curiosity and Explorative Learning (SCEL). The positive estimates for ACR (.433) and SML (.526) indicate a positive association with SCEL. This suggests that as the values of ACR and SML increase, SCEL outcomes also tend to improve. Conversely, the interaction of ACR and CAC has a negative unstandardized estimate (-.117), signifying an inverse relationship, where an increase in ACR in combination with CAC decreases SCEL. The Critical Ratio (C.R.) values measure the strength of the association in terms of standard deviations, where values greater than approximately ±1.96 indicate statistical significance at the 5% level. Based on this, ACR (6.656), SML (6.878), CAC (2.826), InterACRxSML (4.853), and InterACRxCAC (-5.326) have significant C.R. values, highlighting that their effects on SCEL are statistically meaningful. This implies that ACR and SML are strong positive predictors of SCEL, while CAC has a moderate positive effect. The positive interaction term InterACRxSML signifies that ACR in conjunction with SML enhances SCEL. However, the interaction between ACR and CAC negatively impacts SCEL, as indicated by InterACRxCAC. Notably, demographic factors such as Gender, Age, Education, Owned PC, and Study with PC show no statistically significant impact on SCEL, as evidenced by their low C.R. values. This suggests that these variables do not meaningfully influence SCEL in the context of this model.

5. CONCLUSION

This study demonstrates that AI-Suggested Content Resources (ACR) and Student Motivation Level (SML) are significant positive predictors of Student Curiosity and Explorative Learning (SCEL), highlighting the roles of relevant AI content and student motivation in enhancing curiosity-driven learning. While the Complexity of AI-Suggested Content (CAC) has a moderate positive effect on SCEL, the interaction between ACR and SML further boosts SCEL outcomes. Conversely, the combination of ACR and CAC negatively impacts SCEL, suggesting potential content overload or engagement challenges. Demographic factors such as age, gender, education, and computer ownership were not significant, indicating they do not meaningfully influence SCEL in this context. These findings suggest that prioritizing content relevance and fostering motivation are key to enhancing explorative learning and offering valuable insights for AI-driven educational strategies.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Michael Gyan Darling	✓	✓		✓	✓	✓		✓	✓	✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request. All responses were anonymized to protect the identity of the participants and ensure compliance with data privacy standards.

Informed Consent

Informed consent was obtained from all participants involved in this study. Prior to data collection, participants were briefed on the objectives of the study, their rights to privacy, and the voluntary nature of their involvement. They were assured that their responses would remain confidential and used strictly for academic purposes.

Ethical Approval

This study was conducted in accordance with the ethical standards of research involving human participants. Ethical approval was obtained from the institutional review board (IRB) of the Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development (AAMUSTED), Kumasi – Ghana. All protocols involving human subjects complied with institutional and national ethical guidelines.

Conflict of Interest Statement

The conduct of this study was free from any conflict of interest. The data for this study will be provided promptly upon request to the corresponding author.

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